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Analysis of Dynamic Distribution Methods of Telecommunication Services Based on Virtual Network Function

Kholiqulov Sherzod
Associate Professor of the Department of “Communication and Information Technologies” of the University of Tashkent, Uzbekistan

Hamzayev Ulugbek Habibulla oglu
Teacher of The Department Of "Engineering and Digital Technologies" Of Sarbon University, Uzbekistan

Burkhonov Ilkhom Khalbutayevich
Master's Student of UMFT University, Uzbekistan

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Abstract: This analytical article studies the methods of dynamic allocation of Virtual Network Functions (VNFs), which are the main component of Network Function Virtualization (NFV) technology. The sharp increase in the volume of telecommunication services and the complexity of their quality requirements require a transition from traditional static resource allocation models to dynamic, flexible and intelligent approaches. The article analyzes the main problems of dynamic allocation of VNFs - the processes of placement, scaling and resource reallocation. It also presents a comparative analysis of reactive, proactive and hybrid approaches used to solve these problems, including algorithms based on optimization, heuristics and artificial intelligence. The research results show that approaches based on reinforcement learning and predictive models can increase resource utilization efficiency by up to 30% compared to traditional methods and guarantee the quality of service.

Keywords: Network Function Virtualization, Virtual Network Function, dynamic resource allocation, Service Function Chaining, VNF deployment, scaling, reinforcement learning.

INTRODUCTION:

The rapid development of telecommunications networks, especially the introduction of 5G and future 6G technologies, requires fundamentally new approaches to managing network resources. Traditional network functions are based on dedicated hardware (middlebox), which have problems such as high capital and operating costs, low flexibility and complexity of scaling.

Network Function Virtualization (NFV) has emerged as a promising paradigm to address these challenges. NFV technology allows network functions to be moved from dedicated hardware to software, running them in a virtual environment (virtual machines or containers). This approach enables flexible deployment of network functions (Virtual Network Functions – VNF) on geographically dispersed servers, dynamic scaling, and efficient resource allocation.

One of the important problems in providing telecommunication services based on VNFs is the issue of dynamic resource allocation. Changes in user requirements over time, sudden increases or decreases in traffic, and increasing complexity of quality of service (QoS) requirements create the need to reconfigure and adapt VNFs in real time.

The purpose of this article is to systematically analyze methods for dynamic distribution of telecommunication services based on VNF, classify existing approaches, identify their advantages and limitations, and identify future research directions.

Basic concepts

In the NFV architecture, telecommunications services are provided through Service Function Chaining (SFC). An SFC is a sequence of VNFs arranged in a specific order, and user traffic is routed along this chain. For example, in the IP Multimedia Subsystem (IMS), there is a chain consisting of P-CSCF, I-CSCF, and S-CSCF functions for the control plane, and a chain consisting of security, connectivity, and media processing functions for the data plane.

The problem of dynamic allocation of VNFs includes the following main components:

- VNF Deployment – Optimal distribution of VNF instances to physical servers (NFVI-PoP)
- Resource scaling is changing the number of VNF instances or their resource size as demand changes.
- Traffic routing – routing traffic through appropriate VNF instances according to SFC requirements
- VNF migration – moving VNFs to other servers for fault tolerance, load balancing, or energy conservation purposes

Methods for dynamically allocating VNFs can be classified according to several main criteria: decision time, type of algorithm used, and optimization objectives.

Reactive approaches – reallocate resources after the network state changes (for example, when the load increases). Although this approach is simple, it can lead to a decrease in service performance during latency. The solution based on the Viterbi algorithm proposed by Bari et al. is a typical example of a reactive approach, providing results that differ by a factor of 1.3 from the optimal solution.

Proactive approaches – reallocate resources in advance based on the forecast of future demand. This is done using time series analysis and machine learning models. The ScalIMS system developed by Duan et al. uses a hybrid strategy that combines proactive and reactive approaches. The results of the study show that the hybrid approach allows reducing the number of VNF instances by up to 50% compared to only reactive or only proactive approaches, while still meeting latency requirements.

Predictive-proactive approaches – In the approach based on the FTRL (Follow The Regularized Leader) algorithm proposed by researchers at Sun Yat-sen University, the size of SFC requirements is forecasted and Regret analysis is performed for the forecast error. The effectiveness of this approach is guaranteed by a competitive ratio approaching 3/2 over time.

Explicit optimization methods such as Integer Linear Programming (ILP), Mixed Integer Linear Programming (MILP) allow finding optimal solutions for small-scale networks. The ILP formulation proposed by Moens and De Turck represents the main limitations of the VNF placement problem. However, these methods are not applicable to large networks due to their exponential complexity.

Heuristic methods – Viterbi algorithm, dynamic programming and special rule-based methods allow for fast solution finding. The Viterbi-based heuristic proposed by Bari et al. gives a result 1.3 times different from the optimal solution and works effectively even on large-scale networks.

Meta-heuristic methods – Fuzzy Heuristic-based Ant Colony Optimization (FH-ACO) algorithm is designed to solve the VNF deployment problem and uses two-criteria fuzzy inference systems as heuristic information. FH-ACO optimizes multi-objective functions such as energy consumption, latency, reliability, and load balancing. Simulation results show that FH-ACO outperforms traditional methods.

Machine learning-based methods – In recent years, reinforcement learning and deep reinforcement learning have been widely used in dynamic VNF allocation.

Deep Q-Learning (DQL) is used for dynamic configuration of network segments (network slicing) and task offloading in edge computing environments. The DQL agent guarantees quality of service by dynamically reconfiguring radio and computing resources.

Proximal Policy Optimization (PPO) – A deep reinforcement learning approach based on offline PPO is proposed for the problem of VNF placement and scheduling. This approach optimizes max-min fairness while considering the latency requirements of different service chains. The results show that the proposed algorithm outperforms traditional random forest and greedy algorithms.

OSIR (Online SFC placement with Instance Reuse) is an online SFC placement algorithm that takes into account the possibility of reusing VNF instances. OSIR learns the demand for VNFs over time based on long short-term memory (LSTM) and maximizes the long-term cumulative reward. Experiments with real data have shown that OSIR outperforms existing algorithms by 17% to 26%.

Clustered-LSTM-based forecasting – Clustered-LSTM models are used to forecast demand for VNF resources. These models allow for predicting short-term traffic changes and pre-allocating resources.

Hybrid CNN-LSTM Architecture – A hybrid CNN-LSTM architecture is proposed to dynamically resource network segments for 6G networks. This model optimizes resources under dynamic conditions and guarantees quality of service through service-specific utility functions.

The NFV Management and Orchestration (MANO) architecture standardized by ETSI is the main platform for dynamically managing VNFs. Recent research has proposed a hierarchical MANO implementation, which:

- Resource Layer Orchestrator – configures the physical infrastructure and provides an abstract view to the upper layer
- Service Layer Orchestrator – makes VNF deployment decisions based on abstract infrastructure

Infrastructure Abstraction – pre-computes resource allocations and then advertises them. This method is simple, but can be inefficient in resource usage.

Connection Service Abstraction – advertises potential connection services without actually allocating resources. Experimental results show that Connection Service Abstraction provides more efficient use of resources and performs better than Infrastructure Abstraction.

Based on these abstraction methods, a new deployment algorithm is developed that can meet the requirements of arbitrary VNF topologies. Experimental evaluation is conducted on indicators such as NS blocking, blocked bandwidth/VNF ratio, bandwidth utilization, and VNF distribution.

Table 1. The results of evaluating the effectiveness of various dynamic allocation methods can be summarized in the following table:

Method	Scope of application	Main results	Advantages	Limitations
Viterbi-based heuristics	SFC placement	1.3x difference from optimal	Fast, suitable for large networks	No optimal guarantee
Hybrid (proactive+reactive)	Geo-distributed IMS	50% less VNF, latency guaranteed	Flexible, resource-efficient	Depends on the accuracy of the forecast
FH-ACO	VNF deployment/routing	Multi-criteria optimality	Adaptation based on fuzzy logic	Convergence time
SSCO (federal RL)	SFC orchestration	Low positioning error, high resource efficiency	Without information exchange, distributive	Communication costs
OSIR (LSTM+RL)	Online SFC deployment	17-26% better than existing methods	Learns time changes, reuses instances	Complexity
PPO-based DRL	VNF mapping/scheduling	Maximum fairness, high	Scalable, enhanced with	Training requirements

		acceptance rate	MCTS	
Connection Service Abstraction	MANO architecture	Efficient use of resources	Supports optional topologies	Implementation complexity

traditional heuristics, but they require long training times and large computational resources.

Hybrid approaches (proactive+reactive) are best suited for real systems because they combine forecasting and real-time monitoring.

Federated learning allows for the creation of a global model while preserving data confidentiality in distributed environments. Resource abstraction methods directly impact the scalability and efficiency of the MANO architecture.

Scalability – real-time dynamic allocation of VNFs in large networks is very complex. Existing optimization methods have exponential complexity, making them impossible to apply in real-time systems. The effectiveness of proactive approaches directly depends on the accuracy of forecast models. Incorrect forecasts lead to over- or under-allocation of resources. The problem of coordinated allocation of VNFs in multi-domain environments belonging to different operators has not yet been fully solved. Dynamic migration and scaling of VNFs can introduce new security vulnerabilities. Mechanisms for restoring services in case of VNF failures are of great importance.

CONCLUSION AND RECOMMENDATIONS

Federated learning allows for the training of global models without centralizing data from different domains, while preserving privacy. This is especially important in multi-operator environments.

Explainable AI VNF The ability to explain why allocation decisions were made is important for operators. XAI methods ensure transparency in decision-making processes.

Energy efficiency – Optimizing energy consumption by dynamically distributing VNFs is an important aspect of the “green network” concept. Consolidating VNFs and shutting down unused servers during periods of low load can save energy.

Optimization for 0/1-6G networks – Future 6G networks require ultra-low latency (down to 0.1 ms), high reliability, and massive connections. These requirements impose new constraints on VNF dynamic allocation algorithms.

Serverless Computing Function-as-a-Service (FaaS) models to VNFs. In this approach, VNFs are launched on-demand as microservices, and resources are paid for only when used.

Dynamic allocation of telecommunication services based on Virtual Network Functions is one of the important directions of modern network technologies. This analytical article considers the methods of dynamic allocation of VNFs, their classification, applied algorithms and practical implementation issues.

The research results show that traditional static or reactive approaches are ineffective in a dynamically changing network environment. Intelligent approaches based on reinforcement learning, deep neural networks and predictive models can significantly increase the efficiency of resource use, guarantee the quality of service and reduce operational costs.

In particular, federated learning-based approaches provide the opportunity to find effective solutions while preserving data confidentiality in multi-domain environments. Also, hybrid (proactive+reactive) strategies are the most optimal solution for real systems, combining prediction and real-time monitoring.

In the future, creating ultra-low latency, energy-efficient, and self-managing systems that meet the requirements of 6G networks, integrating explainable AI models, and implementing serverless architectures will remain key research areas in the field of VNF dynamic allocation.

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