A Reliable Node Mapping and Intelligent Link Mapping in Network Virtualization over 5G

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ABSTRACT

Network virtualization (NV) is a viable way to run several virtual networks on a substrate network simultaneously. Virtual network embedding (VNE) efficiently maps virtualized networks (VNs) with different resource requirements for nodes and links to the substrate network with limited resources. Node mapping is carried out using the node degree centrality (NDC) ranking algorithm, which takes into consideration important network features. In this paper, an intelligent parallel algorithm based on a genetic algorithm (GA) is utilized for link embedding. This scheme minimizes the redundant reutilization of physical links and reduces the demand for network bandwidth. In addition, machine learning (ML) is incorporated into the network slicing process in order to correctly classify the substrate network and virtual request network. Using the k-nearest neighbor (KNN) algorithm, networks are automatically classified and resources are distributed accordingly. The findings of the simulations show that the NDC and GA algorithms improve the performance in terms of both network acceptance rate and network resource efficiency.

KEYWORDS

Network virtualization, Network slicing, Virtual network embedding, Genetic algorithm.

1 INTRODUCTION

Nowadays, a tremendous number of end users, devices, and types of applications can be found on both wireless and wired networks, consuming a significant quantity of traffic. NV is seen as a promising paradigm for the design of future generations of networks, such as 5G and beyond [1]. Network slicing allows for the creation of many virtual networks, or slices, on the same substrate network [2]. There are two important technologies for network slicing implementation: software-defined networking (SDN) and network function virtualization (NFV). With NFV, network services like firewalls and load balancing are implemented as software conditions known as virtual network functions (VNFs) [3]. It is possible to think of a VNF as a network service in NFV. NV permits several virtual network requests (VNRs) to share the substrate network's (SN) resources, permitting the independent existence of many VNs on a common SN. It is known as the Virtual Network Embedding (VNE) problem when VNRs with varying topologies and limited resources are embedded on the underlying network infrastructure. Virtual Node Mapping (VNoM) and Virtual Link Mapping (VLiM) are the two main components of the VNE process that allow the mapping of required VNs to the SN [4]. The processes of node mapping and link mapping are shown in Figure 1.

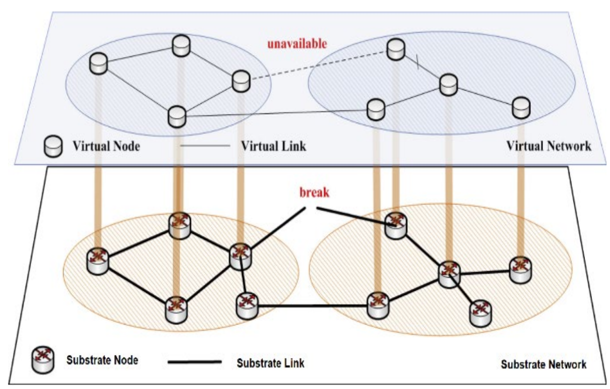

Figure 1: Node and Link Mapping Process

The next-generation wireless networks (NGWNs) will be able to support a wider variety of services that have diverse bandwidth, latency, and maintenance needs [5]. Enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable low-latency communications (uRLLC) are the three categories that are used to classify the virtual network services [6]. NGWNs face a major challenge in developing a framework that can handle a wide range of services and maximize resource utilization. New network design innovations are needed to accomplish the aims of increasing network capacity and providing a wide range of services with rigorous quality of service (QoS) criteria. Advances in machine learning (ML), facilitated by the development of AI, have opened the way to the use of AI in next-generation wireless networks [7]. This paper presents the following main contributions:

- To create network slices using KNN, where the data is prepared based on the network features.
- To carry out the VNE procedure in order to allocate the resources for requested services. The NDC ranking approach is employed for node mapping while the GA algorithm is utilized for link mapping.
- To clearly demonstrate the results of simulations, which show that the NDC-GA algorithm is better than the traditional methodologies in many instances.

The rest of this paper is organized as follows: Section 2 discusses the related works. Section 3 summarizes the network model. Section 4 discusses the proposed virtual embedding scheme. Section 5 presents the simulation results, and Section 6 concludes the paper.

2 RELATED WORKS

A large number of research activities have been studied in ML-based slice construction and virtual embedding processes in 5G networks. The use of ML techniques, such as random forest sampling, allows for arbitrary slice selection and distribution. The random forest outperforms other methods in this scenario, effectively distributing the slices for network traffic while maintaining a high level of accuracy [8]. Using ML and hybrid learning models, makes it possible to effectively slice the network, improving the performance of the sliced subset of the network. This classification has been sliced according to eMBB, mMTC, and URLLC use cases [9]. When embedding virtual nodes, it is important to build VNE coordination between the node mapping and link mapping phases [10]. This will help keep embedding overheads to a minimum. Using mixed integer programming, we can address the problem of mapping nodes onto an augmented graph that has been created over a real network [11]. In order to achieve successful node and link mapping in [12], the restricted meta heuristic optimization strategy for selecting physical nodes was created. This approach is used to choose nodes for allocating resources. For the VNoM problem, the work provided in [13] uses a simple node ranking method that takes into account the conditions of nearby links, and the K shortest routes algorithm is used to solve the VLiM problem. In addition, while the K-shortest strategy is still employed for the VLiM issue, [14] introduces a node ranking algorithm that takes into account global resources of linkages. However, the K shortest routes technique relied on [13, 14] is extremely rigid because it relies on a single path for each virtual link. In order to reduce the amount of time spent recycling links, [15] suggests a genetic algorithm with the ability to break links into many branches, which is subsequently used to map nodes. A genetic methodology based path splitting (GAPS) algorithm for resolving the VLiM problem is introduced with the intention of enhancing the VLiM method. Based on a study of existing approaches, the proposed work employs KNN in order to classify the services, and an NDC-GA based strategy is built in order to supply the resources for the virtual services that have been requested.

3 NETWORK MODEL

3.1 Substrate Network Model

The substrate network can be represented by the weighted undirected graph $G_{SN} = (N_{SN}, L_{SN})$, in which N_{SN} represents the substrate node sets and L_{SN} represents the substrate link sets. For the analysis of node properties, we take into account the node's CPU capacity C_{SN} as well as the link capacity LC_{SN}. The other note, the bandwidth, denoted by BW_{SN}, is the attribute of the link that is taken into consideration.

3.2 Virtual Network Request Model

The virtual network request can be defined by the weighted undirected graph $G_V = (N_V, L_V)$, where N_V represents the sets of virtual network nodes and L_V represents the sets of virtual request links. This graph can be found in the virtual network request definition. The notation C_V represents the CPU computing power of the virtual node, while the notation LC_V represents the link capacity of the node. The bandwidth requirement of request links is denoted by the notation BW_V. The value of the LT_V variable denotes the lifetime of the virtual network request.

3.2 Performance Analysis Metrics

The creation and embedding of network slices is an optimization problem that must take into account a variety of different conditions. Seeking to maximize the classification accuracy [16], acceptance ratio (AR), and resource efficiency (RE) of the substrate network is a goal of both the creation and embedding processes.
The classification accuracy of slices is denoted as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

The following equation describes the number of resources that are efficiently allocated to fulfil the request at time t.

$$RE = \sum_{V \in N_V} \frac{(C_V \text{ x } LC_V) + BW_V}{(C_V \text{ x } LC_V) + BW_V \text{ . hop } (L_{SN})} \tag{2}$$

The equation that can be used to describe the acceptance ratio is as follows:

$$AR = \sum_{t-0}^{T} \frac{SVNR(t)}{TVNR(t)} \tag{3}$$

where TVNR(t) denotes total VNR and SVNR(t) denotes successful VNR at time t.

4 PROPOSED SYSTEM

In the proposed work, the distribution of resources for a specific request is performed in two phases. During the first phase, the primary goal is the creation of slices for the virtual request and the substrate nodes. It is the responsibility of phase II to assign resources for requested slices. This is done with the goal of ensuring that each virtual request is granted access to the most positive distribution of resources in the substrate network. We use the KNN method of classification to accomplish the slicing process. The NDC-GA scheme is used to assist in the process of allocating resources for newly formed slices. The steps that would be used to implement the proposed strategy are depicted in Figure 2.

4.1 Slice Classification using KNN

ML encompasses a variety of research into methods for developing algorithms that can learn about the properties of a system. ML can be used to enhance the systems that supply resources for network slicing. The KNN algorithm is a non-parametric classification method. It is possible to predict the class of unlabeled data by using a labeled training dataset that contains data points that have been divided into different classes. The fixed value of k (k = 3) supports the classification of the unknown tuple. The distance between the test sample and the given training samples should be determined using the euclidean method. Network features are utilized to allocate the correct slices like eMBB, mMTC, and URLLC. In order to use the KNN technique for slice classification, it must be trained using a data set containing network attributes from VNR and SN. The training process makes it possible to assign new known input values and new unknown slices to the prediction model, thereby increasing the probability that the model will be able to provide results for new data. So, once the KNN has been trained, the prediction model may be able to correctly classify the services that are needed.

4.2 Embedding using NDC-GA

The process of embedding a VN requires a mapping of both the nodes and the links. The process of node mapping can be accomplished by picking substrate nodes that have enough resources. Link mapping necessitates having sufficient link resources on the path between chosen nodes in the SNs that have been assigned to a path in a VNR.

4.2.1. Node Mapping through NDC

During the process of node mapping, the ranking values for each node are calculated with the use of the NDC ranking method. The ranking value is used to organize the nodes in a non-decreasing order, and then resources are allotted for VNR services. The NDC value is calculated by using the formula,

$$R_{NDC(i)} = C_i \text{ x } \frac{D(i) \sum_{l \in L\{i\}} BW(l)}{\sum_{j=1}^{N} SP(i,j)} \tag{4}$$

where D represents the degree of node i and SP is the shortest path connecting nodes i and j.

4.2.1. Link Mapping through GA

The GA algorithm is an attractive optimization method for handling both constrained and unconstrained optimization problems through the adoption of the natural selection concept. Initialization, selection, crossover, and mutation are the four main operators in a classic GA [17].

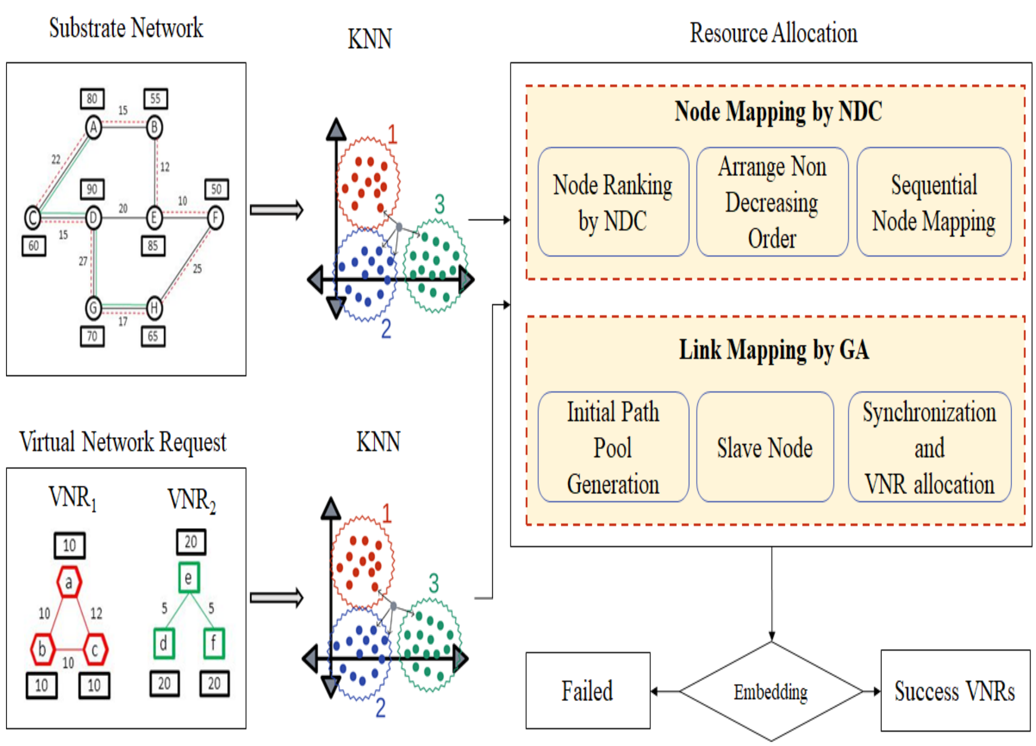

Figure 2: Proposed Architecture of Network Embedding through NDC-GA

All multiple paths that traverse the links with the smallest sum of connected weights are identified using the Dijkstra's shortest path algorithm. Since the GA can dynamically update the link weight, all paths may be easily modified to best suit the current network conditions. Each iteration of the link embedding process and fitness function calculation is performed until a threshold value of N is reached. The optimal situation is realized when the best connections are achieved at the lowest possible link bandwidth using this iterative procedure. The GA-based parallel scheme is shown in Figure 3.

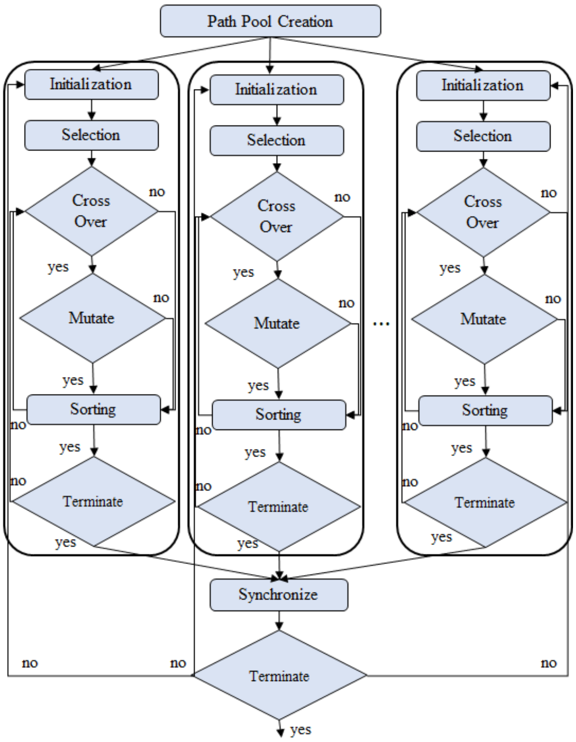

Figure 3: Parallel Operation Scheme in Link Mapping Process

5 SIMULATION RESULTS

It starts with an undirected graph of the substrate and virtual networks, each with their own set of nodes and links. A Barabasi-Albert [18] scale free network method is employed to construct a graph. The testing parameters used in this investigation are detailed in Table 1. Slices have been developed for the performance datasets of both substrate and virtual networks, each of which has been built with its own set of network features in consideration. The databases are divided into three groups named eMBB, mMTC, and URLLC based on the research areas from which they were collected. Figure 4 shows how the KNN methodology operates under various training-to-testing ratios, which is an indication of the classification accuracy. In order to offer the required virtual request services, resources are allotted in accordance with a method that is based on NDC-GA. When analyzing this scheme, it is essential to take into account the number of virtual request nodes, which may be broken down into a number of different ranges from 5 to 35, as well as the 100 nodes that compose the substrate network. Figure 5 illustrates the resource efficiency that can be obtained in a number of different system operating settings by comparing the results of several simulations.

Table 1: Simulation Parameters

Substrate Network		
Definitions	Description	Range
N_{SN}	Number of SN nodes	100
C_{SN}	The distribution of CPU for each node	U[20-50]
LC_{SN}	The distribution of link capacity of each nodes	U[20-50]
BW_{SN}	The distribution of bandwidth of each links	U[20-50]
Virtual Network Request		
Definitions	Description	Range
T_V	The total number of VNRs arrived in the time frame	U[5-35]
N_V	The distribution of nodes for each VR	20
C_V	The distribution of CPU capacity	U[5-25]
LC_V	The distribution of link capacity	U[5-25]
BW_V	The distribution of bandwidth	U[5-25]
LT_V	The time duration of each VNR	U[10-35]

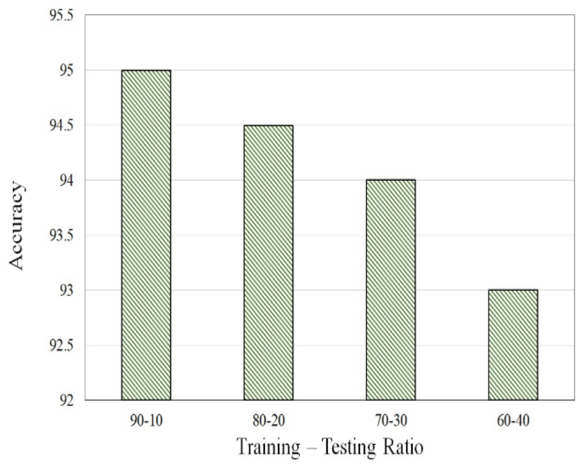

Figure 4: Classification Accuracy

When more VNRs are added to a network, the efficiency of the system falls. The resource efficiency of the NDC-GA technique is higher than that of a number of other approaches, including DPGA [1], MMGAPS [15], and NTANRC [17]. The acceptance ratio of the NDC-GA approach is presented graphically in Figure 6. According to the information displayed in this figure, the acceptance ratio is reported to have a minimum value of 0.6 and a maximum value of 1. When compared to a variety of other methods, such as DPGA, MMGAPS, and NTANRC, it demonstrates that the NDC-GA method that we have recommended provides a higher acceptance ratio.

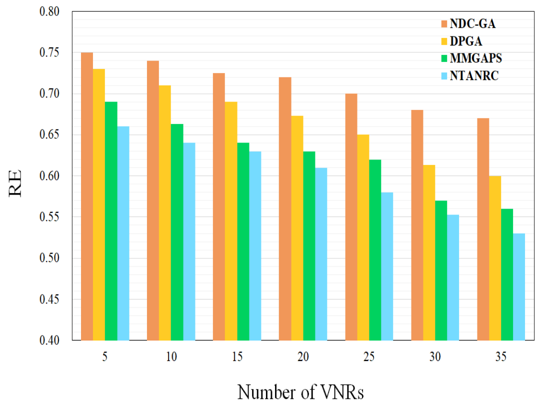

Figure 5: **Resource Efficiency of NDC-GA with other Algorithms**

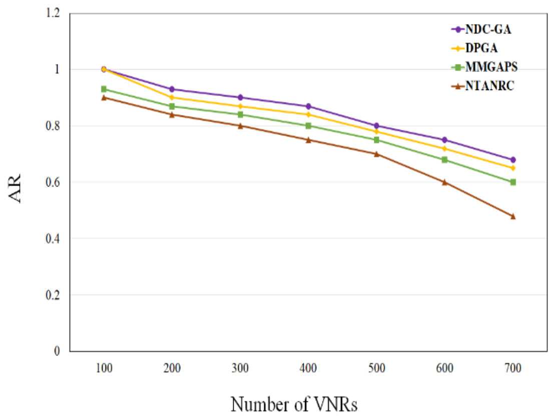

Figure 6: Acceptance Ratio of NDC-GA with other Algorithms

6 CONCLUSIONS

In the proposed work, KNN-based classification was performed to categorize the SN and VNR nodes. The NDC-GA scheme has been utilized for allocating resources for newly created slices. During the embedding process, the NDC approach was utilized for mapping the nodes, whereas the GA method was utilized for the formation of links between the nodes. To show that both resource efficiency and the acceptance of requests can be improved with the use of the NDC-GA technique, the recommended solutions were assessed by utilizing a wide variety of network operating conditions in association with a number of different VNRs. The performance of the proposed algorithm was evaluated by comparing its results to those of existing approaches. Finally, the NDC-GA based framework has been shown to be better than alternative approaches. The planned work can be improved by incorporating a stronger service-level commitment and security implications.

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