Network Resource Management for Virtual Networks with Learning Algorithms

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***Abstract*—**
Network virtualization is a technique to have multiple virtual networks share resources of multiple substrate networks. This allows virtual networks to be decoupled from underlying hardware and leads to more flexibility. A big challenge of network virtualization is to efficiently manage network resources. There are various algorithms to allocate network resources to virtual networks. Recently, machine learning algorithms are proposed to manage network resources. This paper presents nonlearning algorithms and learning algorithms. Important aspects of both type of algorithm are discussed and compared. Many aspects show that learning algorithms can be more efficient in the long-term.

***Index Terms*—network virtualization, virtual network embedding, dynamic resource allocation, resource management, machine learning**

1. Introduction

The structure of the internet is dependant on the underlying physical infrastructure. Changing the structure is connected with high costs since hardware has to be replaced and added. Therefore the physical infrastructure is fixed. Network virtualization is a possible solution to the ossification of the internet. To increase the flexibility of the internet and networks in general, multiple virtual networks are mapped to substrate networks. The virtual networks share the resources of the substrate networks. Virtual network embedding is the process of efficiently embedding virtual networks to substrate networks with limited resources (Figure 1). There has been a lot of research on virtual network embedding. Embedding virtual networks is known to be NP-hard [21]. Another part of network virtualization is to dynamically allocate resources. Dynamic resource allocation is the process of allocating resources to different virtual networks during its runtime. Dynamically allocating resources requires the knowledge of multiple virtual networks to efficiently allocate resources without affecting the Quality of Service that the virtual networks provide. This leads to the need for monitoring the multiple virtual networks which requires more calculation and decreases the effiency of the whole system if the reward of the dynamic allocation is not high enough. Therefore past research had a higher focus on virtual network embedding than on dynamic resource allocation. However, recently there is research on dynamic resource allocation as it is becoming more interesting and efficient due to the use of machine learning. Machine learning became more popular in many different fields of computer science because of its nature of increasing its performance over time and its wide range of application cases, e.g. face recognition, language processing, finding the fastest path with consideration to the traffic. Machine learning is a technique based on the human ability to learn through experience. Machines simulate the learning ability of humans to learn by repeating certain actions and evaluating the reward of their actions. They gradually learn and improve over a long period of time until they are optimized. Recent works like [13] and [18] show many possible approaches to network virtualization by using learning algorithms to efficiently manage resources.

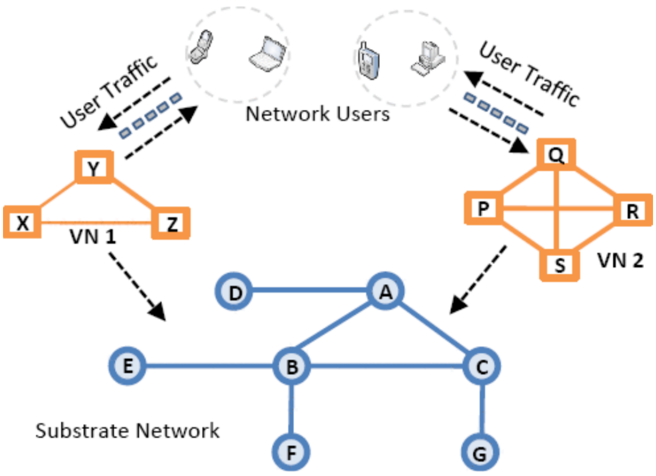

Figure 1: Virtual Network Resource Allocation, Figure 1 of [13]. The substrate network (hardware) consisting of nodes (A-G) and links is fixed. To be more flexible, virtual networks consisting of virtual nodes (P-S, X-Z) and links are mapped on the substrate network. Network users have access to the virtual networks without knowing about the underlying infrastructure of the substrate network.

This paper presents both nonlearning algorithms and learning algorithms for network virtualization and shows different aspects of both kind of algorithms. The high potential of learning algorithms, what possibilities they present and how their limitations can be remedied are shown in this paper. The rest of the paper is structured as follows. In section II different approaches to nonlearning algorithms and their characteristics are presented, in section III recent learning algorithms are presented. In section IV the aspects of nonlearning and learning algorithms are compared. Section V discusses the results of section V and summarizes the results of this paper.

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2. Nonlearning Algorithms

Virtual network embedding has been a well known problem. There are various approaches to the virtual network embedding problem.

Policy-based: Miyamura, Kamamura and Shiomoto [1] propose a policy-based approach to resource management with each virtual network having its own reserved resources. If needed, a virtual network could get access to resources that are shared between them.

Divide and conquer: Zhang et al. [3] propose an approach to divide substrate networks into many partitions to deal with large-scale networks.

Distributed multi-agent architecture: Soares and Madeira [4] developed a dynamic, distributed multi-agent architecture where each agent is located in the substrate network nodes. This leads to less complexity as actions are performed locally and automatic actions by agents in the form of self-management and self-healing.

Cognitive: Han et al. [5] propose a cognitive management scheme for managing virtual network resources that focuses on the topology and centrality.

Hierarchical Katayama et al. [6] use a hierarchical approach to the virtual network embedding problem. Submanagers are used, which manage multiple substrate network nodes to reduce complexity.

Sharing-based: Mao et al. [8] propose a sharing based network embedding algorithm where network resources are divided into equal time slots before starting with the embedding process.

Prediction-based

The nonlearning approaches are often based on assumptions that the demand of resources from the virtual networks do not change much. Therefore it is rather unflexible, limiting these algorithms to having to know the amount of allocated resources beforehand. As stated by Mijjumbi et al. [13] most of the approaches are static and focus on embedding virtual networks. The allocated resources are not changing during the lifetime of the virtual network. There is no dynamic allocation of resources, in some cases there is a possible migration of the virtual links between the virtual nodes, but the allocated resources are fixed. Reconfiguring the mapping of virtual networks to substrate networks is not available or only in case of failures. But if the demand of resources is not changing much during its lifetime, nonlearning approaches are fitting for the virtual network.

3. Learning Algorithms

Recently there have been many approaches to virtual network resource management that use machine learning to allocate network resources from substrate networks to virtual networks. Most of the learning algorithms are based on reinforcement learning and neural networks. Reinforcement learning is a method to make an agent learn based only on rewards it gets for its actions. Based on past actions, a utility function is approximated, showing the utility of each action in each state. Q-Learning is a reinforcement learning technique.

Q-Learning: Mijumbi et al. [13] proposed an approach to use Q-learning to dynamically manage resources after embedding the virtual network. An agent chooses an action based on the Q-values Q(s,a) of each action in that state. The action is chosen random, but actions with a higher Q-value have a higher probability to be chosen. After each learning episode, the Q-values are updated based on the received reward. The Q-values are updated based on the Q-learning rule in (1).

$$Q(s_p, a_p) \leftarrow (1-\alpha)*Q(s_p, a_p)+\alpha \left\{ \begin{matrix} r_p + \lambda max Q(s_n, a) \\ a \in A \end{matrix} \right\} \quad (1)$$

The parameter s_p represents the present state, a_p the present action, s_n the next state and r_p the immediate reward for taking the action a_p. The updated Q-values are comprised of the past Q-value and the new reward. The parameter $0 \leq \alpha \leq 1$ determines how fast the agent is learning. Having a learning rate of α closer to 1 makes the agent learn more from new experiences but also past experiences get less important. Therefore α is often set near 0 to make the agent learn slowly but steadily. The discount factor λ determines whether immediate rewards or future rewards are more important. A discount factor of λ closer to 1 gives more important to future rewards. With each learning episode, the Q-values converge towards an optimal solution.

Mijumbi et al. used 8 different values to describe the percentage of used resources. Each state is represented by the percentage resource allocation, the percentage of unused virtual resources and the percentage of unused substrate resources. So there are 8 * 8 * 8 = 512 different states. They used 9 different actions to change the percentage of used resources, so there are 9 * 512 = 4608 different state-action pairs and Q-values.

Autonomic and distributed: Mijumbi et al. [11] propose an autonomic and distributed way to manage resources in virtual networks. Each virtual network is managed by an autonomous agent. The agents use reinforcement learning and they cooperate with each other to automatically manage the resources. These virtual networks can heal, configure, protect and optimize themselves through reinforcement learning. **Ant colony optimization:** Cao et al. [7] propose an ant colony optimization algorithm to optimize virtual network embedding. The ant colony optimization algorithm mimics ants that follow pheromones secreted by other ants to get to their food. Paths that are more frequently used contain more pheromones, so by following paths with stronger scents of pheromones, the ants are improving their effiency until it is optimal.

Neuro-fuzzy: Mijumbi et al. [12] propose a neuro-fuzzy approach to manage network resources. It is an reinforcement based approach that is distributed and dynamically allocates resources to the virtual networks.

Autonomous neural network Mijumbi et al. [14] also proposed an autonomous neural network based resource allocation management.

Statistical Learning: Li [15] developed a dynamic resource management approach based on statistical learning that guarantees no violation of the Quality of Service of the virtual networks.

Radial basis function neural network: Zhang et al. [18] use a radial basis function neural network to embed the virtual networks. By using training samples they simulate an embedded virtual network and learn with the simulation. After the learning period the virtual network is embedded based on the expected usage of resources.

Learning algorithms are mainly used to dynamically allocate resources throughout the runtime of the virtual network and to improve the network. Also as seen in case of [18], radial basis function neural networks can be used to simulate the training process, presenting the possibility to apply learning algorithm on the embedding of virtual networks. Learning algorithms have high potential as they approach nearly optimal solutions after enough learning time. Learning algorithm are probabilistic so they can try other steps and possibly learn through these experiences. That leads to the problem that learning algorithm can never be optimized as there is always some probability that it does not follow the optimal strategy. Another big problem of learning algorithms is their initialization. At the time of initialization the virtual networks have no knowledge as they had no time to learn. The period of time or number of test samples that is needed to learn an sufficient efficient strategy can be quite big. So at the beginning learning algorithms are bound to fail a lot. Having a virtual networks that is expected to fail at the start could become a problem.

4. Comparison of nonlearning and learning algorithms

Most nonlearning algorithms are focused on the embedding of the virtual network. There is less focus on dynamically reallocating virtual network resources during the runtime of the virtual network while learning algorithms are mainly used to dynamically allocate resources during the runtime. Nonlearning algorithms are based on assumptions. If the assumptions are right and do not change significantly during the runtime of the network, then nonlearning algorithms are efficient. Learning algorithms are more dynamic and flexible in comparison to nonlearning algorithms, so for changing demands of resources they are more fit. Also being able to predict changing demand of resources and proactively adjusting to changes is a big advantage of using learning algorithms. As shown by Mijumbi et al. in [13] the number of accepted networks is much larger with dynamic learning algorithms than with static nonlearning algorithms (Figure 2). The biggest disadvantage of learning algorithms in comparison to nonlearning algorithms is their bad performance at the initialization state and the large period of time needed to become as efficient as nonlearning algorithms. Also shown in [13], for the packet drop rate, dynamic learning algorithms need some time to learn to be as efficient as static approaches (Figure 3). Another minor disadvantage of learning algorithm is that while learning there is some minor work put in learning, in comparison to nonlearning algorithms which do not work proactively. Mijumbi et al. in [14] compared their artificial neural network with a dynamic approach based on reinforcement learning and two static approaches (Figure 4). Simulations showed that artificial neural networks are significantly better that the other approaches. Also, the dynamic approach based on reinforcement learning showed better results than both static approaches.

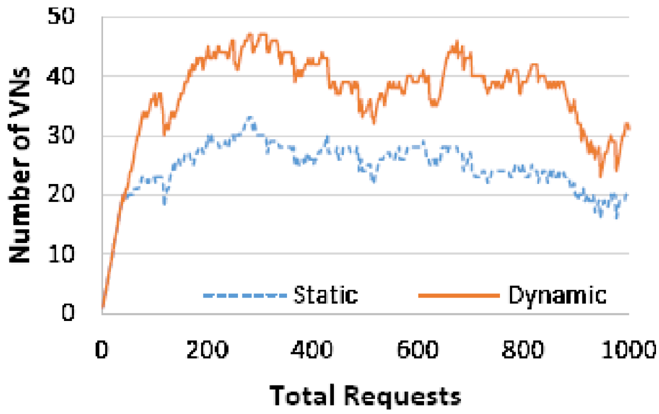

Figure 2: Number of Accepted Networks, Figure 9 of [13]

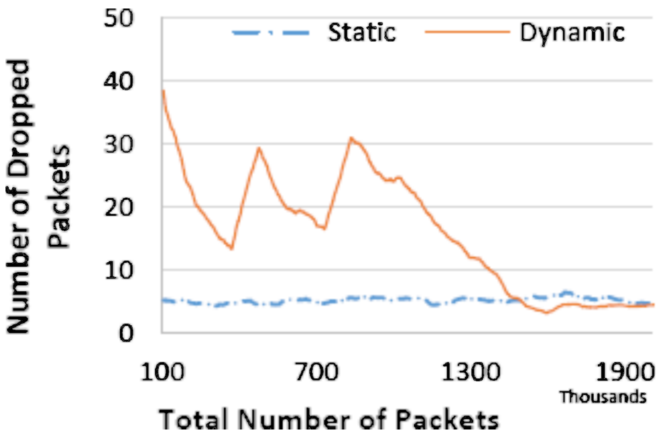

Figure 3: Node Packet Drop Rate Variation, Figure 10 of [13]

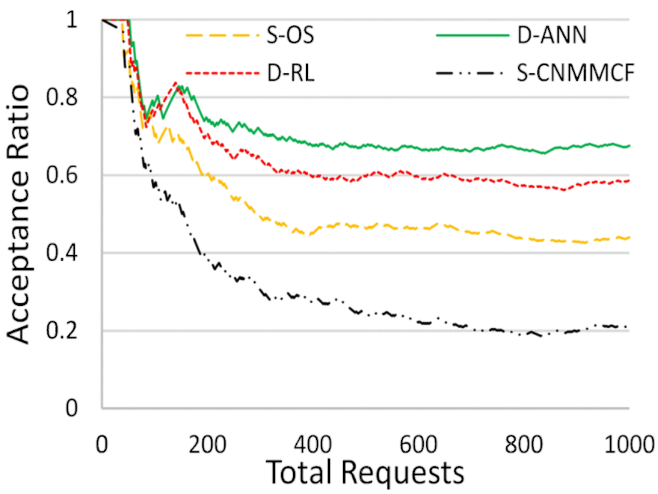

Figure 4: Acceptance ratio, Figure 3 of [14]. The two dynamic approaches D-ANN (Dynamic, based on Artificial Neural Networks) and D-RL (Dynamic, based on Reinforcement Learning) were compared to two static approaches S-CNMMCF (Static, Coordinated Node Mapping and MCF for link mapping) and S-OS (Static, link based optimal one shot Virtual Network Embedding). It is visible that the dynamic approaches perform much better than the static ones.

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5. Conclusion and Future Work

In this paper various approaches to managing resources in network virtualization were presented. First traditional nonlearning algorithms to solve virtual network embedding were explained, then recent research on the topic learning algorithms was presented. Both types of algorithms showed potential in managing network resources, but in comparison learning algorithms are more useful in most cases and promise more potential in effiency.
Nonlearning algorithms have a short-term advantage over learning algorithm because of the weak performance of learning algorithms at the initialization state. Also in networks without significant changes in network resource demand, nonlearning algorithms perform well from the start. However for most networks, especially for the future internet the ability to dynamically reallocate resources will be essential. Learning algorithms show great potential to improve efficiency and flexibility. Mijumbi et al. adress in [16] the disadvantage of learning algorithms at the start and suggest following solution: Initiating an offline learning step to let the learning algorithm improve first. This solution would remedy the bad performance of learning algorithm at the start. This solution is similar to the approach of Zhang et al. in [18], to use other virtual networks as test samples to nurture their radial basis function network algorithm in a first step before embedding the virtual networks. Therefore learning algorithms would be adventegeous to nonlearning algorithms in most cases, if a first learning step is introduced. For future work it would be interesting to research if there are different patterns of agents using learning algorithms. This could shorten the time needed to learn as different evaluations for each action can be implemented from the start. Also, it would be interesting to research how to optimize using learning algorithms on networks with human users. Maybe learning algorithms could also be used to predict the usage of the network of different people based on their past usage.

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