Dynamic Service Function Chain Embedding for NFV-Enabled IoT: A Deep Reinforcement Learning Approach

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Summer term 2020

Internet of Things (IoT) technology is gaining prominence in recent days and the number of IoT devices is increasing at an exponential rate. Using advancements in network technologies like Network Function Virtualization (NFV) this huge demand can be facilitated. NFV can be used to replace hardware network functions as software called Virtualized Network Functions (VNF). The VNFs related to one application is logically connected to form Service Function Chain (SFC). Resource allocation in the IoT network should be done dynamically because of its heterogeneous nature. This report explains briefly the contents of paper [1], where authors have proposed the Deep Reinforcement Learning (DRL) method to allocate resources for VNF in NFV-enabled IoT networks.

1 Introduction

Modern technological developments in communication and information sectors have paved a way for making the Internet of things (IoT) to reality. To support a vast number of heterogeneous devices and applications of IoT, adaptation to new methods like Network Function Virtualization (NFV) is necessary. In NFV, network functions are deployed as software called Virtual Network Functions (VNF) on the physical node instead of using the proprietary hardware like domain name system, firewalls, load balancers, etc.. These software entities required by a particular application, are logically arranged to form a chain called Service Function Chain (SFC). Computing, and, networking resources are allocated to them on the substrate network, either in terminal devices or edge servers, and this process of resource allocation is termed as SFC embedding.

IoT network applications differ in their requirements of VNFs required for its processing traffic. Hence, the algorithms using the static methods for SFC embedding does not give efficient results. Authors in [1] propose, handling the dynamic NFV-enabled IoT network requirement of SFC embedding with Deep Reinforcement Learning (DRL) methods. The network and computing resources of IoT networks can be allocated adaptively using DRL based learning methods improving resource efficiency and reducing the average service latency.

2 System Model

2.1 Service Function Chain Embedding in NFV-Enabled IoT

IoT network constitutes of terminal devices with less computing resources, for better utilization of these resources, VNFs with large resource requests are broken down into more than one sub-VNFs called Virtual Network Function Components (VNFCs). VNFCs are connected through virtual links forming a new request topology called VNF-Forward Graph (VNF-FG). The process of dividing VNF into VNFCs is not discussed by the authors in paper [1].

In IoT networks, the SFC embedding process includes orchestrator, service chain, virtualization layer, and IoT network layer [1] as we see in Figure 1. The orchestrator is responsible for running an optimization algorithm and decide on managing the SFC of an IoT service. The service function chain shows VNFCs of firewall, load balancing, encryption, packet inspection, and decryption in the mentioned order, required for processing data. The resources from mobile devices to edges servers are represented in the IoT network layer and virtualized infrastructure for the physical IoT network layer is represented in the virtualization layer. For better connectivity, the base stations are connected with the edge server using fiber links.

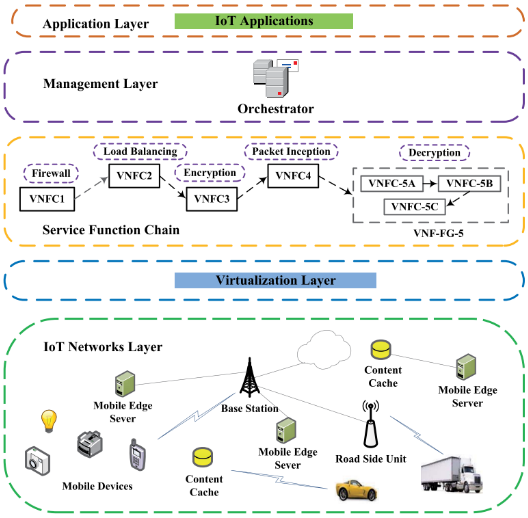

Figure 1: Service function chain embedding in the NFV-enabled IoT framework. Source: [1]

2.2 Problem Model

The VNFCs should be embedded in the substrate network considering the different arrived requests. With multiple SFC requests arriving in discrete time steps at the physical network, these requests are processed in a round-robin manner. Within an SFC, VNFCs are allocated resources in order of their logical execution. The resource demand of each SFC is known only when the service request is received. Authors propose fixed embedding, where the VNFCs are not preempted once allocated from the start of the service to the end of the last VNFC completing its execution. Hence, in the NFV-enabled IoT network, the response of the environment for an action from the agent depends on all the previous VNFC embedding.

IoT has a variety of applications like smart building, augmented reality, sensor networks, and many more. Hence the data stream pattern in the IoT network is stochastic in the model. SFC embedding is considered with transition probabilities from one state to another making it as finite Markov property problem [1] with which we can apply Reinforcement Learning (RL) patterns to efficiently find a solution.

3 Problem Formulation

In this section different parameters considered for SFC embedding in IoT network for making it as a DRL problem are discussed.

3.1 System State and Action

The main objective of SFC embedding is to reduce the average processing delay of SFC. Same IoT nodes and data transfer link will be shared between VNFCs of different SFC making the process more complicated. In IoT network with N nodes, each node share computing and memory resources which is given by $\{i_c, i_m\}$ and $\{b_{ij}\}$ is the link bandwidth between two nodes i *and* j, where $i, j \in \{1, 2....N\}$, availability of these resourses, represents the state space. The resource demand of VNFCs are represented as sum of different Gaussian functions, and resource consuming state of substrate networks is obtained by sampling at random points. The current state is represented in vector form s, $s = \{\{1_c, 2_c, .., N_c\}, \{1_m, 2_m, .., N_m\}, \{b_{i,j}\}\}$ [1].

With information on all the available resources and the requirements, the central management should choose an action of allocating resources to the VNFCs, based on the current state. In action space, $a \in \{1, 2, .., N\}$ agent allocate resources to one VNFC at a time and state transition is observed in the state space. With this feedback the agent moves to the allocation of next VNFC of the service chain in the next time step.

3.2 Reward

In the proposed DRL scheme of dynamic SFC embedding, authors have considered the reward metric as a total delay for allocating resources to an SFC.

Which includes, the sum of VNFCs transmission delay (d_t) in the physical links of NFV infrastructure and the its processing delays (d_{proc}) at the physical nodes [1], represented as $d_{total} = d_t + d_{proc}$. For stability purpose, authors assume that user traffic between two active VNFCs will not be rerouted in later allocations. In the DRL algorithm, the agent's main purpose is to accumulate maximum rewards over the long run rather than the immediate rewards which will result in processing the VNFCs with minimum average delay.

The proposed method deployment in the NFV-enabled IoT network is with NFV-MANO (Management and Orchestration Node of NFV framework). NFV-MANO receives all the requests for the resource service and forms the SFC of VNFCs. The agent present in the NFV-MANO allocates the resources based on the current condition of the IoT network.

4 Deep Reinforcement Learning Approach

Reinforcement Learning (RL) consists of 4 main components: strategy, reward function, value function, and model of the environment. RL can be classified as model-based or model-free depending on whether an environment is available or not. The agent in the RL follows a policy (strategy) to perform actions to get maximum reward in the long term based on the value-functions. Q-learning is used in the training process of the agent, where Q-function is the action-value function. In the proposed work, authors have made use of the deep neural network, experience replay, and target network methods along with Q-learning to analyze the high dimensions of state space and action space generated by the NFV-enabled IoT network. Experience replay helps in reducing correlated data.

5 Simulation and Results

5.1 Simulation Environment

IoT network is heterogeneous, the resources for embedding is obtained from different terminal devices and edge servers. Due to this random nature it is very difficult to realize it in simulation. For this SFC embedding algorithm authors have considered random networks, small-world networks [3], and BA scale-free networks [2] as simulation topologies. Random network topology simulates the irregularity nature of IoT substrate networks which is designed based on edge probability and will be helpful in performance evaluation. Small world network contains large clustering coefficients and short average path length and BA scale-free network will help stimulate the practical IoT scenarios with nodes are scale-free and connectivity or node-degree distribution uses power-law form [1].

5.2 Implementation

DRL based dynamic SFC embedding algorithm [1] is implemented using Python 3.6 with TensorFlow 1.4.0 for deep neural networks implementation and NetworkX library for simulating environments discussed in 5.1. Authors have not made the implementation public, hence it has to be done using the algorithm and simulation settings mentioned by them in [1].

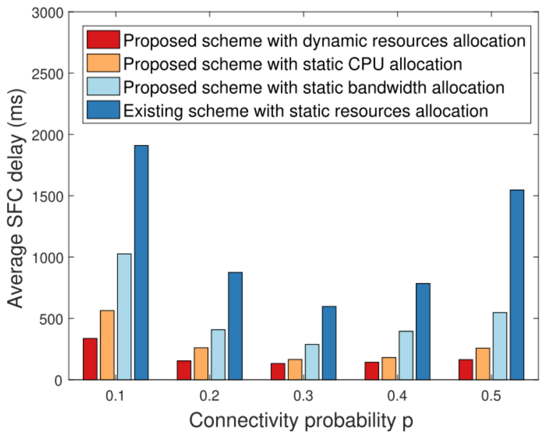

Figure 2: The average delay of a SFC in random network topologies with different node connectivity probabilities; Source: [1]

5.3 Results

The proposed scheme is compared with other schemes like static resource allocation using a heuristic algorithm, static computing resource allocation, and static bandwidth allocation. The performance of the algorithm is as shown concerning the average delay in the random network with an increase in connectivity probability (Fig. 2). Connectivity probability is directly proportional to the number of edges hence the delay increases after 0.3. Small world network results show average delay with a count of neighboring nodes (Fig. 3). An increase in nodes will increase the number of edges affecting positively at first but after the count 3 delay increases. Fig. 4 shows the evaluation of the BA scale-free network and results show the average delay of SFC embedding increases with the increase in the number of initial nodes. From the graphs we can observe that a dynamic resource allocation scheme with the DRL method gives the best results compared to other schemes in all the 3 simulated networks.

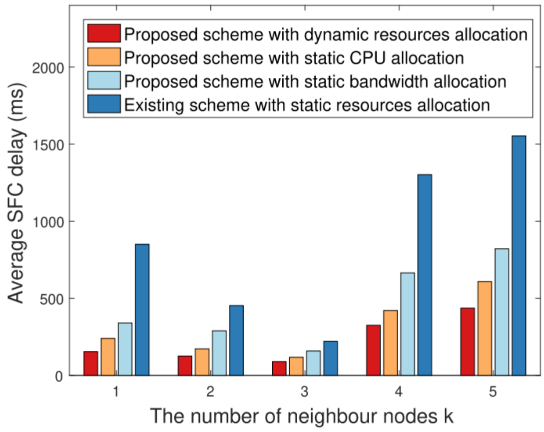

Figure 4: The average delay of a SFC in small-world network topologies with different number of neighbor nodes; Source: [1]

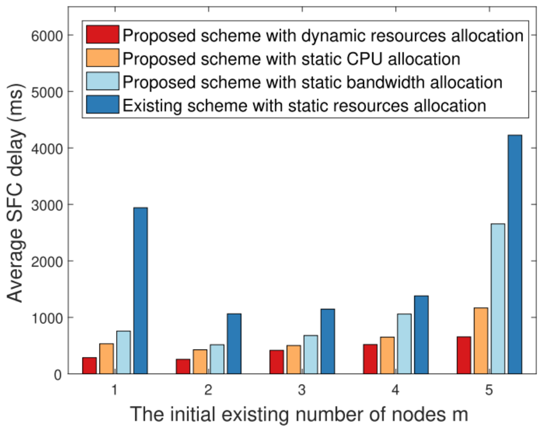

Figure 3: The average delay of a SFC in BA scale-free network topologies with different initial existing nodes; Source: [1]

6 Conclusion

For NFV-enabled IOT networks the SFC embedding is a complex task because of the heterogeneous and dynamic property of IoT. Authors of [1] have proposed DRL based solution to the SFC embedding problem by dividing the VNF into small VNFCs. The state space, action space, and rewards have been discussed with experience replay and target network for DQL to enhance the convergence performance. Results have been evaluated by considering different topologies which shows the proposed scheme gives better performances.

7 Future Work

Different RL algorithms or as proposed by the authors, convolutional neural networks can be adopted to NFV-enabled IoT network scenario and check whether there will be any improvement in the performance of SFC embedding.

References

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