Evolutionary Multi-Objective Virtual Network Function Placement: A Formal Model and Effective Algorithms

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Abstract: Data centers are critical to the commercial and social activities of modern society but are also major electricity consumers. To minimize their environmental impact, it is imperative to make data centers more energy efficient while maintaining a high quality of service (QoS). Bearing this consideration in mind, we develop an analytical model using queueing theory for evaluating the QoS of a data center. Furthermore, based on this model, we develop a domain-specific evolutionary optimization framework featuring a tailored solution representation and a constraint-aware initialization operator for finding the optimal placement of virtual network functions in a data center that optimizes multiple conflicting objectives with regard to energy consumption and QoS. In particular, our framework is applicable to any existing evolutionary multi-objective optimization algorithm in a plug-in manner. Extensive experiments validate the efficiency and accuracy of our QoS model as well as the effectiveness of our tailored algorithms for virtual network function placement problems at various scales.

Keywords: Virtual network function, queueing theory, QoS modeling, evolutionary multi-objective optimization.

1 Introduction

Recent research indicate that data centers will be responsible for 3% to 5% of total energy consumption worldwide by 2030 [1]. With the pressing need to address climate change, there are environmental as well as business imperatives to improve the efficiency of data centers wherever possible. Over the past decade, data centers have become significantly more energy efficient by reducing overhead [2] such as heat management and energy provisioning. Despite these efforts, the total energy consumed by data centers still doubled between 2010 and 2020 [3] due to increased demand, and there are diminishing returns to reducing overhead further. A recent study showed that future efficiency improvements can be made by using fewer network components and better operational policies [3]. One route to achieve this is through virtualization, i.e., the emulation of hardware with software. Physical computing devices can be virtualized into virtual machines (VMs), and several VMs can be executed on a single physical device. By placing applications on VMs and packing multiple VMs onto the same server, we can maximize the utilization of hardware and consume less energy to provide the same quality of service (QoS). In addition, VMs can be moved and scaled to meet traffic demands without over or under allocating resources. A recent study found that simply utilizing servers more effectively with virtualization would result in a 10% reduction in data center energy consumption in the USA [4]. This reduction increases to 40% if the majority of service providers move to ‘hyper-scaled’ data centers which have more powerful servers with a larger capacity.

Historically, virtualization was applied to general purpose servers that contribute some of the computing power required to provide services. More recently, purpose built network functions have also been considered as targets for virtualization. A network function is a network component that performs a specific task such as load balancing or packet inspection. Services, such as phone call handling or video streaming, usually direct traffic through several network functions in a prescribed

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order. Traditionally, these functions were provided by ‘middleboxes’ through purpose-built hardware. However, middleboxes cannot be scaled or moved like VMs thus limiting the flexibility of the data center. Virtual network functions (VNFs) provide the same functionality as middleboxes but with software running on VMs. Although each VNF instance may perform relatively worse than its equivalent middlebox, the added flexibility can improve the overall performance and reduce costs.

In a nutshell, a VNF placement problem (VNFPP) aims to find the optimal number and placement of VNFs in order to optimize the QoS (e.g., minimizing the expected latency and packet loss) of each service, balanced against the energy consumption of the data center. A VNFPP instance defines a set of services and a data center topology. Each service is defined by its packet arrival rate and a service chain, i.e., the sequence in which VNFs must be visited. A solution to the VNFPP defines where to place VNFs for each service and how packets should traverse the data center. The VNFPP has been widely recognized as a challenging combinatorial optimization problem given its NP-hardness, multiple conflicting objectives and a proportionally small feasible solution space. Whilst some of these challenges can be addressed with existing techniques, three key challenges remain for the VNFPP.

- The first one lies in the QoS evaluation itself. There exist some tools, such as discrete event simulators, that can provide accurate measurements of QoS. However, they are too time consuming to be incorporated into an optimization routine. In contrast, some heuristics, such as the number of applied VNF instances and the average utilization of servers, have been proposed as efficient surrogates for QoS. However, there is no established evidence to support the equivalence of using such heuristics versus accurate measurements of the QoS. Queueing theory has been widely recognized as a powerful tool to produce fast and accurate models of QoS for various networking problems. Although there have been some attempts to use queuing theory in the context of VNFPP, packet loss and its consequences have been ignored, limiting the accuracy of existing models.

- Second, the curse-of-dimensionality has been proven to be the Achilles’ heel of existing methods when solving VNFPPs. For example, linear programming, one of the most popular methods in the literature, is only useful for problems with tens or hundreds of servers. Meta-heuristic methods have recently shown some encouraging results on larger-scale VNFPP with up to 1,000 servers. However, none of them are close to industrial-scale scenarios.

- Last but not the least, a VNFPP usually has complex constraints that can confound optimization. For example, there are routing constraints that require the solution to visit VNFs in a prescribed order. Additional constraints arise in practice that limit the number of instances of each VNF or where they can be placed. These constraints significantly squeeze the feasible search space thus hindering an effective search.

Evolutionary algorithms (EAs) have been well recognized for solving challenging multi-objective optimization problems (MOPs), but their potential applications in the context of VNFPPs have rarely been explored. In this work, we provide a domain-specific evolutionary optimization framework to address the above longstanding problems. Our major contributions are as follows.

- By using queueing theory, we developed an analytical model that provides an efficient and accurate way to evaluate the QoS with regard to the expected latency, the packet loss of each service and the overall energy consumption of the underlying data center, all of which constitute the three-objective VNFPP in this paper.

- We developed a problem-specific solution representation for the VNFPP along with a tailored initialization operator that together promote a fast convergence and a feasibility guarantee. Both operations can be seamlessly incorporated into any evolutionary multi-objective optimization (EMO) algorithm.

- We validate the effectiveness and accuracy of the proposed algorithm under various settings. In particular, we consider problems with up to 8,192 servers, which is 8 times larger than all reported results. The performance of our tailored EMO algorithms are compared against their generic counterparts as well as state-of-the-art heuristics.
In the remainder of this paper, Section 2 provides a pragmatic overview of some selected developments on VNFPP. Section 3 gives our VNFPP definition followed by a rigorous derivation of our analytical model in Section 4. Section 5 develops the problem-specific solution representation and a tailored initialization operator along with their incorporation with EMO algorithms. The effectiveness of our proposed analytical model along with the tailored EMO algorithms are validated in Section 6. Finally, Section 7 concludes this paper and sheds some lights on future directions.

2 Related Works

This section provides a pragmatic overview of some selected developments in VNFPP according to the type of its solver, i.e., exact, heuristic and meta-heuristic methods.

2.1 Exact Methods

Exact methods are designed to produce solutions with theoretical optimality guarantees. They have an exponential worst-case time complexity [27], thus are usually limited to small-scale VNFPPs. Furthermore, exact methods typically require linear objective functions which contradicts the nonlinear nature of QoS. To resolve this issue, some researchers use a simplified model of latency where the waiting time at a switch is constant whereas in practice the waiting time depends on the switch’s utilization [13, 28, 29]. Bari et al. [17] proposed to use dynamic programming to minimize a linear model of the operational cost under a latency constraint. Likewise, [30], Miotto et al. developed a NFV optimization framework that applies linear programming to minimizing both the number of VNF instances and the length of routes also under a latency constraint.

An alternative option is to use piece-wise linearization to linearize accurate models of QoS. In an early work on VNFPP, Baumgartner et al. [31] proposed to minimize the total cost of bandwidth and VNF placement while meeting latency constraints for each service. After performing piece-wise linearization, they applied linear programming to this problem. Oljira et al. [13] used the same technique as in [31] for modeling and optimization and additionally considered the virtualization overheads when calculating the latency at each VNF. In [8], Addis et al. proposed two different models for VNFPP. One models the waiting time as a convex piece-wise linear function of the sum of arrival rates while the other sets the latency as a constant when it is below a threshold. Later, Gao et al. [10] extended this work and proposed additional constraints for affinity and anti-affinity rules that require solutions to place certain VNFs on the same server or apart respectively. In [9], Jemaa et al. proposed a VNFPP formulation where VNFs can only be placed either in a resource constrained cloudlet data center near the user or an unconstrained cloud data center. They use exact methods to optimize latency, cloudlet and cloud utilization simultaneously.

2.2 Heuristic Methods

In contrast to exact methods, heuristic methods attempt to find approximate solutions and usually use surrogate models as alternative measures of the QoS. One common surrogate model is to use the available link or server capacity as a proxy for the latency and energy consumption. Guo et al. [32] formulated a VNFPP that aims to minimize the link and server capacity of a solution and allow VNFs to be shared across services. They first pre-processed the network topology to find the most influential nodes according to the Katz centrality. Then, VNFs are placed according to a convex piece-wise linear function of the sum of arrival rates while the other sets the latency as a constant when it is below a threshold. Later, Gao et al. [10] extended this work and proposed additional constraints for affinity and anti-affinity rules that require solutions to place certain VNFs on the same server or apart respectively. In [9], Jemaa et al. proposed a VNFPP formulation where VNFs can only be placed either in a resource constrained cloudlet data center near the user or an unconstrained cloud data center. They use exact methods to optimize latency, cloudlet and cloud utilization simultaneously.
proposed a heuristic that places the most commonly used VNFs on the central nodes determined by the betweenness centrality. This increases the likelihood that a short route can be constructed for each service. In [36], Vizarreta et al. proposed to set the waiting time as a constant while keeping the starting and ending nodes fixed. In particular, they first find the route that has the lowest cost and satisfies the latency and robustness constraints. Then, the route is adjusted until it can accommodate each VNF of the service. Beck et al. [37] used a similar surrogate model to optimize the average path length and bandwidth usage. The heuristic searches the servers up to a small number of hops away and places the next VNF of each service on the nearest server that can accommodate it. If no such server is available, the earlier VNFs of the service are removed.

Some researchers proposed to first use heuristics to place VNFs and then use accurate models to evaluate the solutions. Although this provides additional information to the decision makers, it does not improve the quality of solutions. For example, Zhang et al. [38] proposed a best fit decreasing method to place VNFs and used a simple queueing model to evaluate the solution. In [39], Chua et al. proposed a heuristic that iterates over the servers and places each VNF of each service at the first server with a sufficient capacity. In order to evenly distribute traffic, the available capacity for each server is limited. If every server has been considered before placing all VNFs, the heuristic increases the available capacity and reiterates the servers. Gouareb et al. [40] proposed a three-part heuristic that first assigns VNFs with the greatest resource demands to the servers with the largest capacity. Then, it uses either horizontal or vertical scaling to satisfy demand before finding the shortest routes between VNFs to form services. The heuristic was found to produce solutions an order of magnitude worse than an exact solver that uses an accurate model.

There also exist some attempts that try to bridge the gap between heuristics and exact methods. For example, Marotta et al. [14] proposed to combine heuristics and linear programming. They apply a heuristic to place VNFs and make these placements robust to changes in the required resources for each VNF. Thereafter, linear programming is applied to find routes between VNFs while ensuring the satisfaction of latency constraints for each service. However, since the network is not considered until the final step, it is not guaranteed to find a solution. Agarwal et al. [41] use linear programming to assign a confidence score for whether a VNF should be assigned to a server. Then they use a greedy heuristic that considers the confidence score and the available capacity of the server to find VNF placements [16, 42–74].

2.3 Meta-heuristic Methods

As a subset of heuristic methods, meta-heuristic methods have been widely used for NP-hard problems [75–79]. Yet, few studies can be found for VNFPs. In [80], Rankothge et al. proposed a genetic algorithm (GA) to optimize VNF placement and routing by minimizing the number of servers and switches. In [24], Cao et al. used GA to minimize the bandwidth consumption and maximize the link utilization with a binary matrix solution representation for VNF placement and routing decisions. In [81] and [82], a similar binary string representation is applied in multi-objective GAs. Specifically, [81] applied NSGA-II [83] to place primary and backup VNFs in small data centers while [82] explored the effectiveness of different multi-objective GAs on a variety of QoS indicators. In [26], a Pareto simulated annealing method is applied to find a set of trade-off solutions that optimize several indicators including a linear model of the expected latency, the number of hops, the number of VNF instances and the CPU utilization. Soualah et al. [84] proposed to use a Monte Carlo tree search to place VNFs and find routes between them so as to minimize the expected server utilization. To the best of our knowledge, our previous work [16] is the only one that combines meta-heuristics with a queueing model for VNFP. We applied a queueing model to predict the expected latency and overall energy consumption and used NSGA-II to find a set of Pareto optimal solutions. However, this work did not consider the packet loss and is only applicable to small-scale VNFPs.

3 Problem Formulation

In this section, we start with a descriptive statement of the VNFP. Then, we give the formal definition of the multi-objective VNFP considered in this paper followed by an analysis of its feasible search
space.

3.1 Problem Statement

A data center consists of a large number of servers, each of which can accommodate a limited number of VMs. Traffic is transmitted between servers across the network topology, i.e., a set of switches that interconnect all servers as an example shown in Fig. 1. Traffic between VMs on the same server communicate via a virtual switch on the server. In this paper, we refer to the servers and switches, which constitute a data center, as the data center components.

A solution to a VNFPP specifies one or more paths through the network topology for each service. In particular, a path is a sequence of data center components that visit each VNF of a service in a prescribed order. Furthermore, each solution also specifies the amount of traffic that should be sent along each path.

The goal of the VNFPP is to provide a number of services by placing VNFs on VMs in the data center and defining the paths so as to maximize QoS and minimize capital and operational costs. In this paper, we formulate a three-objective VNFPP that takes two service metrics (i.e., latency and packet loss) and a cost metric (i.e., energy consumption) into account. In particular, low latency and packet loss are critical QoS measures while energy consumption is one of the largest operational expenditures of running a data center [85].

3.2 Mathematical Formulation

We first list some core terminologies important to the mathematical formulation of the objective and constraint functions of the VNFPP in this paper. \( S \) is the set of services that must be placed and \( \mathcal{V} \) is the set of VNFs. A service \( s = \{s_1, \cdots, s_n\} \in S \) is a sequence of VNFs. The network topology is represented as a graph \( \mathcal{G} = (\mathcal{C}, \mathcal{L}) \), where \( \mathcal{C} \) denotes the set of data center components and \( \mathcal{L} \) denotes the set of links connecting them. A route is a sequence of data center components where \( \mathcal{R}^s \) is the set of paths for \( s \), \( R^s_i \) is the \( i \)th path of \( s \) and \( R^s_{i,j} \) is the \( j \)th component of this path. The complete notations are listed in Table I of Appendix A.

Overall, the VNFPP considered in this paper is defined as a MOP of the following three metrics.

- The total energy consumption (denoted as \( E_C \)).
- The mean latency of the services (denoted as \( L \)):

\[
L = \sum_{s \in S} \frac{W_s}{|S|},
\]

where \( W_s \) is the expected latency of \( s \in S \).
- The mean packet loss of the services (denoted as \( P \)):

\[
P = \sum_{s \in S} \frac{P^d_s}{|S|},
\]

where \( P^d_s \) is the packet loss probability of \( s \in S \).

\(^{1}\)The appendix document can be downloaded from [here](#)
In addition, there are five constraints associated with this VNFPP. Three of them are core constraints applicable to any VNFPP and are defined as follows.

- Sequential data center components in a route must be connected by an edge:
  \[(R_{i,j}, R_{i,j+1}) \in \mathcal{L}.\] (3)

- Each server can accommodate up to \(N^V\) VNFs:
  \[\sum_{v \in V} A_{cs}^v < N^V,\] (4)
  where \(A_{cs}^v\) is the number of instances of the VNF \(v\) assigned to the server \(c_s\).

- All VNFs must appear in the route and in the order defined by the service:
  \[\pi_{R_i}^{s_i} \neq \emptyset, \quad \pi_{R_i}^{s_i} < \pi_{R_i}^{s_i+1},\] (5)
  where \(\pi_{R_i}^{s_i}\) is the index of the VNF \(s_i\) in the route \(R_i\).

In practice, security and legal concerns can impose additional constraints.

- A business may require an exclusive access to the servers in use due to security or performance restrictions. These requirements can be expressed through anti-affinity constraints that restrict which services can share servers. For each service \(s \in \mathcal{A}\) where \(\mathcal{A}\) is the set of anti-affinity services, the anti-affinity constraints are defined as:
  \[A_{s_1}^{c_s} \cdot A_{s_2}^{c_s} = 0, \quad \forall v_1 \in s, v_2 \notin s.\] (6)

- VNFs may be provided under a license that restricts the number of instances of a VNF that can be created. These are known as the max instance constraints:
  \[\sum_{c_s \in C_s} A_{cs}^v \leq N^M_v,\] (7)
  where \(N^M_v\) is the maximum number of instances of the VNF \(v\) and \(C_s\) is the set of all servers.

### 3.3 Analysis of Feasible Search Space

It is acknowledged that VNFPP is a NP-hard problem \cite{5, 7} with various constraints. However, the relative size of the feasible region against the entire space has been overlooked in the literature. A small feasible region can make it significantly difficult to find feasible solutions, let alone optima.

In the context of VNFPP, a solution is feasible if at least one instance of every VNF has been placed. Here we plan to verify that the relative size of the feasible region, which is the probability of a randomly selected solution being feasible, is small. However, due to the NP-hardness of the VNFPP, there is no closed form solution of this relative size. Therefore, we estimate an upper bound instead. In particular, we consider the case where each VNF can be placed at any location independent of whether other VNFs have been placed therein. In the following paragraphs, we first verify that this is indeed an upper bound and then we provide a quantitative estimation to show that it is proportionately small.

**Lemma 1.** The feasible region under the independence assumption is larger than the exact feasible region\footnote{The proof can be found in the Appendix B.}
Based on the independence assumption, the probability of a VNF being placed is calculated as:

$$P^p_v = 1 - \left(1 - \frac{1}{|\mathcal{V}|}\right)^N,$$

where $N$ is the number of VMs. Hence, the probability at least one VNF is not placed is calculated as:

$$P^{-p} = 1 - (P^p_v)^V.$$

Fig. 2 plots the probability of generating a feasible solution for a data center with different capacities. From these trajectories, we find that the ratio of the feasible region against the entire search space approaches zero even for very low utilizations. The anti-affinity and max instance constraints further reduce the size of the feasible region, thus leading to a significantly increased difficulty.

4 System Model

In this section, we develop an analytical model to derive the three metrics that constitute the objective functions of our VNFPP given in Section 3. They can be calculated for each service by examining the queues in the network. Each data center component consists of one or more buffers where packets are queued before being served. The arrival and service rates at a data center component determine the expected length of each queue, which in turn determine the waiting time and the probability of packet loss as well as the energy consumption. This information can then be used to calculate the latency, packet loss and energy consumption for each path of each service. In the following paragraphs, we first derive the approximation of the arrival rate for each data center component, based on which we calculate the three metrics.

4.1 Arrival Rates of Data Center Components

To calculate the arrival rate we must establish some reasonable assumptions about the system’s behavior. In line with [86], we assume the traffic generated by end users follows a Poisson distribution with a mean rate $\lambda_s$. As end users access the service independently, the total traffic arrival rate of a service can be calculated as the superposition of multiple independent Poisson processes. When packets arrive at a data center component, they are served with a first-in-first-out queueing strategy. To make the analytical model applicable to the practical implementation, instead of exploiting the infinite queueing strategies in [87], we assume each data center component has a finite buffer length.
Figure 3: Three VNFs (A, B, C) are visited in sequence through a single switch (SW). This forms a loop causing the arrival rate at the switch to be dependent on its own packet loss.

$B_c$. If the buffer becomes full, the newly arrived packets would be dropped to avoid system congestion. Finally, since packets are processed independently the time for a data center component to process a packet follows an exponential distribution with service rate $\mu_c$. Under these conditions, we model the service processing at each data center component as an M/M/1/B$_c$ system.

Next we can calculate the arrival rate of each data center component. Let $\lambda_c$ be the arrival rate of a data center component $c \in C$. It is the sum of the packet flow rates of all paths entering this data center component. Due to the finite buffer size, the effective arrival rate $\lambda_e^c$ is less than the arrival rate and calculated as $\lambda_e^c = \lambda_c (1 - P_d^c)$, where $P_d^c$ is the packet loss probability and is calculated as [88]:

$$P_d^c = \begin{cases} (1 - \rho)^{B_c}, & \text{if } \lambda \neq \mu \\ \frac{1}{B_c + 1}, & \text{otherwise} \end{cases}$$

where $\rho = \lambda_c / \mu_c$.

If the packet loss at a data center component were fixed then the arrival rate at each component would simply be the sum of the packet flow rates of the routes through that component. In practice, since the packet loss at a data center component depends on the arrival rate at the earlier components on the same path, dependency loops can form if the same component is visited multiple times in a sequence (as demonstrated in Fig. 3). In this case, the packet loss probability at the revisited component becomes a function of its own arrival rate thus resulting in a dynamic system. Since the arrival rate at each component changes over time in a dynamic system, it is significantly more complex to derive the performance metrics based on the arrival rate. Existing works unfortunately neglect this factor by either considering models without packet loss (e.g., [38,41,89]) or simply ignoring the dynamic feature of the system and only calculating the arrival rate at the outset instead (e.g., [14,39]). In this paper, we propose an iterative method to calculate the expected arrival rate over time. We first show that the arrival rates at all data center components naturally converge towards a fixed point given infinite time. Then, we elaborate the method that derives the expected arrival rate.

**Lemma 2.** The arrival rate at each data center component converges towards a fixed point as time approach infinity\(^3\).

A naive method of calculating the arrival rate, based on [2], is to evaluate the upper and lower bounds of the arrival rate until they converge. This is impractical since the theoretical result requires infinite time. Instead, this paper proposes to approximate the arrival rate by calculating the bounds until they converge to the point that further iterations are unlikely to change the expected arrival rate more than a threshold $\delta > 0$. As the pseudo-code shown in Algorithm 2 in the Appendix C, it first initializes the packet loss at each data center component to 0 to simulate there being no packets in any queue (lines 3 to 4). In the main loop, the algorithm first calculates the current arrival rate and packet loss for each data center component by using the previous settings of packet loss (lines 6 to 8). From [2] we can see that the current arrival rate will be either a lower or upper bound of the arrival rate. Next the algorithm calculates the mean of the upper and lower bounds of the arrival rate for each data center component (line 12) and the divergence from the previous mean for each component (line 14). If the maximum divergence from the mean across all components has remained below $\delta$ for

\(^3\)The proof can be found in the Appendix B.
while increasing the model accuracy by requiring the mean to be more stable before being considered converged. The model is less sensitive to $\gamma$ which is required for the rare scenario where the bounds temporarily appear converged. We found that $\delta = 5.0$ and $\gamma = 10$ give a balanced trade-off between efficiency and accuracy.

### 4.2 Service Packet Loss

The packet loss probability of a service is the expected packet loss considering the probability of selecting each path:

$$P^d_s = \sum_{i=1}^{\left|R^s\right|} P^d_{R^s_i} \cdot P_{R^s_i},$$

where $P^d_{R^s_i}$ is the probability that a packet is dropped at any component on the path $R^s_i$. It is calculated as:

$$P^d_{R^s_i} = 1 - \prod_{c \in R^s_i} \left( 1 - P^d_c \right).$$

### 4.3 End-to-End Latency

The end-to-end latency of a service is the expected waiting time over all paths. It is calculated as:

$$W_s = \sum_{i=1}^{\left|R^s\right|} W_{R^s_i} \cdot P_{R^s_i},$$

where $W_{R^s_i}$ is the average latency for $R^s_i$ and it is calculated as the sum of the waiting time at each data center component:

$$W_{R^s_i} = \sum_{c \in R^s_i} W_c,$$

where $W_c = N/\hat{\lambda}_c$ is the waiting time at the component $c \in R^s_i$ and $\hat{\lambda}_c = \lambda_c \cdot (1 - P^d_c)$ is its effective arrival rate and $N$ is its expected queue length [88]:

$$N = \begin{cases} \rho \frac{1 - \rho (B_c + 1) (1 - \rho (B_c + 1))}{(1 - \rho) (1 - \rho (B_c + 1))}, & \text{if } \lambda \neq \mu \\ B_c / 2, & \text{otherwise} \end{cases}.$$ 

### 4.4 Energy Consumption

The total energy consumption of a data center is the sum of energy consumed by each of its components. The energy consumption process follows a three-state model with off, idle and active states. Specifically, a component is off if its arrival rate is zero; it is idle while it is not processing any packet; otherwise, the component is active. A data center component does not consume any energy when it is off. Thus, we only need to consider the energy consumption of its active and idle states, denoted as $E^A$ and $E^I$, respectively. The total energy consumption of a data center is the sum of energy consumed by all its components:

$$E_C = \sum_{c \in \mathcal{C} \setminus \mathcal{C}_{vm}} U_c \cdot E^A + (1 - U_c) \cdot E^I,$$

where $\mathcal{C}_{vm}$ is the set of VMs and $U_c$ is the utilization of the data center component $c$. To calculate $U_c$, we need to consider both single- and multiple-queue devices. The utilization of a queue is given by:

$$U_c = \begin{cases} 0, & \text{if } \lambda = 0 \\ \frac{1}{B_c + 1}, & \text{if } \lambda \leq \mu \\ \frac{1 - \rho}{1 - \rho (B_c + 1)}, & \text{otherwise} \end{cases}.$$
5 Proposed Evolutionary Optimization Framework for VNFPPs

In this section, we propose a tailored evolutionary optimization framework to solve the three-objective VNFPP defined in Section 3. There are two tailored features: one is a genotype-phenotype solution representation, detailed in Section 5.1, that guarantees feasible solutions for the underlying VNFPP; the other is a tailored initialization operator, detailed in Section 5.2, built upon the solution representation to produce a good initial population. Note that these tailored features can be readily incorporated into any existing EMO algorithm as shown in Section 5.3. Although these operators are specifically designed for the Fat Tree network topology [90] (see Fig. 1) given its wide adoption in industry [91], we argue that our model and problem formulation are generally useful for any network topology.

5.1 Genotype-Phenotype Solution Representation

One of the key challenges when designing and/or applying EAs to real-world optimization problems is how to encode the problem into a solution in EA. In this paper, we propose a genotype-phenotype solution representation for our VNFPP. In particular, the genotype is a string of characters where each character can be either a service \( s \in S \) or a sentinel \( \text{NONE} \), i.e., the corresponding VM is not in use. The phenotype is a set of paths and the corresponding path probabilities required for the VNFPP.

The mapping between them defines how to transform the genotype into the corresponding phenotype. Due to the existence of complex constraints defined in Section 3, a simple mapping does not always lead to a feasible solution. The main crux of our genotype-phenotype solution representation is the use of problem-specific heuristics at the mapping stage that avoid generating infeasible solutions. It consists of three steps: balance, placement and routing.
5.1.1 Balance

The balance step adds and/or removes service instances to guarantee the feasibility after the genotype-phenotype mapping. This is implemented by ensuring that the genotype has at least one instance of each service and the total number of VMs being used does not exceed the available number in the data center. The pseudo-code is given in Algorithm 3 in Appendix C. It first identifies the location of all unused VMs along with the location and number of each service instance (lines 6 to 14). Using this information, the algorithm can calculate the number of VMs the solution will require after the mapping (lines 16 to 23) and identify missing services that have no service instances (lines 24 to 28). The algorithm then places a service instance for any missing services on a free VM if possible (lines 29 to 33). Finally, if there is insufficient space to place a missing service instance or the expanded length of the solution would exceed the total capacity, the algorithm removes the service instance with the lowest contribution and, if necessary, replaces it with a service instance for a missing one (lines 35 to 43). In particular, the contribution of an instance is evaluated as the change in the service instance utilization if it were removed:

\[ C_i^s = \frac{\lambda_s}{\mu_{s1} \cdot (i - 1)} - \frac{\lambda_s}{\mu_{s1} \cdot i}, \]  

where \( C_i^s \) is the contribution of the \( i \)th instance of \( s \) and \( \mu_{s1} \) is its service rate of the first VNF. As the arrival rate is distributed over each VNF, a service with several instances will have some instances with a low contribution. On the other hand, if a service has only one instance, it will have an infinite contribution. This minimizes the impact on the service quality when removing solutions.

5.1.2 Placement

The placement step uses a first feasible heuristic, a variant of the first fit heuristic from the cloud computing literature [92], to place the VNFs of a service in the phenotype close to the position of the service instance in the genotype without violating any constraint. The first feasible heuristic is executed on each service instance. It places the first VNF of the service on the nearest VM to the service instance that would not result in a constraint violation. This is repeated from the new position for the next VNF instance until all VNFs are placed. As anti-affinity services reserve the whole of a server, they must be placed first to ensure the service is not fragmented across multiple servers and does not reserve more space than necessary. Fig. 4 presents three examples of the placement step for different scenarios.

5.1.3 Routing

Finally, the routing step finds the set of shortest paths between the VNFs of each service instance to complete a solution. A Fat Tree network can be efficiently traversed by stepping upwards to the parent switch until a common ancestor between the initial and the target VNFs is found. In the Fat Tree network topology, there can be several routes between VNFs sharing the same distance. In this paper, we apply the equal-cost multi-path routing strategy [93] to distribute the traffic evenly over all shortest paths between sequential VNFs. This strategy has been shown to be optimal for Clos data center networks such as the Fat Tree [94].

5.2 Tailored Initialization Operator

In this paper, we propose a tailored initialization operator adapted to the characteristics of VNFPP and thus boost an effective exploration of the search space.

The goal of initialization is to generate a set of diverse initial solutions to ‘jump start’ the search process afterwards. Note that both the placement and the number of instances in the VNFPP can influence the solution quality. Uniform sampling, one of the most popular initialization strategies, varies the placement of service instances but the expected number of instances remains the same across all solutions. To amend this problem, we propose a variant of uniform sampling where service instances are placed uniformly at random, but the number of instances of each service varies across the population. More specifically, we first calculate the maximum number of instances of each service...
that can be accommodated in a data center. Thereafter, the solution is initialized by placing some fraction of this number of instances of each service. For the $i$th solution, the number of instances of the service $s$ is calculated as:

$$N_{i,s}^I = \left\lfloor i \frac{N}{\sum_{s \in S} |s|} \right\rfloor,$$

(21)

where $N$ is the population size. For example, if the population size $N = 100$, the 100th solution will have twice as many instances of each service as the 50th solution.

5.3 Incorporation into EMO Algorithms

The solution representation and initialization operators proposed in Section 5.1 and Section 5.2 can be incorporated into any EMO algorithm. In this paper, we integrate it into NSGA-II [83] as a proof of concept. It is worth noting that we do not need to make any modification on the environmental selection of the baseline algorithm. We use the classic uniform crossover and mutation as the reproduction operators to vary and exchange information on the number and position of service instances.

6 Empirical Study

We seek to answer the following four research questions (RQs) through our experimental evaluations.

- **RQ1:** How accurate is the QoS model developed in Section 4 compared to others in the literature?
- **RQ2:** Is an accurate QoS model beneficial compared to surrogate models used in the literature?
- **RQ3:** How does the tailored EMO algorithm compare against the state-of-the-art peers?
• **RQ4**: How well do the proposed operators cope with challenging constraints in VNFPP?

### 6.1 Parameter settings

The parameter settings used in this work are listed in Table II in the Appendix D. To reflect the mechanism of real switches, the service rate and queue length of each switch in our model are the sum of the service rates and queue lengths of each port. For example, a switch with 8 ports will have a service rate of \(8 \times 20 = 160\) requests/ms. To create a VNFPP instance, we generate enough services to hit the target minimum data center utilization. For example, if the data center has 1,000 VMs, the expected service length is 5 and the target data center utilization is 50%, then there will be 100 distinct services. Next, the service arrival rate and length and the VNF service rate are set for each service and VNF by sampling from a Gaussian distribution with the means and variances specified in Table II in the Appendix D.

### 6.2 Evaluation of QoS Model Accuracy

#### 6.2.1 Methods

The QoS model developed in Section 4 stands for the foundation of this study. Its correctness and accuracy determine whether our algorithm is applicable to real-world problems. To answer RQ1, we evaluate the accuracy of the model by comparing its predictions against benchmark measurements taken from a simulated data center.

To create the benchmark, we generate 100 VNFPP problems for a data center with 412 servers to constitute a diverse set of candidate solutions. Then, we apply our initialization operator to generate 100 randomly generated candidate solutions for each problem. Next, we evaluate each solution by using our proposed model and select four solutions for evaluation: 1) the one with the lowest latency; 2) the one with the lowest packet loss; 3) the one with the lowest energy consumption; and 4) the one that best balances all objectives. By using diverse solutions, we can rule out any inaccuracy reflected by the model. For example, if the model is poor at predicting the latency, the data set will contain a solution with a high expected latency that highlights this issue.

To get accurate measurements for the benchmark, we apply a discrete event simulator (DES) to calculate each metric of a solution. A DES simulates the transmission of each packet through the data center to produce accurate measurements of the QoS and energy consumption. In our experiments, the DES is based on the same assumptions introduced in Section 4 and it is used to evaluate each solution for a range of arrival rates.

We compare our model against two other accurate models used in the literature.

- **M/M/1 queueing model**: As one of most popular models in the literature [9, 31, 95], it models the data center as a network of queues and assumes that each queue has an infinite length. Under this assumption, there is no packet loss. However, if the arrival rate at a queue is greater than or equal to its service rate, the length of the queue will tend towards infinity that leads the waiting time to approach infinity and the utilization to approach 100%.

- **M/M/1/Bc queueing model**: In contrast, this model consider queues with a finite length. Existing M/M/1/Bc queueing models like [39] consider packet loss but not feedback loops. In essence, they calculate the instantaneous arrival rate and packet loss at each data center component when the services are first started.

#### 6.2.2 Results

Fig. 5 shows the estimates of each metric by different models benchmarked against the ground-truth measurements. The closer the model matches the benchmark, the more accurate the model is. From the results, we find that our proposed model is significantly more accurate than the other peer queueing models. This reflects how our model correctly captures the impact of feedback loops on the QoS and energy consumption.
Figure 6: An illustrative example of the final population found by NSGA-II using our proposed model and models from the literature. More diverse solutions with lower objective values indicate more appropriate models.

Figure 7: The lower quartile, median, and upper quartile of the HV of the population obtained by using different surrogate models to evaluate the objective functions of our VNFPP.

In contrast, the M/M/1/B\(_c\) queueing model, which does not account for feedback loops, is overly pessimistic with a high latency, packet loss and energy consumption. This is because the M/M/1/B\(_c\) model calculates the instantaneous arrival rate at the start of operation. As shown in Lemma 2, this is always higher than the arrival rate after convergence.

Likewise, these results also demonstrate the drawbacks of the commonly used M/M/1 model. First, the model falsely assumes that the queue at a component can grow to an infinite length and as a consequence believes that packet loss is zero in all situations. As a result, the model becomes less reliable as the arrival rate increases and packet loss becomes large.

Response to RQ1: Due to an understanding of the impact of feedback loops, our proposed model gives significantly more accurate estimates of the QoS and energy consumption than other models when packet loss is considered.
6.3 Benefit of Queueing Models

6.3.1 Methods

To answer RQ2, we compare the quality of solutions obtained by our tailored EMO algorithm when using different QoS models including three queueing models studied in Section 6.2 and three popular surrogate models briefly introduced as follows.

- **Constant waiting time or packet loss (CWTPL):** As in [35] and [36], this model assumes that the waiting time at each data center component is a constant. In addition, we also keep the packet loss probability at each component as a constant. Based on these assumptions, we can evaluate the latency and packet loss for each service and apply the metric of the energy consumption developed in Section 4.4. All these constitute a three-objective problem that aims to minimize the average latency, packet loss and total energy consumption.

- **Resource utilization (RU):** As in [33, 81] and [32], this model assumes that the waiting time is a function of the CPU demand and the CPU capacity of each VM. In addition, the demand is assumed to determine the packet loss probability as well. Based on these assumptions, we evaluate the latency for each service and apply the metric of the energy consumption developed in Section 4.4. All these constitute a two-objective problem that aims to minimize the average latency (and by extension the packet loss) and the total energy consumption.

- **Path length and used servers (PLUS):** This model uses the percentage of used servers to measure the energy consumption (e.g., [25, 30, 96]) and the length of routes for each service as a measure of service latency, packet loss or quality (e.g., [5, 19, 37]). All these constitute a two-objective problem that aims to minimize the path length and the number of used servers.

In our experiments, we generate 30 problem instances of the Fat Tree data center with 432, 1,024, 2,000, 3,456, 5,488 and 8,192 servers respectively. At the end, the non-dominated solutions found by our tailored EMO algorithm with different QoS models are re-evaluated by using the QoS model developed in Section 4. The quality of these non-dominated solutions is evaluated by the Hypervolume (HV) indicator [97] that measures both the convergence and diversity of the population, simultaneously.

6.3.2 Results

From the results shown in Figs. 6 and 7, we find that the solutions obtained by using our proposed model and the M/M/1/B queueing model are comparable with each other while they are significantly better than those obtained by using other models in terms of the population diversity.

Specifically, populations obtained with the M/M/1 queueing model have poor diversity. This can be attributed to the inability of the M/M/1 queueing model to distinguish solutions by the latency or packet loss metrics. In particular, most solutions obtained by using the M/M/1 queueing model have an infinite latency and no packet loss. This is because if the arrival rate at any data center component is larger than the service rate, the waiting time at that component tends towards infinity. Hence the average latency also tends towards infinity. As all solutions have the same latency and packet loss, the optimization algorithm can only distinguish solutions based on their energy consumption. As a result, only solutions with low energy consumption survive.

For a similar reason, the surrogate models also failed to produce diverse solutions. Despite their differences, none of the surrogate models provide any incentive to vary the number of service instances. For example, both the CWTPL and PLUS models benefit from shorter average routes. However, increasing the number of service instances will also increase the number of servers yet is unlikely to decrease the average service length. Likewise, for the RU model, increasing the number of service instances increases the energy consumption and makes it more difficult for the algorithm to find servers with a low resource utilization.

Response to RQ2: The queueing models that account for the packet loss lead to significantly more diverse solutions compared to the other queueing model(s) as well as the surrogate models.
6.4 Comparison with Other Approaches

6.4.1 Methods

To answer RQ3, we compare the performance of our tailored EMO algorithm with five state-of-the-art peer algorithms for solving VNFPPs. Specifically, the following two meta-heuristic algorithms use the NSGA-II as the baseline but have different solution representations.

- **Binary representation**: In [81], a string of binary digits are used to represent the placement of primary and secondary VNFs. To implement a fair comparison, we only consider the placement of the primary VNFs.

- **Direct representation**: In this case, a solution is directly represented as a string of VNFs.

The three heuristic algorithms are as follows.

- **BFDSU [38]**: This is a modified best-fit decreasing heuristic that considers each VNF in turn and selects a server that can accommodate the VNF according to a predefined probability. In addition, the result is weighted towards selecting a server with a lower capacity.

- **ESP-VDCE [82]**: This is specifically designed for the Fat Tree data centers. It uses a best fit approach but exclusively considers the servers nearest to where other VNFs of the same service have been placed.

- **Stringer [39]**: This is also designed specifically for the Fat Tree data centers and it uses a round-robin placement strategy to place each VNF of each service in a sequence. The heuristic limits the available resources of each service and places a VNF on the first server with a sufficient capacity. If there is insufficient capacity in the data center for a VNF, the resources of each server are increased and the heuristic restarts from the first server.

Note that these heuristics assume that the number of service instances is known a priori. Since each heuristic can only obtain a single solution, we generate a set of subproblems, each of which has a different number of service instances and is independently solved by a heuristic, to obtain a population of solutions at the end. In particular, we use the following two strategies to generate subproblems in our experiments.

- One is to use the initialization operator developed in Section 6.5 to serve our purpose. For the ith subproblem, the number of instances of the service s is calculated as $N^I_{i,s}$ in equation (21).

- The other is to use the population obtained by our tailored EMO algorithm as a reference. For the ith subproblem, the number of instances of each service is the same as the ith solution obtained by our tailored EMO algorithm.

In our experiments, we generate 30 VNFPP instances for six data centers with different sizes. To compare the performance of different algorithms, we use the QoS model developed in Section 4 to evaluate the objective functions of the solutions obtained by different algorithms and use the HV indicator as the performance measure.

6.4.2 Results

From the results shown in Fig. 9, it is clear that our proposed algorithm outperforms other competitors on all test cases. Although the binary solution representation has been successfully applied to solve VNFPP on small data centers (e.g., [81, 82, 98]), it does not scale well in the larger-scale problems considered in our experiments. Likewise, the direct solution representation is only able to obtain feasible solutions to small data centers, as shown in Fig. 6, and exclusively finds solutions with high energy consumption. In particular, since a solution is only feasible when there is an instance of each VNF, solutions with more VNFs are more likely to be feasible than those with less VNFs and lower energy consumption. This leads the algorithm with the direct representation to be biased towards solutions with a high energy consumption. In contrast, since our proposed representation guarantees
Figure 8: An illustrative example of the final populations found by NSGA-II using our proposed algorithm and algorithms from the literature. Subproblems for the heuristic were generated using our proposed initialization operator. The binary solution representation is omitted as it resulted in no feasible solution at all.

Figure 9: The lower quartile, median, and upper quartile of the hypervolume of the population for different algorithms on 30 VNFPP instances using the initialization operator to generate subproblems for the heuristics.

Figure 10: The lower quartile, median, and upper quartile of the hypervolume of the population for different algorithms on 30 VNFPP instances using the solutions of our proposed algorithm to generate subproblems for the heuristics.

As shown in Fig. 9, solutions obtained by the heuristic approaches tend to be clustered. Furthermore, as shown in Fig. 10, our tailored EMO algorithm still outperforms the heuristic approaches when the diversity of the subproblems is improved. Both BFDSU and Stringer tend to produce longer path lengths thus lead to significantly worse solutions than our proposed algorithm. Since Stringer restricts the capacity of each server, it causes services to be placed across multiple servers. Likewise, the stochastic component of BFDSU can cause it to place VNFs far away from any other VNF of the service. In contrast, our proposed algorithm incorporates useful information into the optimization process and places sequential VNFs close by thus leading to better solutions.

The second benefit of our algorithm is that it can iteratively improve the placements to minimize the energy consumption and QoS. Although ESP-VDCE does consider the path length, it otherwise uses a simple first fit heuristic that cannot consider how service instances should be placed in relation to each other. As a consequence, the performance of ESP-VDCE depends on the order in which services are considered whereas our proposed algorithm considers the problem holistically and can make informed placement decisions.
Response to RQ3: Our proposed tailored EMO algorithm obtains significantly better solutions in terms of both convergence and diversity compared to other state-of-the-art peer algorithms.

6.5 Effectiveness on Constraint Handling

6.5.1 Methods

RQ4 aims to validate the effectiveness of our proposed solution representation for handling challenging anti-affinity and limited licenses constraints. We generated 30 problem instances for a small data center with 412 servers. Note that we only compare our proposed algorithm with the meta-heuristic approach with the direct solution representation in our experiments given the poor performance of the binary solution representation reported in Section 6.4 and the inability of the heuristic approaches to solve constrained VNFPPs.

For the anti-affinity constraints, we considered different numbers of anti-affinity services and similarly, for the limited licenses constraints we considered different numbers of limited license VNFs and different numbers of licenses for each VNF. Since different VNFs have different service rates, we calculate the expected maximum number of instances of each VNF that could be accommodated by the data center (i.e. the maximum value of $N^I$ in the equation (21)) and restrict the solution to use a fraction of this number of licenses.

6.5.2 Results

From the results shown in Figs. 11 and 12, it is clear to see that the direct representation cannot find any feasible solution due to the narrow feasible search space. In contrast, our proposed operators are still able to find a diverse set of feasible solutions even for these highly constrained problems. As shown in Fig. 11, our algorithm produces consistently good results on the anti-affinity problems. This is a benefit of our proposed solution representation which ensures the satisfaction of the anti-affinity constraints. Since the solutions are guaranteed to be feasible, the algorithm should only optimize the number and placement of service instances. Any degradation in the HV indicator can be attributed to the narrower feasible search space causing better alternatives to be infeasible. In particular, anti-affinity constraints prevent VNFs of other services from being placed on a server thus can prevent a server from being fully utilized.

According to our empirical results, the limited licenses constraints appear to be more challenging. As shown in Fig. 12, populations obtained by our proposed algorithm have a better HV value when a large number of licenses is allowed, whereas it falls down when fewer licenses are available. Furthermore, the percentage of VNFs that are affected has little impact. The lower HV values can be explained by a loss of diversity as a result of the feasible solution space being constrained. If any VNF in a service is constrained by a limited license constraint, this limits the number of service instances that can be placed. Hence the percentage of VNFs that can be placed is less significant as it is likely that a VNF in the service is already constrained.

Response to RQ4: From our empirical results, we find that our proposed genotype-phenotype solution representation is superior for handling highly constrained VNFPP.

7 Conclusion

By utilizing data center resources efficiently, we can provide high quality services and minimize their environmental impact. This work provided an efficient and accurate analytical model with which to evaluate the QoS of large data centers. To solve our VNFPP, we proposed a problem specific solution representation along with a tailored initialization strategy to guarantee the generation of feasible solutions, both of which are directly pluggable into any EMO algorithm. There are four main findings from our comprehensive experiments.

*Only the small data center is considered here in view of the poor scalability of the direct representation reported in Section 6.4.*
Figure 11: The lower quartile, median and upper quartile of the HV from our proposed solution representation and the direct solution representation. The direct solution representation resulted in no feasible solution at all.

Figure 12: Mean normalized HV considering the proportion of VNFs (10% - 90%) that have some restriction and the number of licenses available (80%, 20%, 5%) of the expected desired amount.

- Our proposed model is significantly more accurate than the existing competitors, especially when data center components become self-dependent.
- Widely used surrogate models provide insufficient information to produce diverse solutions when being used to solve our VNFPP. In contrast, accurate models that consider packet loss are effective.
- Our proposed algorithm produces significantly better solutions than its competitors, especially when solving large scale VNFPPs.
- Our proposed solution representation is highly effective for challenging constraints. In contrast, alternative solution representations fail to find feasible solutions.

Many extensions are still possible for future exploration while we only name a few as follows.
• This paper investigates the specific case of Fat Tree network topologies. It would be interesting to extend this work to arbitrary topologies.

• The impacts of different types of VNF and service vary across exact and heuristic approaches. It would be interesting to determine how an alternative problem formulation would affect the design and results of a meta-heuristic alternative.

• It is not uncommon that demands may change over time when running a data center in practice. Thus, extending the QoS model as well as the optimization routine to a dynamic optimization scenario is of practical importance.

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