Depth-Optimized Delay-Aware Tree (DO-DAT) for Virtual Network Function Placement

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Abstract—With the constant increase in demand for data connectivity, network service providers are faced with the task of reducing their capital and operational expenses while ensuring continual improvements to network performance. Although Network Function Virtualization (NFV) has been identified as a solution, several challenges must be addressed to ensure its feasibility. In this paper, we present a machine learning-based solution to the Virtual Network Function (VNF) placement problem. This paper proposes the Depth-Optimized Delay-Aware Tree (DO-DAT) model by using the particle swarm optimization technique to optimize decision tree hyper-parameters. Using the Evolved Packet Core (EPC) as a use case, we evaluate the performance of the model and compare it to a previously proposed model and a heuristic placement strategy.

Index Terms—NFV, Machine Learning, PSO, SFC, MANO.

I. INTRODUCTION

With network connectivity demands at an all-time high and continuing to increase, Network Service Providers (NSPs) are tasked with the challenge of accommodating additional bandwidth requests on their networks while concurrently maintaining or improving their Quality of Service (QoS). To adapt their networks to accommodate this demand, NSPs must create a network with increased flexibility, portability, and scalability. The concept of Network Function Virtualization (NFV) has been proposed as a candidate solution for addressing these challenges. NFV architecture isolates network functions and executes them as software-based applications independently from the underlying hardware [1]. By abstracting the individual network functions from their underlying hardware and creating Virtual Network Functions (VNFs), NSPs may experience a reduction in capital and operational expenditures, and an increase in operational efficiencies [2].

NFV technology, however, is not without its own challenges, including performance, availability, and reliability. NSPs are obliged to adhere to specific standards when delivering a service to a customer. These standards are outlined through QoS guarantees, performance metrics, and thresholds pertaining to jitter, packet loss, delay, and availability. When evaluating the feasibility of an NFV-enabled network, adherence to QoS guarantees is essential and must be considered.

One of the key metrics outlined in QoS guarantees is performance, which can be described by different metrics such as delay or availability and can pertain to an individual VNF instance or a set of interconnected VNF instances known as a Service Function Chain (SFC).

Our previous work presents the Delay Aware Tree (DAT), which uses a decision tree to address the NP-Hard VNF Placement Problem [3]. The DAT shows promising results when compared to current heuristic solutions. However, the DAT placement strategy, on average, produces 34 μs of additional delay per computational path when compared to current heuristics due to sub-optimal fitting. When considering the incoming adoption of 5G networks and the new ultra-low latency requirements (<1ms) in industrial internet of things use cases, this added delay hinders the adoption of the DAT. As such, in this work, the maximum depth hyperparameter (related to fitting) of the DAT is optimized in an effort to improve the delay observed across all computational paths and outperform current heuristics. To optimize the maximum depth of the DAT, we propose the optimization of a performance-based objective function, which considers both the delay and QoS guarantees when evaluating the fitness of a set of hyperparameter values.

In order to illustrate the proposed solution, the virtual Evolved Packet Core (vEPC) is selected as a use case; however, the solution presented in this paper is generalizable to any SFC. There are four VNF instances forming the SFC for vEPC being: the Home Subscriber Service (HSS), the Mobility Management Entity (MME), the Serving Gateway (SGW), and the Packet Data Network Gateway (PGW).

The remainder of this paper is structured as follows. Section II discusses the state-of-the-art. Section III outlines the methodology. Section IV presents and analyzes the results obtained. Finally, Section V concludes the paper.

II. RELATED WORK

There has been significant work in the field of VNF placement in recent years. Some methods used to address the VNF placement problem include optimization problem formulations [4], latency-aware placement schemes [5], Monte-Carlo tree-based chaining algorithms [6], and matching theory approaches [7]. The abovementioned works however, are not capable of learning from historical observations; to address this inadequacy, ML-based solutions are explored. Wahab et al. [8] propose an ML approach for efficient placement and adjustment of VNFs and minimizing operational costs while considering capacity and efficiency constraints. Khezri et al. [9] propose a deep Q-learning model considering the reliability requirements of a given service function chain. Zhang et al. [10] propose an intelligent cloud resource manager that uses deep reinforcement learning when mapping services and applications to resource pools. Sun et al. [11] propose Q-learning as a method of addressing the time-accuracy tradeoff.
between heuristic and optimization models. Khoshkholghi et al. [12] propose a genetic algorithm with the objective of minimizing a resource-based cost function. Compared to these studies, our work advances the state-of-the-art as we capture carrier-grade functionality constraints (i.e., availability) as well as the dependency constraints while simultaneously generating placements that produce multiple computational paths (CPs) (i.e., multiple components serving the same SFC) which enables the minimization of end-to-end SFC delay as well as enhanced availability. Our work also considers HyperParameter Optimization (HPO) and analyzes its effect on the overall performance of the model.

HPO is used to improve the performance of ML algorithms. The tuning and optimization of tree-based machine learning models has been explored using searches, heuristics and metaheuristics [13], [14], visual methods [15], and Bayesian optimization [16]. The main metric for assessing performance in these works has been predictive accuracy.

This work extends our previous work by introducing a method of optimizing the performance of the DAT through HPO. Due to the nature of this multi-class, multi-output classification problem, predictive accuracy is not sufficient as a metric for evaluating our model. The main contributions of this paper include: a domain-based HPO model, which optimizes the maximum depth parameter of the DAT using the meta-heuristic Particle Swarm Optimization (PSO) technique, the introduction of a regularization term, which severely penalizes invalid placement predictions, and the creation of the Depth-Optimized Delay-Aware Tree (DO-DAT), which exhibits improved performance compared to placement strategies published in literature and facilitates automation in NFV management and orchestration.

III. METHODOLOGY

The following section outlines the various stages leading to the development of the DO-DAT.

A. Problem Formulation

The problem formulation for this work is conducted in a two-fold manner, the first dealing with the problem formulation of the DAT and the second dealing with the problem formulation of the PSO depth optimization.

1) DAT: The methodology behind the construction of the DAT, as defined by our previous work [3], takes the previous placements made by the near-optimal heuristic BACON algorithm [17]. Inherently, the problem formulation for the DAT follows the MILP problem formulation for the BACON algorithm outlined in the work of Hawilo et al. [17] and constructs a dataset that is used to train the DAT. The BACON problem formulation has the objective of minimizing the delay experienced by two dependent VNFs forming an SFC. To capture the carrier-grade requirements associated with this technology, several constraints were included in the problem formulation, including capacity constraints (placement cannot exceed computational resource capacity), network-delay constraint (placement cannot violate latency requirement), availability constraint (placement cannot violate co-location and anti-location requirements), redundancy constraint (placement must improve availability through the placement of redundant components), and dependency constraint (placement must ensure that dependent VNFs forming an SFC are placed in a manner which enables the execution of the SFC).

2) PSO depth optimization: The PSO depth optimization is conducted through the development of a unique optimization function related to the domain of the NFV-enabled network. By adopting this process, it is possible to move past the point of matching the performance of the BACON algorithm and instead focus on the continual development of the predictive placement model as a whole. The PSO optimization takes place once during the initial construction of the DO-DAT.

When considering the construction of a decision tree, the maximum depth of the tree has been identified as a key hyperparameter in the overall fitting of the model. In an effort to prevent over and underfitting, this work presents a joint optimization objective that considers both the average delay across all CPs of a predicted placement as well as a penalty factor related to fitting. In the previous construction of the DAT, improper model fitting manifested itself through invalid predicted placements, which were instances where the constraints imposed on the initial BACON problem formulation were not captured by the DAT and therefore resulted in predicted placements which were considered invalid. The penalty factor term operates like a regularization term in the objective function penalizing invalid predicted placements during the training phase of the model.

The formulation of the multi-objective optimization problem consolidated into a single objective function is defined below. The hyperparameter set is defined in (1)

\[
\{h\} = \{\text{maxDepth}\} \tag{1}
\]

The objective of the optimization is to minimize the delay across all CPs as well as the number of invalid predicted placements. Let \(i\) represent the trial number and \(j\) represent the CP; the average delay across all CPs can be defined as:

\[
\text{avg}_{\text{delay}, CP} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{k} \text{delay}_{i,j}}{n} \tag{2}
\]

Where \(n\) is the total number of trials and \(k\) is the total number of CPs.

The regularization term used is expressed through (3) where \(ip\) represents invalid placement predictions. In order to be effective, the regularization term must have an equal order of magnitude compared to the quantity being regularized; since the average delay per CP value is in the order of thousands of microseconds, 1000 was selected as a coefficient to ensure that the regularization term firstly is of equal magnitude and additionally has a severe penalty on the overall objective.

\[
\text{regTerm} = 1000 \times \log_{2}(ip + 1) \tag{3}
\]

It is evident that as the number of invalid predictions approaches zero, so does this regularization term suggesting that in the ideal case where there are zero invalid predictions, the effect of this regularization term is zero, as seen in (4).
The constraint on the hyperparameter values is defined by:
\[
\left( b \leq \text{model}(h) \leq a \right)
\]
where the functional range is defined on the interval \([a, b]\).

C. Data Analysis

Upon the creation of the various topologies through the data generation and initial placements using the BACON algorithm, the next stage in the methodology relates to the feature extraction. In order to predict the placement of VNF instances on network servers, a snapshot of the network conditions is taken and used as input features to the model. The output labels are the placements of the components on the network servers; as previously stated, this is a multi-class, multi-output problem; therefore, there is a set of outputs predictions, each with their respective set of possible labels. Given that, \( s \) represents a network server, and \( v \) represents an instance to be placed, the following holds true:

\[
\text{outputs} = \{ v_1, v_2, ..., v_n \}
\]
\[
\text{labels} = \{ s_1, s_2, ..., s_n \}
\]

From the network snapshot, several features are extracted, including instance resource requirements, server resource capacity, delay tolerance between interdependent instances, delay between server, and instance dependency levels.

D. Model Construction

The construction of the DO-DAT follows a 3 step process. The first stage involves the determination of the range of under/overfitting with respect to the tree depth. PSO optimization is initially run given a range of \([2,100]\) for the maximum depth hyperparameter. The value of 100 is selected as the upper bound for the range of values that the maximum depth hyperparameter can assume as a benchmark to limit the initial search space; if an optimal solution is not achieved in the defined search space, the upper bound is increased by a factor of 2 until an optimal solution is found. Since the evidence of under/overfitting in the DAT was manifested through the number of invalid placement predictions, the goal of this PSO optimization stage is to determine the depth which minimizes their occurrence.

The result from the first stage is then used to determine the range of values to be further considered. The range of values is determined by considering when the number of invalid placement predictions falls below an initial error threshold set at 7.5% (10% is the pre-defined maximum tolerable placement error, by setting the initial threshold to 7.5%, we can be more conservative with our placements and reduce the search space for the subsequent steps) and when steady-state is reached, meaning that there is no further improvement observed for several iterations. The optimization performed in the second stage considers the entire objective function, (6) evaluated across the previously determined range. The result of this optimization shows the effect of the range of depths on the joint consideration of invalid predictions and delay.

The final stage of the construction of the DO-DAT is to identify the optimal tree depth obtained from the previous stage and construct the model using this hyperparameter value.
IV. RESULTS AND ANALYSIS

The following is a presentation of the results obtained as well as an analysis of their implications on the DO-DAT. The generation of the dataset, data processing and ML models are implemented using Python on a PC with an Intel Core™ i7-8700 CPU @ 3.20 GHz CPU, 32 GB RAM, and an NVIDIA GeForce GTX 1050 Ti GPU.

A. Functional Range

The first set of results pertains to the PSO optimization and its effectiveness in presenting the optimal value of the tree depth. Fig. 1 displays the effect of varying the depth of the tree on the number of invalid placement predictions.

![Fig. 1. Effect of max depth on invalid predictions](image1)

As seen, the number of invalid placement predictions decreases while the tree depth is less than 25 and stabilizes at this minimum value of 0 while the tree depth is greater than 25. At a max depth of 20, the number of invalid placement predictions (error rate) is 7.5%. Since steady-state is observed beyond 25, 10 additional tree depths were considered to evaluate the effect of the overfitting on the optimization. Therefore, the range of tree depths spanning [20,35] is selected as the functional range of the first stage and is further evaluated by taking into consideration the full objective function (6).

B. Optimal Depth

Results from the optimization of the functional range of interest are presented in Fig. 2. From this figure, we can see the objective function \( P(h) \) is decreasing on the interval [20,28] and plateaus on the interval [29,35]. The interval [28,30] represents the interface between under and overfitting of the DAT, and therefore, since there is no further significant improvement on the interval [29,35], the optimal depth is 29.

![Fig. 2. Effect of depth on \( P(h) \)](image2)

C. Performance Comparison

The following figures compare the placement of BACON, DAT, and DO-DAT. Fig. 3 illustrates the delay across the various CPs in the small scale network. As observed in this Fig. 3, DO-DAT exhibits improved performance when compared to both the BACON and DAT placement strategies.

![Fig. 3. Delay across computational paths of the small network](image3)

Fig. 4 displays the delay experienced between interconnected dependent instances, forming a vEPC SFC.

![Fig. 4. Delay between dependent VNF instances forming a vEPC SFC](image4)

As seen in Fig. 4, the DO-DAT is the best performing placement strategy as it has successfully placed the VNF instances with less delay exhibited between dependent VNF instances. These results can be further extended to the second network topology, as expressed in Fig. 5, where it can be seen that DO-DAT, when considered across all CPs, produces more paths with less delay compared to the other placement strategies. This is further illustrated in Table 1, where the ratios of which strategy produces a placement with the least delay per each of the 36 CPs seen in Fig. 5 are listed. In all cases, the DO-DAT outperforms the other two strategies and establishes itself as the clear winner when considering the reduction of end-to-end delay across all CPs.

| Ratio Description | Ratio |
|--------------------|-------|
| BACON vs. DAT vs. DO-DAT | 13:9:14 |
| BACON vs. DO-DAT | 13:23 |
| DAT vs. DO-DAT | 12:24 |

This is reinforced when considering Fig. 6, which shows a Probability Density Function (PDF) of the difference between the DO-DAT and BACON algorithms in terms of placement delay; a similar comparison between BACON and DAT was...
D. Runtime Complexity

One of the benefits of the use of ML in networks is the reduction of system complexity. This is evident through the runtime complexity analysis of our proposed model. When considering the BACON algorithm, it has a runtime complexity of $O(n^2 s t)$ where $s$ denotes the number of available servers in the network [17]. Our previous work outlines the time complexity of constructing a decision tree as $O(n_{features} \times n_{samples} \times \log n_{samples})$ when creating the tree and $O(\log n_{samples})$ when executing a query [20]. Additionally, the DO-DAT has an additional offline optimization component with the complexity defined by $O(n^2 t)$ where $n$ denotes the population and $t$ the iteration [21]. Since the building of the tree and the optimization are completed entirely offline, only the querying phase is considered during the runtime analysis.

V. CONCLUSIONS AND FUTURE WORK

The work presented in this paper described a key step towards an implementable, intelligent, and delay-aware VNF placement strategy. Through the optimization of the max tree depth, we addressed the under/overfitting phenomenon, which plagues large decision trees and negatively impacts performance. The DO-DAT uses ML and PSO to provide an effective, real-time placement solution, which outperforms existing placement strategies and improves QoS through the reduction of the delay between VNF instances, forming an SFC. Future work will consider the use of ML to address additional services offered by the VNF orchestrator.

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