Dynamic and Application-Aware Provisioning of Chained Virtual Security Network Functions

R. Doriguzzi-Corin\textsuperscript{α}, S. Scott-Hayward\textsuperscript{β}, D. Siracusa\textsuperscript{α}, M. Savi\textsuperscript{α}, E. Salvadori\textsuperscript{α}

\textsuperscript{α}CREATE-NET, Fondazione Bruno Kessler - Italy
\textsuperscript{β}CSIT, Queen’s University Belfast - Northern Ireland

Abstract—A promising area of application for Network Function Virtualization is in network security, where chains of Virtual Security Network Functions (VSNFs), i.e., security-specific virtual functions such as firewalls or Intrusion Prevention Systems, can be dynamically created and configured to inspect, filter or monitor the network traffic. However, the traffic handled by VSNFs could be sensitive to specific network requirements, such as minimum bandwidth or maximum end-to-end latency. Therefore, the decision on which VSNFs should apply for a given application, where to place them and how to connect them, should take such requirements into consideration. Otherwise, security services could affect quality of service experienced by customers.

In this paper, we propose PESS (Progressive Embedding of Security Services), a solution to dynamically provision security services by selecting the most appropriate combination and placement of VSNFs that cater to the needs of each application, while optimizing resource utilization. We provide PESS mathematical model and heuristic solution. Simulation results show that, compared to state-of-the-art application-agnostic models, PESS reduces computational resource utilization by up to 50\%, in different network scenarios. This result ultimately leads to a three-fold reduction in end-to-end latency of application traffic.

Index Terms—NFV, Network Service Chaining, Progressive Embedding, Application-Aware Network Security.

I. INTRODUCTION

Network security implemented by Telecommunication Service Providers (TSPs) has traditionally been based on the deployment of specialized, closed, proprietary Hardware Appliances (HAs). Such HAs are inflexible in terms of functionalities and placement in the network, which means that even slight changes in the security requirements generally necessitate manually intensive and time-consuming re-configuration tasks, the replacement of existing HAs or the deployment of additional HAs.

The Network Function Virtualization (NFV) \textsuperscript{1} initiative has been proposed as a possible solution to address the operational challenges and high costs of managing proprietary HAs. The main idea behind NFV is to transform network functions (e.g. firewalls, intrusion detection systems etc.) based on proprietary HAs, into software components (called Virtual Network Functions (VNFs)) that can be deployed and executed in virtual machines on commodity, high-performance servers. By decoupling software from hardware, this approach allows any (security) network function to be deployed in any server connected to the network through an automated and logically centralized management system.

The centralized management system, called NFV Management and Orchestration (NFV MANO), controls the whole life-cycle of each VNF. In addition, the NFV MANO can dynamically provision complex network services in the form of sequences (often called chains) of VNFs. Indeed, Network Service Chaining (NSC) is a technique for selecting subsets of the network traffic and forcing them to traverse various VNFs in sequence. For example, a firewall followed by an Intrusion Prevention System (IPS), then a Network Address Translation (NAT) service and so on. NSC and NFV enable flexible, dynamic service chain modifications to meet the real time network demands.

A promising area of application for NSC and NFV is in network security, where chains of Virtual Security Network Functions (VSNFs), i.e., security-specific VNFs such as a firewall or an IPS, can be dynamically created and configured to inspect, filter or monitor the network traffic. The flexibility of the NSC and NFV paradigms brings many benefits, among others: (i) highly customizable security services based on needs of the end-users, (ii) fast reaction to new security threats or variations of known attacks, and (iii) low Operating Expenditure (OpEx) and Capital Expenditure (CapEx) for the operator. On the other hand, compared to specialized HAs, VSNFs may have a significant impact on the performance of the network and on the Quality of Service (QoS) level experienced by the users. The virtualization overhead, the utilization level of the servers and the techniques adopted to implement the VSNFs are the most significant contributors to the QoS degradation.

We argue that, for a wide adoption of NSC and NFV technologies in network security, the provisioning strategies should take into account not only the security requirements, but also specific QoS needs of applications (a list of common classes of applications is provided in Table \textsuperscript{1} with their corresponding security and QoS requirements). Omitting the latter may lead, for instance, to a model that blindly forces all the user traffic to traverse the whole chain of VSNFs. As a result, computationally demanding VSNFs such as IPSs may cause a noticeable performance degradation to latency-sensitive applications (e.g. online games \textsuperscript{2}) or bandwidth sensitive applications (e.g. video streaming). On the other hand, beyond the overall resource consumption and QoS requirements, the model must also take into account the specific security best practices and policies. Omitting such aspects may result in the inappropriate placement of a firewall in the middle.

\textsuperscript{1}https://www.euro NFV.org
\textsuperscript{2}https://www.netsim.org
of the network, thus allowing unauthorized traffic to reach hosts that should be protected.

In this paper, we present PESS (Progressive Embedding of Security Services), a novel approach to provision security services by composing chains of VSNFs according to the specific security and QoS needs of the user applications. PESS defines an Integer Linear Programming (ILP) formulation and a heuristic algorithm to tackle the provisioning problem in dynamic network scenarios, where the service requests are not known in advance. In contrast, advance knowledge of service requests is assumed by the majority of related works. Although the PESS formulation and implementation presented in this paper focus on security-specific services, the proposed approach is also suitable for more complex scenarios, where heterogeneous network services provided by means of generic VNFs coexist (e.g., security, video broadcasting, content caching, etc.).

To the best of our knowledge, this work is the first attempt to tackle the challenges of progressively provisioning application-aware security services onto operational infrastructures, in which the QoS performance of existing services may be compromised by adding new services.

A preliminary ILP formulation of our application-aware approach has been introduced in [6]. This work extends [6] with the following contributions:

- A mathematical formulation for the progressive provisioning of security services (the PESS ILP model). With respect to the ILP model presented in [6], this work formulates the estimation of the processing delay based on residual computing resources of the physical nodes, and it formalizes the impact on the end-to-end latency of operational services when allocating computing resources for new requests.

- A heuristic algorithm, called PESS heuristic, to obtain near-optimal solutions of the embedding problem in an acceptable time frame (in the order of a few milliseconds even in large network scenarios).

- An evaluation of the heuristic’s performance in terms of quality of the solutions (deviation from optimality) and scalability performed on real-world and randomly generated topologies.

- Comparison of the proposed application-centric approach against the baseline approach, in which security services are provided without taking into account the specific requirements of applications.

The remainder of this paper is structured as follows: Section II reviews and discusses the related work. Section III details the mathematical formulation of the ILP model, while Section IV describes the heuristic algorithm that we implemented to solve the problem. In Section V, the heuristic algorithm is evaluated on real-world and random topologies. Finally, the conclusions are provided in Section VI.

II. RELATED WORK

With the recent “softwarisation” of network resources, a plethora of research initiatives has emerged in the last few years to address the problem of the optimal placement of chained VNFs. Most of these tackle the problem by using linear programming techniques and by proposing heuristic algorithms to cope with large scale problems. In this section, we classify and review the most relevant works for our studies.

A. QoS-driven VNF Placement

QoS-driven approaches primarily focus on the QoS requirements of specific services without considering network security aspects. In this regard, the proposed mathematical models include bandwidth and latency constraints (similar to Constraints [10] and [12] presented in Section III) or define objective functions that require minimization of the total bandwidth and latency of created chains.

The ILP model in [12] considers computing and bandwidth constraints to minimize the costs related to (i) VNF deployment, (ii) energy consumption of the servers, and (iii) forwarding traffic. The end-to-end delay requirement is formulated as a penalty in the objective function. However,
the computation of the end-to-end delay only considers link propagation delays without including the processing delay introduced at each VNF. In [8], the placement problem is formulated as a Mixed Integer Quadratically Constrained Problem with respect to bandwidth, number of used nodes and latency. The processing delay at each VNF is also not considered in this work. The study in [9] proposes an ILP formulation and a heuristic algorithm for the VNF placement problem focusing on QoS parameters such as end-to-end delay and NSC availability. The ILP model formulation presented in the paper does not discuss how the processing delay introduced by the VNFs is computed. This limitation is reflected in the assumptions made for the evaluation, where the processing delay is considered independent from the VNF type/implementation and from the computing capacity of the physical node where VNFs are placed.

### B. Placement of VSNFs

In addition to the research work on QoS-driven VNF placement, there are a number of works that specifically consider the placement of VSNFs. In [10], the authors provide a model to determine the best placement of security VNFs based on the user requirements and the cost for the network operator. However, the proposed approach does not take into account the specific QoS requirements of the user’s applications. This may lead to inefficient deployments where resources are over-provisioned to cover as many application classes as possible. Of greater concern is that the proposed model could unnecessarily apply computationally demanding VSNFs (e.g., IDS, DPI) to latency-sensitive traffic (e.g., online gaming), resulting in a significant drop in the user’s quality of experience.

The method proposed in [11] is based on light-weight, protocol-specific intrusion detection VNFs. The system dynamically invokes a chain of these IDSs according to the traffic characteristics. The placement of the chains is based on a user-defined or common shortest-path algorithm such as Dijkstra, without consideration of the application QoS requirements or available network/computing resources.

In [12], the authors argue that reactive mechanisms used by cloud providers to deploy VSNFs do not ensure an optimal resource allocation. To address this, the authors propose a novel resource allocation scheme, which estimates the behaviour of the traffic load by monitoring the history of the current VSNFs, and pro-actively provisions new instances of those VSNFs as a countermeasure to any incoming resource pressure. The proposed algorithm does not tackle the problem of VSNF chaining. Instead, it focuses on the optimal placement of new instances of VSNFs, which are part of existing chains. It also assumes infinite network and computing resources.

### C. Security-driven VSNF Placement

Although the literature reviewed in Section II-B addresses the placement of VSNFs, few solutions have been proposed with a focus on the network security requirements of the VSNF placement. In [13], the authors propose a model for the placement of VSNFs by taking into account security deployment constraints. Such constraints are necessary to avoid incorrect deployment of security functions such as placing an IDS on an encrypted channel. The authors propose an ILP formulation of the problem and validate their model by measuring the execution time in four different scenarios and by comparing the model with other heuristics in terms of placement cost. However, the proposed optimization algorithm is always computed for all flows in the network. Therefore, it does not scale well. The authors mitigate the problem by partitioning the network into independent blocks. Nevertheless, the partitioning scheme is limited to fat-tree topologies. Furthermore, the end-to-end latency is not considered among the constraints of the proposed model, which limits its application space.

### III. PESS VSNF Placement Model

The PESS model (Fig. 1) is a mathematical model to progressively embed service requests, formed by one or multiple VSNF chains, onto a physical network substrate by considering the available resources and realistic constraints.

PESS takes as input a model of the physical network including the current status of computing and network resources of servers and links, a security service request and the TSP’s security policies (expressed in the form of constraints for PESS). The output of PESS is the mapping of the VSNFs onto the physical network (position of the VSNFs and one or more paths between them) and an updated model of the physical network taking into account the resources used to provision the service. The updated model is used as input for the next request.

**Physical network model.** We represent the physical network as a weighted graph \( G = (N, E) \), i.e. a graph where weights are assigned to nodes and edges.

Without loss of generality and to simplify the model, we assume that every node \( i \in N \) is a NFVI-POP (Network Function Virtualization Infrastructure Point of Presence) characterized by the computing resources \( \gamma_i \in \mathbb{N}^+ \) expressed in CPU cycles/sec. A link \( (k, l) \in E \) is a wired connection between two nodes \( k \) and \( l \in N \). It is characterized by its capacity \( \beta_{k,l} \in \mathbb{N}^+ \) and its propagation delay \( \lambda_{k,l} \in \mathbb{N}^+ \). Both are expressed as positive integer numbers representing bandwidth (bits/sec) and latency (sec).

**Regions** in a physical network are defined as subsets of nodes sharing some high-level features. Examples of regions are: (i) a set of nodes in the TSP network providing the same cloud service (e.g. multimedia caching, data storage, etc.), or (ii)
the set of egress nodes that connect the TSP network to the Internet (called border region in the rest of this paper).

**Security service request.** We model a security service request as a set of independent weighted directed graphs:

\[ \mathcal{G}_s = \{ (U^c, U^c_{pairs}) : c \in C_s \} \]

where \( C_s \) is the set of unidirectional chains composing the service request. Each graph includes nodes and arcs. Nodes \( U^c = A^c \cup V^c \) comprise user and remote applications \( A^c \), the endpoints of chain \( c \) as well as a subset of all VSNFs \( V^c \). Each arc in \( U^c_{pairs} \) delinearizes the order of traversing the VSNFs in \( V^c \) between endpoints in \( A^c \).

Each chain \( c \in C_s \) is characterized by its requirements in terms of minimum bandwidth \( \beta^c \) and maximum latency \( \lambda^c \). Each endpoint in \( A^c \) is characterized by an identifier, which specifies where the endpoint must be placed in the physical network. The user application is characterized by a remote endpoint serving the cameras and accessible over the Internet. The chain is characterized by the set of egress nodes that connect the TSP network to the Internet (called border region in the rest of this paper).

**Security service request.** We model a security service request as a set of independent weighted directed graphs:

\[ \mathcal{G}_s = \{ (U^c, U^c_{pairs}) : c \in C_s \} \]

where \( C_s \) is the set of unidirectional chains composing the service request. Each graph includes nodes and arcs. Nodes \( U^c = A^c \cup V^c \) comprise user and remote applications \( A^c \), the endpoints of chain \( c \) as well as a subset of all VSNFs \( V^c \). Each arc in \( U^c_{pairs} \) delinearizes the order of traversing the VSNFs in \( V^c \) between endpoints in \( A^c \).

Each chain \( c \in C_s \) is characterized by its requirements in terms of minimum bandwidth \( \beta^c \) and maximum latency \( \lambda^c \). Each endpoint in \( A^c \) is characterized by an identifier, which specifies where the endpoint must be placed in the physical network. The user application is characterized by the identifier of a region in the physical network (called EP2). For instance, the border region if the endpoint represents a remote gaming server located outside the physical network. The user application is characterized by the identifier of a region in the physical network (called EP2).

**Illustrative example.** An example of a security service request \( G_s \) for a CCTV system (see Table I) is represented in Fig. 2. The request in the example is composed of three chains \( c_1, c_2, \) and \( c_3 \), each one identified by the type of traffic and its direction.

![Diagram](image)

**Fig. 2.** Example of security service request for the CCTV system.

Chain \( c_1 \) is applied to the live video stream captured by the cameras and accessible over the Internet. The chain comprises a L3 firewall to ensure that the stream is only transmitted to authorized endpoints. As specified in Table I, the most relevant requirement in this case is the bandwidth (\( \beta^{c_1} \)) which depends on the frame rate, frame size and video codec of the CCTV system. In this case, a deep inspection of the video stream packets (e.g., with an IPS) would not provide any additional protection but would possibly reduce the frame rate of the video streaming, thus compromising the detection of anomalous events. On the other hand, the bi-directional control/management traffic is inspected by the IPS and the firewall included in chains \( c_2 \) and \( c_3 \). Such VSNFs protect the CCTV system from attacks such as Mirai (4) perpetrated through bots maliciously installed on Internet-connected devices, while the latency requirements \( \lambda^{c_2} \) and \( \lambda^{c_3} \) guarantee the responsiveness of the remote control of the CCTV cameras (pan, tilt, zoom, etc.).

**A. ILP formulation**

**Definitions.** Let us first define two binary variables:

- \( x_{i,u}^c = 1 \) iff node \( u \in U^c \) is mapped to \( i \in N \).
- \( y_{k,l,i,j,u,v}^c = 1 \) iff physical link \( (k,l) \in E \) belongs to the path between nodes \( i \) and \( j \) to which \( u,v \in U^c \) are mapped.

The residual capacity of a link, \( \beta'_{k,l} \), is defined as the total amount of bandwidth available on link \( (k,l) \in E \):

\[
\beta'_{k,l} = \beta_{k,l} - \sum_{c \in C_s, \ i,j \in N} \beta^c \cdot y_{k,l,i,j,u,v}^c
\]

thus, it is the nominal capacity of link \((k,l)\) minus the bandwidth required by the chains \( c \in C \) already mapped on that link.

Similarly, the residual capacity of a node is defined as its nominal CPU capacity minus the computing resources used by the VSNFs \( v \) instantiated on the node:

\[
\gamma'_i = \gamma_i - \sum_{(c \in C_s, u \in U^c)} \gamma_u^c \cdot x_{i,u}^c
\]

**Problem formulation.** Given a physical network \( G \), for each security service request \( G_s \), find a suitable mapping of all its unidirectional chains on the physical network, which minimizes the physical resources of \( G \) expended to map \( G_s \), also known as the embedding cost.

Hence, the solution of the problem is represented by a set of \( x_{i,u}^c \) and \( y_{k,l,i,j,u,v}^c \) such that the cumulative usage of physical resources for all the chains in \( G_s \) is minimized:

\[
\min \sum_{c \in C_s, \ i,j \in N} \beta^c \cdot y_{k,l,i,j,u,v}^c + \alpha \sum_{c \in C_s, u \in U^c} \gamma_u^c \cdot x_{i,u}^c
\]

Here, \( \alpha \) is a factor that can be used to tune the relative weight of the cost components (we have used \( \alpha = 1 \) for the experiments described in Section V).

\( b_{k,l} \) and \( c_i \) are the costs for allocating bandwidth and CPU:

\[
b_{k,l} = \frac{1}{\beta'_{k,l} + \delta} \quad c_i = \frac{1}{\gamma'_i + \delta}
\]

They penalize nodes and links with less residual capacity with the aim to increase the chances of accommodating...
more security service requests on the given physical network. $\delta \rightarrow 0$ is a small positive constant used to avoid dividing by zero in computing the value of the function.

B. Constraints

Routing Constraint $[4]$ ensures that each node $u \in U^c$ is mapped to exactly one physical node $i \in N$. With Constraint $[5]$, a physical link $(k, l)$ can belong to a path between two nodes $i$ and $j$ for an arc $(u, v) \in U^c_{pairs}$ of chain $c \in C_s$ only if $u$ and $v$ are mapped to these nodes. Constraint $[4]$ ensures that the path created for arc $(u, v)$ starts at exactly one edge extending from node $i$ to where VSNF (or start/endpoint) $u$ is mapped. Similarly, $[4]$ ensures the correctness and the uniqueness of the final edges in the path. Constraints $[5]-[7]$ can be easily linearized with standard techniques such as the ones presented in $[13]$. Constraint $[8]$ is the classical flow conservation constraint. That is, an outbound flow equals an inbound flow for each intermediate node $l$ (intermediate nodes cannot consume the flow). Together with Constraint $[8]$, Constraint $[9]$ prevents multiple incoming/outgoing links carrying traffic for a specific flow in the intermediate node $l$.

\[ \sum_{i \in N} x^c_{i,u} = 1 \quad \forall c \in C_s, \forall u \in U^c \]  
\[ y^c_{k,l,i,j,u,v} \leq x^c_{i,u} \cdot x^c_{j,v} \quad \forall c \in C_s, \forall i,j \in N, \forall (u,v) \in U^c_{pairs}, \forall (k,l) \in E \]  
\[ \sum_{[(i,k) \in E, i \in N]} y^c_{i,k,i,j,u,v} \cdot x^c_{i,u} \cdot x^c_{j,v} = 1 \quad \forall c \in C_s, \forall (u,v) \in U^c_{pairs} \]  
\[ \sum_{[(k,j) \in E, i \in N]} y^c_{k,j,i,j,u,v} \cdot x^c_{i,u} \cdot x^c_{j,v} = 1 \quad \forall c \in C_s, \forall (u,v) \in U^c_{pairs} \]  
\[ \sum_{k \in N} \sum_{(k,l) \in E} y^c_{k,l,i,j,u,v} \leq 1 \quad \forall c \in C_s, \forall i,j \in N, \forall l \in N, l \neq i,l \neq j, \forall (u,v) \in U^c_{pairs} \]  
\[ \pi^c + \sum_{i \in N} x^c_{i,u} \cdot \lambda^c_{i,u} + \sum_{i,j \in N, (k,l) \in E} y^c_{k,l,i,j,u,v} \cdot \lambda^c_{k,l} \leq \lambda^c \quad \forall c \in C_s \]  

$\pi^c$ is an estimation of the propagation delay between the TSP network and the remote endpoint of chain $c$, in case the endpoint is outside the TSP network. We assume that this value is independent from the TSP's network egress node. Clearly $\pi^c$ is 0 for those chains whose remote endpoint is part of the TSP network (e.g., a cloud data center managed by the TSP).

In our model, the propagation delay $\lambda^c_{k,l}$ is a fixed value (i.e., traffic-load independent) proportional to the length of the physical link $(k,l)$.

The processing delay $\lambda^c_{i,u}$ is the time spent by a packet to traverse VSNF $u$ on physical node $i$. It contributes to the overall end-to-end delay of chain $c$ only if VSNF $u$ is placed on node $i$ (i.e., $x^c_{i,u} = 1$). $\lambda^c_{i,u}$ includes the time taken by the VSNF to process the packet and the overhead of the virtualization technology (VMware, KVM, QEMU virtual machines).

| Parameters | Sets |
|------------|------|
| $N$ | Set of physical nodes |
| $E$ | Set of physical links |
| $C_s$ | Set of all unidirectional chains already embedded in the network |
| $U^c$ | Set of all unidirectional chains in the service request $y_c$ |
| $U^c_{pairs}$ | Set of unidirectional arcs in the chain $c$ |
| $V^c$ | Set of VSNFs in the chain $c$. $V^c \subseteq U^c$ |
| $R_u$ | Region of $N$ where VSNF $u$ must be placed (region constraint) |
| $M$ | Region of $N$ where no VSNFs can be placed (veto constraint) |

$e_{P1}, Ep_{P2}$ | Physical endpoints of a service request. $e_{P1} \in N, Ep_{P2} \in N$ |

$\gamma_i$ | Nominal computing resources of node $i$ (CPU cycles/sec) |
| $\gamma_i'$ | Residual computing resources of node $i$ (CPU cycles/sec) |
| $\gamma_u$ | CPU cycles required by $u$ to process one bit of a network packet (CPU cycles/bit) |
| $\gamma_u'$ | Computing resources required by node $u$ of chain $c$ (CPU cycles/sec). |
| $\beta_{k,l}$ | Nominal capacity of link $(k, l)$ (bits/sec) |
| $\beta_{k,l}'$ | Residual capacity of link $(k, l)$ (bits/sec) |
| $\beta$ | Minimum bandwidth required by chain $c$ (bits/sec) |
| $\lambda_{k,l}$ | Propagation delay: the time spent by a packet to traverse the link $(k, l)$ (sec) |
| $\lambda^c_{i,u}$ | Processing delay: the time spent by a packet to traverse VSNF $u$ of chain $c$ placed on node $i$ (sec) |
| $\lambda^c$ | Maximum latency tolerated by chain $c$ (sec) |
| $\pi^c$ | Estimated latency between the TSP network and the remote endpoint of chain $c$ (sec). $\pi^c = 0$ if the endpoint belongs to the TSP network. |
| $\sigma^c$ | Average packet size of chain $c$ (bits) |
| $b_{k,l}$ | Cost for allocating a unit of bandwidth on link $(k,l)$ |
| $c_{k,l}$ | Cost for allocating a unit of CPU on node $i$ |

**Decision variables**

- $x^c_{i,u}$: Binary variable such that $x^c_{i,u} = 1$ iff node $u \in U^c$ is mapped to $i \in N$.
- $y^c_{k,l,i,j,u,v}$: Binary variable such that $y^c_{k,l,i,j,u,v} = 1$ iff physical link $(k,l) \in E$ belongs to the path between nodes $i$ and $j$ to which $u,v \in U^c$ are mapped.
Docker containers, etc.). For simplicity, we do not model the delays due to the CPU scheduler operations implemented on the physical node [16]. Based on the observations in [17], [18], λ_u^c is modeled as a convex function of the traffic load of the chain, and its value is computed by considering the impact of other VSNFs co-located on the same physical node.

\[
\lambda_{i,u}^c = \frac{\gamma_u \cdot \sigma^c}{(\gamma_i - \gamma_u \cdot \beta^c) + \delta} = \frac{\gamma_u \cdot \sigma^c}{(\gamma_i^c - \gamma_u^c) + \delta}
\]  

(13)

In Eq. (13), γ_u \cdot \sigma^c is the average amount of CPU cycles used by VSNF u to process a packet of chain c (virtualization overhead included). The latency overhead caused by co-located VSNFs depends on the amount of computing resources of the node they use or, equivalently, on the residual computing resources of the node. γ_i^c - γ_u^c is the amount of CPU cycles/sec used by VSNF u on node i, which depends on the traffic load of the chain. δ is a small positive constant used to avoid dividing by zero in the case that u consumes all the residual computing resources of node i.

Constraint (14) ensures that the current security service g_s does not compromise the end-to-end latency of chains \( \hat{c} \in C \) in operational security services (also called operational chains) in the rest of the paper.

\[
\pi^\hat{c}_c + \sum_{i \in N, u \in \mathcal{V}^c} x_{i,u}^\hat{c} \cdot \lambda_{i,u}^c + \sum_{i,j \in N, (k,l) \in E} y_{k,l,i,j,u}^c \cdot \lambda_{k,l}^c \leq \lambda^\hat{c} \quad \forall \hat{c} \in C
\]  

(14)

In Eq. (14), \( \pi^\hat{c}_c \) and \( y \) are the values of decision variables \( x \) and \( y \) computed for previous security service requests. \( \lambda_{i,u}^c \) is the updated value of the processing delay introduced to the traffic of chain \( \hat{c} \) by VSNF \( \hat{u} \) when running on node i.

\[
\lambda_{i,\hat{u}}^c = \frac{\gamma_{\hat{u}} \cdot \sigma^c}{(\gamma_i^c - \sum_{(c \in C_s, u \in \mathcal{V}^c)} x_{i,u}^c) \cdot \gamma_u^c + \delta}
\]  

(15)

In Eq. (15), the value of \( \lambda_{i,\hat{u}}^c \) is updated by considering the computing resources consumed on node i by VSNFs of the security request \( g_s \). Approximation of Eq. (15) can be achieved by using piecewise linearization techniques and Special-Ordered Set (SOS) variables and constraints available in most commercial solvers (e.g., [20]).

**Security constraints** ensure that the TSP’s security policies are applied. Specifically, Constraint (16) forces a subset \( C^s \) of the chains in the request to share the same VSNF instance in case of stateful flow processing.

\[
x_{u,i}^{c_1} = x_{u,i}^{c_2} \quad \forall c_1, c_2 \in C^s \subset C_s, i \in N, u \in \mathcal{V}^c
\]  

(16)

Constraint (17) forces the algorithm to place the VSNF \( u \in \mathcal{V}^c \) in a specific region of the network defined as a subset of nodes \( R_u \subset N \).

\[
\sum_{u \in R_u} x_{i,u}^c = 1 \quad R_u \subset N, R_u \neq \emptyset, u \in \mathcal{V}^c
\]  

(17)

We use Constraint (17) to enforce the security close to the user by placing VSNFs on \( e p l \) (\( R_u = \{ e p l \} \)), or to protect a portion of the TSP’s network, such as the border region or a distributed data center (\( R_u \subset \mathcal{E} \)) from potentially malicious user traffic. Similarly, the *veto* Constraint (18) can be used to prevent the placement of any VSNFs on a pre-defined subset of nodes \( M \subset N \). A TSP may choose to do this to protect specific nodes (called *veto nodes*) that host sensitive data or critical functions from user traffic.

\[
\sum_{u \in M, u \in \mathcal{V}^c} x_{i,u}^c = 0 \quad \forall c \in C_s, M \subset N, M \neq \emptyset
\]  

(18)

Finally, for each chain \( c \in C_s \), the correct order of VSNFs in \( \mathcal{V}^c \) is ensured by Constraints (19), plus Constraint (17) applied to user and remote applications \( u \in \mathcal{A}^c \) with \( R_u = \{ e p l \} \) and \( R_u = \mathcal{E} \) respectively. Note that, the order can be specified per application (chain), as different applications may require the same VSNFs but in different order.

These four security constraints enable fulfillment of the security policies/practices defined by the TSP e.g. the order in which the VSNFs are executed, the position of the VSNFs in the network, and the operational mode of VSNFs (either stateful or stateless).

**IV. THE PESS HEURISTIC ALGORITHM**

The embedding problem presented in Section III has been solved using a commercial solver. However, given the complexity of the ILP model, the solver is unable to produce solutions in an acceptable time frame, as required for dynamic scenarios such as the ones under study. For this reason, we have also implemented a heuristic algorithm to find near optimal solutions in much shorter time.

The logic behind the PESS heuristic is based on assuring that Constraints (11-18) are applied in an efficient manner. In particular, the security constraint (16) ensures that a stateful VSNF specified in two or more chains in the same service request \( g_s \) is placed on the same node. However, as different chains might share more than one stateful VSNF (possibly in a different order), the correct placement of a multi-chain security service request may become a computationally expensive operation. For this reason, given a path between \( e p l \) and one of the nodes \( e p l < E P \), the heuristic places all the VSNFs specified in \( g_s \) on maximum three nodes of the path with the following strategy: (i) place each region-specific VSNF \( u \in \mathcal{V}^c \) (\( R_u \neq \emptyset \)) either on \( e p l \) or on \( E P \), depending on \( R_u \) (i.e., either \( R_u = \{ e p l \} \) or \( R_u = \mathcal{E} \)), (ii) place all the other VSNFs in \( g_s \) on the node with the highest residual capacity in the path to minimize the embedding cost (Eq. 3).

The solution is obtained by selecting the candidate path between \( e p l \) and \( E P \) where the embedding of all the chains in \( g_s \) fulfills the constraints described in Section III at the lowest cost, as computed with the objective function (Eq. 3).

**Initial solution.** The embedding process starts at line 4 in Algorithm I with a greedy approach based on the Dijkstra’s algorithm. At this stage, we compute the shortest path tree between the two endpoints \( e p l \) and \( E P \) using the residual bandwidth as link weight computed as \( b_{k,l} \cdot \beta^c \) in Eq. (3). The Dijkstra algorithm stops when all the nodes \( e p l < E P \) are marked as visited, i.e., before building the whole tree of paths. For each path between \( e p l \) and \( E P \), the algorithm places the VSNFs in the chains according to the aforementioned strategy, the order of the VSNFs as specified in the service request, the
Algorithm 1 the PESS algorithm.

Input: Physical network substrate \((G)\), security service request \((G_s)\), set of active chains in the network \((C)\).

Output: The mapping of the security service onto the physical substrate \((solution)\), None if no feasible mappings are found.

1: procedure PESS\((G, G_s, C)\)
2: \(β ← \sum_{c∈C} β_c\) \(\triangleright \) total required bandwidth
3: \(γ ← \sum_{c∈C, u∈V(c)} γ_u\) \(\triangleright \) total required CPU
4: \(P = \{p_{ep1,ep2} | ep ∈ EP2\} ← \text{DIJKSTRA}(ep1, EP2, β)\)
5: if \(P = \emptyset\) then
6: return None
7: end if
8: \(S = \{s_{ep1,ep2} | ep ∈ EP2\} ← \text{EMBED}(P, β, γ)\)
9: \(N_S ← \{i ∈ S | s ∈ S\}\) \(\triangleright \) physical nodes in the initial solutions
10: \(E ← \{i ∈ N | i ∉ N_S ∪ M, γ'_i > γ_j' \forall j ∈ N_S\}\)
11: \(δ_{(ep1,ep2)} ← \text{argmin}_{s ∈ S} \text{cost}(s)\) \(\triangleright \) best initial solution
12: \(P_1 ← \text{DIJKSTRA}(ep1, E, β)\)
13: \(P_2 ← \text{DIJKSTRA}(ep2, E, β)\)
14: \(S ← S ∪ \text{EMBED}(P_1 ∪ P_2, β, γ)\) \(\triangleright \) expanded solution set
15: solution ← None
16: \(S ← \text{SORTEDDECREASINGCOST}(S)\)
17: for all \(cs ∈ S\) do
18: if \(\text{LATECOPCHAINS}(G, C, cs)\) is True then
19: solution ← cs
20: break
21: end if
22: end for
23: if solution is None then
24: return None
25: end if
26: \(\text{UPDATERESOURCES}(solution, G)\)
27: \(\text{STORESOLUTION}(G, C, solution)\)
28: return solution
29: end procedure

The set of candidate solutions is sorted in descending order of embedding cost (line 11). The algorithm computes Eq. (14) only for the operational chains in the data structure linked to such nodes by using the values of variables \(x\) and \(y\) of solution \(cs\). If the inequality is not satisfied for one of those chains, \(cs\) is rejected.

As the maximum number of physical nodes used to provision a security service is three \((ep1\text{ and }EP2\text{ to fulfill the region constraint and the node with the highest residual capacity in the path})\), the worst-case time complexity of this process is \(O(1)\), thus constant in the number of operational chains and with respect to the size of the network. Therefore, the overall time complexity of the PESS heuristic is \(O(|E| + |N||\log(|N|))\), i.e., the worst-case time complexity of the Dijkstra’s algorithm.

V. EVALUATION

We first assess the PESS heuristic by comparing its solutions against the optimal embeddings as computed by a commercial solver (Gurobi [21]). We then prove the benefits of the proposed application-centric approach against the baseline approach, in which security services are provided without taking into account the specific requirements of applications.

The PESS heuristic has been implemented as a single-threaded Python program, while the ILP model formalized in the

chains in the network (lines 26-27).

Latency of operational chains. Given a candidate solution \(cs ∈ S\), function LATENCYOPCHAINS is invoked to verify whether embedding \(cs\) compromises the end-to-end latency of operational chains (line 18 in Algorithm 1). Instead of verifying the inequality in Eq. (14) for each operational chain, LATENCYOPCHAINS implements a heuristic approach which reduces the time complexity of this operation from \(O(n)\), with \(n\) the number of operational chains, to \(O(1)\).

Each time a chain \(c ∈ C\) becomes operational, the algorithm computes \(⟨γ⟩^c\), a threshold value obtained from Eq. (12) and (13) as follows:

\[
⟨γ⟩^c = \frac{\sum_{i∈N,u∈V(c)} x_{i,u} · γ_u · σ^c}{\lambda^c - π^c} - \delta
\]

In Eq. (19), \(x\) and \(γ\) are the values of decision variables \(x\) and \(y\) used to embed \(c\). \(⟨γ⟩^c\) estimates the minimum average residual computing capacity necessary to satisfy the inequality in Eq. (12). Therefore, the algorithm records and monitors those operational chains with the highest values of \(⟨γ⟩^c\) to establish whether the candidate solution is feasible or not, as inequality in Eq. (12) is violated earlier for such chains than for the others.

The algorithm stores one operational chain per physical node in a data structure, i.e., the chain with the highest value of \(⟨γ⟩^c\) with at least one VSNF mapped on that node. Hence, given the physical nodes mapped in the candidate solution \(cs\), the algorithm computes Eq. (14) only for the operational chains in the data structure linked to such nodes by using the values of variables \(x\) and \(y\) of solution \(cs\). If the inequality is not satisfied for one of those chains, \(cs\) is rejected.
Section III has been implemented with the Gurobi Python API version 7.5 [23]. All experiments are performed on a server-class computer equipped with 2 Intel Xeon Silver 410 CPUs (16 cores each running at 2.1 GHz) and 64 GB of RAM.

1) Topology: The simulations are performed on synthetic topologies randomly generated based on the Barabási-Albert model [23]. We generate topologies of different sizes and densities to evaluate the performance of the PESS heuristic in a variety of generic network scenarios.

We also use the model of a real network; the Italian education and research network (consortium GARR [24]) represented in [25]. In addition to the actual view of the physical topology, [25] also provides the specification of the egress nodes, i.e., the nodes that connect the GARR network to the Internet and that compose the border region in our evaluation (nodes FI1, MI2, PD2, RM2 and TO1, as indicated in [25]). [26] specifies the nominal capacity of all the links in the GARR network. We have built the network model based on this detailed information and by computing the propagation delay of each link with the following formula:

\[ \lambda_{k,l} = \frac{d_{k,l} \cdot r_{index}}{C} \]

where \( d_{k,l} \) is the distance between two nodes \( k \) and \( l \) (computed by approximating the coordinates of the nodes based on their names), \( r_{index} = 1.5 \) is an approximation of the refractive index of optical fibers and \( C \approx 300000 \text{ m/s} \) is the speed of light in the vacuum.

As we have no information related to data center distribution in the GARR network, we have assumed one NFVI-POP for each node of the network with computing capacity of 32x2.1 GHz (a 32-core CPU running at 2.1 GHz).

In the rest of the evaluation, we refer to this topology as the reference network.

2) Security service requests: As introduced in Section III, a security service request is configured by the TSP to provision of security for user’s applications (see the CCTV example in Section III). For evaluation purposes, we automatically generate requests composed of a random number of chains, ranging between 1 and 5. Specifically, each chain comprises a random subset of VSNFs from the list presented in Table III with a maximum of 3 VSNFs per chain.

The CPU requirements for the VSNFs are presented in Table III. It should be noted that the values of \( \gamma_u \) (cycle/bit) reported in Table III are estimated based on the results of experiments reported in scientific papers or product datasheets and obtained under optimal conditions, with only one VSNF running at a time. The impact on the network traffic caused by concurrent VSNFs running on the same node are estimated with Eq. (13) and (15). These values of \( \gamma_u \) have been used to perform the evaluation tests described in the remainder of this section, with the aim of enabling interested readers to replicate the experiments in similar conditions. However, we also obtained comparable results using random values.

### Table III

| VSNF                     | Virtualization | \( \gamma_u \) (cycles/bit) |
|--------------------------|----------------|---------------------------|
| Snort IDS/IPS            | VirtualBox    | 9.5 [24]                  |
| Suricata IDS/IPS         | VirtualBox    | 8.2 [24]                  |
| OpenVPN with AES-NI      | KVM/QEMU      | 31 [24]                   |
| strongSwan with AES-NI   | KVM/QEMU      | 16 [24]                   |
| Fortigate-VM NGFW        | FortiOS       | 9 [24]                    |
| Fortigate-VM SSL VPN     | FortiOS       | 13.5 [24]                 |
| Fortigate-VM IPSec VPN   | FortiOS       | 14.5 [24]                 |
| Fortigate-VM Threat protection | FortiOS | 17.1 [24]                 |
| Cisco ASAv Stateful IDS  | VMware ESX/ESXi | 4.2 [24]              |
| Cisco ASAv AES VPN       | VMware ESX/ESXi | 6.9 [24]              |
| Juniper vSRX FW          | VMware VXN613 | 2.3 [24]                  |
| Juniper vSRX IPS         | VMware VXN613 | 2.3 [24]                  |
| Juniper vSRX AppMonitor  | VMware VXN613 | 1.3 [24]                  |

\( \gamma_u = (\text{CPU clock}) \cdot (\text{CPU usage}) / \text{Throughput}. \) CPU usage is set to 1 (i.e. 100%) when the value is not specified.

### B. Comparison between solver and heuristic

#### Methodology

In this experiment, we compare the PESS ILP-based algorithm implemented with the solver and the PESS heuristic on our reference network (46 nodes and 83 links) and on Barabási-Albert random topologies with 20 nodes and 36 links.

The security service requests are generated using a Poisson process with exponential distribution of inter-arrival and holding times. Once a service expires, the resources allocated to it are released.

We start by simulating the processing of \( 10^5 \) service requests using the PESS heuristic. Once a stable network utilization (load) is reached, we save the subsequent service requests along with the network state and the heuristic solution. In a second stage, we run the solver to compute the optimal solution for each of the requests saved in the previous stage and we compare the results with the recorded heuristic solutions. This process is repeated with values of network load ranging between 1000 and 20000 Erlang.

#### Metrics

1. **Embedding cost ratio between heuristic and optimal solutions**
   - **(i) Embedding cost ratio between heuristic and optimal solutions**
   - **(ii) embedding time**

#### Discussion

As explained in Section IV, the PESS heuristic...
places all the chains of a service request on a single path to efficiently guarantee that the QoS Constraint (12) and the region Constraint (17) are respected. Once the path is found, the heuristic places the VSNFs of all the chains on a maximum of three nodes in the chosen path: the one with the highest residual computing capacity and the ones specified with the region constraint (if any). Such implementation choices reduce the solution space in case of requests with multiple chains and VSNFs. On the other hand, Constraints (12) and (17) also narrow down the solution space for the solver, often resulting in single-path optimal solutions. As a result, we measure a minimal additional embedding cost with the heuristic (in the order of $10^{-4}$ and $10^{-2}$) with respect to the optimal solutions on the two evaluation scenarios (Fig. 3(a) and 3(b)).

It is worth analyzing the reason behind the two orders of magnitude difference between randomly generated topologies and the reference network. When the initial solution is computed, the heuristic algorithm selects the endpoint $e_p2 \in EP2$ to further explore the solution space, thus excluding the other endpoints in $EP2$ (line 11 in Algorithm 1). This strategy improves the scalability of the heuristic in case of large endpoint sets $EP2$, at the cost of slightly reducing the quality of the solutions.

In this regard, on the GARR network the border region is used as endpoint $EP2$ for 80% of the requests, to simulate a real-world TSP network where most of the traffic is directed towards the Internet. Hence, good solutions involving four of the five nodes in the border are not considered during the second stage of the heuristic, possibly leading to less accurate solutions. Conversely, for the experiments with the random topologies in which no special regions are defined, $|EP2| = 1$ for all the requests, resulting in much more precise embeddings.

The running time of both heuristic algorithm and solver depends on the size of the network and on the size of the requests (number of chains and VSNFs). For the heuristic, this time is below 4 seconds on average with the reference network, as reported in Sec. V-D and below 3 seconds on average with the random topologies. On the other hand, the solver takes around 150 and 1500 seconds on average to find the optimal solutions on the random topologies and on the reference network respectively. As shown in Figure 5(b), the evaluation with the reference network is limited to service requests with less than 10 VSNFs. Above this threshold, the solver is either killed by the operating system due to an out of memory error, or it stops when the timeout threshold (set to 7200 seconds) is exceeded.

C. PESS vs application-agnostic provisioning

**Methodology.** We start two experiments in parallel using two identical copies of the same physical network graph. At each iteration, we generate a service request with application-specific QoS and security requirements. In Experiment 1, the security service is provisioned on one copy of the network with the PESS heuristic. In Experiment 2, the service is provisioned on the second copy of the network by simulating the standard approach (adopted, for instance, in [13] and used in this test as baseline), where two application-agnostic chains of VSNFs (one for each direction of the traffic) are applied to the user traffic to fulfill all the application-specific security requirements of the request. At the end of each iteration, the two copies of the network are updated according to the resources consumed by the respective provisioning approach.

As in the previous experiment, security service requests are generated using a Poisson process with exponential distribution of inter-arrival and holding times. We run $10^5$ iterations, starting to collect statistics after the first $8 \cdot 10^4$ requests (once a stable network load is reached). The two parallel experiments are repeated with different network load values.

**Metrics.** Blocking probability, consumption of computing resources, end-to-end latency of the chains and number of active services in the network.

**Discussion.** Fig. 4 compares the performance of the PESS application-aware service provisioning algorithm (PESS in the figure) and the baseline approach (Base) on random networks. The experimental results are plotted as functions of the network load, which is expressed in terms of average number of security service requests in the network (Erlang).

The efficient usage of the computing resources reported in Fig. 4(a) is a major benefit of the application-aware provisioning mechanism proposed in this work. In particular, PESS avoids inefficiencies, such as a high bandwidth video stream being processed by a high resource demanding IPS (see the CCTV example in Section III), ultimately leading to a lower blocking probability and to a higher number of active services in the network, as shown in Fig. 4(b) and 4(c) respectively.

The benefits of PESS in terms of reduced end-to-end latency are reported in Fig. 4(d). The plot illustrates the ratio between the average end-to-end latency of the chains in Experiment 2 (Baseline), and the average end-to-end latency of the chains in Experiment 1 (PESS). At low loads, when the nodes in the networks of both experiments are only partially busy, the value of this ratio is between 2 and 3. In other words, under typical operational conditions, the average end-to-end latency of chains provisioned with our approach is 2-3 times lower. Moreover, when the nodes in Experiment 2 are heavily loaded, the processing delay introduced by busy nodes becomes very high, as modeled with Eq. (12). This phenomenon produces high ratios, represented by the spike in the plot, which gradually decrease at high loads when the nodes in the network of Experiment 1 also become fully loaded.

Fig. 5 reports the results of the simulations performed with the reference network. In this case, we are particularly interested in observing the behavior of our approach in the presence of a critical region (from the security viewpoint) such as the border of the network. In order to analyse this, we empirically configure the random generator of service requests to generate 80% of requests directed towards the Internet (i.e., crossing the border of the network). In Fig. 5(b), it can be noted that both PESS and the baseline have similar blocking probability at low loads (below 6000). This is a consequence of the bandwidth usage on links towards the border region, which
is almost always identical for Experiment 1 and Experiment 2. The two curves start diverging at load 6000, i.e. when the border region runs out of computing resources with the baseline approach (as shown with dashed curves in Fig. 5(a)). The probability curves in Fig. 5(b) begin to re-converge at load 12000, when the border region with PESS also becomes full. Solid curves in Fig. 5(a) indicate that, between loads 1000 and 6000, when the blocking probability of the two experiments is comparable, PESS requires around 50% less computing resources than the baseline to provision the security services.

Similar to the random networks scenario, we can observe a higher number of active services in the network and a lower end-to-end latency. The plots are omitted due to space constraints.

D. Scalability evaluation

Methodology. We evaluate the scalability of the PESS heuristic on Barabási-Albert random topologies of between 10 and 1000 nodes. For each of these topologies, we simulate the processing of 1000 service requests and report the average execution time.

Metrics. Average execution time.

Discussion. In the first experiment (reported in the leftmost plot of Fig. 6) we used $|EP2| = 1$ for all the service requests and we varied the attachment parameter $m$, which determines the number of edges to attach from a new node to existing nodes when generating the random network. This influences the execution time of the shortest path algorithm. For instance, $m = 1$ produces tree-like topologies with $|E| = |N| - 1$. The general rule for computing the number of edges in Barabási-Albert networks is $|E| = m \cdot |N| - m^2$. As illustrated in Fig. 6 even for very large networks with 1000 nodes and 4975 edges ($m = 5$ in the figure), on average, the PESS heuristic can provision a security service in around 200 ms.

In the second experiment, we used a fixed value of $m = 5$ (the worst case in the first experiment) and we varied the size of endpoint $EP2$, as the number of nodes in $EP2$ determines how long PESS takes to compute the initial solution. In the rightmost plot in Fig. 6 the black solid curve is
reference measurement from the first experiment. As shown by the dashed curves in the plot, the average execution time increases linearly with the size of endpoint $EP_2$, up to around 250 ms in the worst case with $|N| = 1000$, $|E| = 4975$ and $|EP_2| = 500$.

As introduced in Section II and formulated in Section III the VSNFs placement model and heuristic proposed in this work target NFV-enabled models where security services are dynamically provisioned and updated based on users’ applications and their security and QoS requirements. Such systems require efficient provisioning strategies to minimize the exposure of such applications to cyber attacks. With respect to these objectives, the experimental results from the PESS scalability evaluation are encouraging and clearly indicate the potential for practical implementation of the proposed application-aware approach in real-world scenarios.

VI. CONCLUSIONS

In this paper, we have tackled the problem of the progressive provisioning of security services by means of virtual security network functions. The proposed approach, called PESS, takes into account security and QoS requirements of user applications, while ensuring that computing and network resources are accurately utilised. We have discussed the rationale behind our design decisions and presented an ILP formulation and a heuristic algorithm that solve the placement problem. Although we have focused our work on security services, the PESS approach is applicable to more complex scenarios, where heterogeneous network services provided by means of generic VNFs coexist.

The evaluation results demonstrate the benefits of PESS for both users and operators, with savings in resource utilization and in end-to-end latency. We have also shown that the heuristic implementation of the proposed application-aware approach produces near-optimal solutions and scales well in large and dense networks, indicating the potential of PESS in real-world scenarios.

REFERENCES

[1] R. Mijumbi et al., “Network Function Virtualization: State-of-the-Art and Research Challenges,” IEEE Communications Surveys Tutorials, vol. 18, no. 1, pp. 236–262, 2016.
[2] R. Hill et al., “Measuring Latency for Video Surveillance Systems,” in Proc. of DICTA, 2009.
[3] M. Claypool et al., “Latency and Player Actions in Online Games,” Comm. of the ACM, vol. 49, no. 11, Nov. 2006.
[4] Y. Chen et al., “QoS Requirements of Network Applications on the Internet,” Inf. Knowl. Syst. Manage., vol. 4, no. 1, pp. 55–76, Jan. 2004.
[5] M. Claypool et al., “Latency Can Kill: Precision and Deadline in Online Games,” in Proc. of ACM MM’04, 2010.
[6] R. Doriguzzi-Corin et al., “Application-Centric Provisioning of Virtual Security Network Functions,” in Proc. of the Third IEEE International Workshop on Security in NFV-SDN (SN-2017), 2017.
[7] F. Bari et al., “Orchestrating Virtualized Network Functions,” IEEE TNMS, vol. 13, no. 4, pp. 725–739, 2016.
[8] S. Mehraghanam et al., “Specifying and Placing Chains of Virtual Network Functions,” in Proc. of IEEE CloudNet, 2014.
[9] P. Vizarreta et al., “QoS-driven Function Placement Reducing Expenditures in NFV Deployments,” in Proc. of ICC, 2017.
[10] C. Basile et al., “Towards the Dynamic Provision of Virtualized Security Services,” Cyber Security and Privacy: 4th Cyber Security and Privacy Innovation Forum, in Proc. of IEEE NFV-SDN, Nov. 2017.
[11] G. Garr network map. [Online]. Available: https://www.garr.it/en/chi-siamo/documenti/7.5/refman/py_constraints.html
[12] Gurobi Optimizer. [Online]. Available: http://www.gurobi.com
[13] A.-L. Barabasi and R. Albert, “Emergence of Scaling in Random Networks,” Science, vol. 286, no. 5439, pp. 509–512, 1999. [Online]. Available: http://science.sciencemag.org/content/286/5439/509
[14] GARR network map. [Online]. Available: https://www.garr.it/en/infrastructures/network-infrastructure/network-map
[26] GARR backbone. [Online]. Available: https://www.garr.it/en/infrastructures/network-infrastructure/backbones

[27] S.A.R. Shah et al., “Performance comparison of intrusion detection systems and application of machine learning to Snort system,” Future Generation Computer Systems, vol. 80, no. Supplement C, pp. 157 – 170, 2018.

[28] D. Lacković et al., “Performance analysis of virtualized VPN endpoints,” in Proc. of 40th MIPRO, May 2017.

[29] FortiGate. [Online]. Available: https://www.fortinet.com/content/dam/fortinet/assets/data-sheets/FortiGate_VM.pdf

[30] Cisco. Cisco Adaptive Security Virtual Appliance (ASAv). [Online]. Available: https://www.cisco.com/c/en/us/products/collateral/security/adaptive-security-virtual-appliance-asav/datasheet-c78-733399.pdf

[31] Juniper. vSRX Virtual FW. [Online]. Available: https://www.juniper.net/assets/us/en/local/pdf/datasheets/1000489-en.pdf