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A Comparative Study of Resource Allocation Algorithms Used in Network Virtualization Function

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Abstract: A new networking technology in the telecom sector called network function virtualization lowers operating and capital costs while enabling network service deployment. In NFV, seeks to tackle challenges by utilizing standardized IT virtualization technology to combine various types of network equipment onto industry-standard, high volume servers, switches and storage systems, which may be situated in data centers, network nodes, or at the end user's location. The Virtual Network Functions (VNFs) worked as software oriented approach, it creates a high flexible and dynamic network to meet more several demand along with a series of research challenges, such as, VNF management and orchestration, service chaining, VNF scheduling for low latency and efficient virtual network resource allocation with Network Function Virtualization Infrastructure (NFVI), among others. However, because network conditions and workloads are dynamic, effective resource management is still a major difficulty in NFV systems. This survey paper presents an overview of resource allocation algorithms in Network Functions Virtualization (NFV). We examine state-of-the-art approaches as Deep Reinforcement Learning (DRL), Parallel VNF Placement Framework (PVFP), RL Based Framework and Online Coordinated Resource Allocation (OCRA), analyzing speed, limitations, and suitability for dynamic environments. This paper has been prepared as an effort to reassess the research studies on the relevance of machine learning techniques in the domain of Network Function Virtualization.
Keywords: NFV, Resource Allocations, Machine Learning.

I. INTRODUCTION

In the past, network operators have provided services in the telecom sector by deploying physical, proprietary devices and equipment for each function that makes up a particular service. Furthermore, the network topology and the placement of service pieces must take into account the stringent chaining and/or ordering of service components. These have resulted in lengthy product cycles, very little service agility, and a significant reliance on specialized hardware, especially when combined with demands for high quality, stability, and strict protocol adherence.

By utilizing virtualization technology, NFV [3], [4] has been suggested as a solution to these issues, providing a fresh approach to networking service design, deployment, and management. Decoupling physical network equipment from the operations that use it is the fundamental concept of NFV. This implies that a TSP can receive a network function, such a firewall, as an instance of ordinary software. This makes it possible to combine a variety of network equipment types onto high-volume servers, switches, and storage that may be found at end user locations, data centers, or dispersed network nodes.

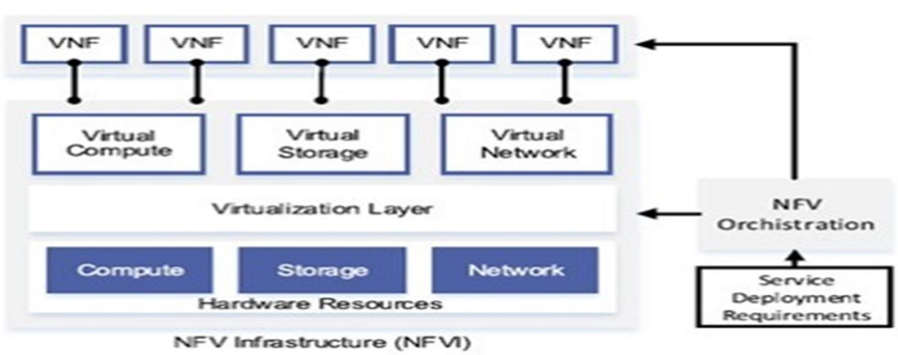

Fig.1.1.Architecture of NFV

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NFV is still in its early stages, and realizing its expected benefits requires addressing several challenges. A key challenge involves the efficient and autonomous management of resources allocated to VNFs, while ensuring the reliability of the services they support. This aspect of resource management is particularly crucial for upcoming 5G networks, which will demand substantial resources and facilitate applications like connected vehicles that require highly dependable networks. There is a necessity for algorithms that define how resources from the Network Functions Virtualizations Infrastructure (NFVI) are distributed among the VNFs. These algorithms should be capable of vertically and/or horizontally scaling VNF resources while balancing two opposing objectives.[9].

II. RELATED WORKS

[1]B. Han, V. Gopalakrishnan, L. Ji, and S. Lee presented Network function virtualization as a way to shorten the time to market for new services and increase the flexibility of network service delivery. In order to divorce the software implementation of network services from the underlying hardware, NFV makes use of virtualisation technologies and commercial off-the-shelf programmable hardware, including general-purpose servers, storage, and switches. As a new technology, NFV presents network operators with a number of difficulties, including ensuring network performance for virtual appliances, ensuring their migration and instantiation dynamically, and ensuring their effective placement.

[2]Rashid Mijumbi, Joan Serrat, Juan Luis Gorricho, Niels Bouten, Filip De Turck, Steven Davy,illustrated a mapping and scheduling virtual functions into virtual networks after first mapping virtual networks onto physical networks. The online virtual function mapping and scheduling problem is formulated in this study along with a collection of techniques for its solution. Its primary goal is to provide basic algorithms that could serve as the foundation for further research in this field. To achieve this,it provides a tabu search-based heuristic along with three greedy algorithms. It evaluated these algorithms under various network situations, taking into account metrics like revenue, cost, total service processing times, successful service mappings, etc. The best greedy algorithm outperforms the tabu search-based algorithm by a little margin, according to simulations.

[3]Long Qu, Chadi Assi, developed a delay aware scheduling algorithm for scheduling virtual network functions and resource allocation with service chains .This paper formulated the dual problem of VNF scheduling and traffic steering as a Mixed Integer Linear Program (MILP), taking into account VNF transmission and processing delays. Its goal is to reduce the total VNFs schedule's makespan and latency. Cloud operators can serve (and allow) more users and accommodate services with strict delay requirements by lowering scheduling latency, which boosts operators' profits. They created a Genetic Algorithm (GA) based approach to effectively solve the problem because of its intricacy. Lastly, numerical analysis is used to confirm its heuristic algorithm's efficacy.The result demonstrated, the schedule makespan may be decreased by 15% to 20% by dynamically modifying the bandwidths on virtual links that connect virtual computers that host the network services.

[4]A. Suzuki et al developed an algorithm that concurrently resolves the combined optimization problem is one method for NFV control to optimize allocations. But this strategy cannot be expanded.because each time a new statistic is added or a combination of metrics is altered, the problem must be recast. Another strategy entails coordinating several control algorithms designated for distinct metrics utilising an extensible network-control architecture. To the best of knowledge, nevertheless, no technique has been created that can maximise allocations using this type of cooperation. In this research, coordinated many control algorithms to provide an expandable NFV-integrated control technique. Additionally, suggest an effective coordination algorithm to further discover that, in the case of several hundred steps, it can cut link-utilization by over half after fewer than 10,000 steps.

[5]Nahida Kiran, Xuanlin Liu, Sihua Wang, Changchuan Yin, formulated a VNFPRA problem is that requires meeting the optimal placement requirements ofVNFs in SDN/NFV-enabled MEC nodes to reduce the deploy-ment and resource cost. This paper proposed a solution problem based on two algorithms (i) an optimal solution for-mulated as a MIP problem and (ii) a genetic based heuristic algorithm. It also proposed a GA-VNFM algorithm to min-imise the total number of VNF migrations. Results show the higher performance of the proposed methods in comparison with four existing algorithms in literature. The results also validated the fact that a coordinated placement of VNFs in SDN,NFV, and MEC can satisfy the objectives of overall reduced cost.

[6]J. Zhang, Z. Wang, C. Peng, L. Zhang, T. Huang, and Y. Liu explained the online virtual network function backup under availability constraints (OVBAC) problem is examined in this paper in order to minimize costs in edge environments. It demonstrated the difficulty of the formulated problem by formulating it according to the properties of the volatility system states obtained from empirical data. It employs Drift-Plus-Penalty (DPP), an online backup deployment strategy that has demonstrated near-optimal performance for the OVBAC challenge. Specifically, at the start of every time slot, DPP must solve an integer programming issue. It suggests a method based on dynamic programming that can solve the issue in pseudo-polynomial time.

Comprehensive data-driven simulations in the real world show that DPP performs noticeably better than widely utilised practice baselines.

[7]Zhiyuan Li , designed that the NFV-RA problem is NP-Hard, the majority of current methods concentrate on heuristic and meta-heuristic algorithms. In this paper, offered an NFV online coordinated resource allocation framework (OCRA) that combines innovative neural networks and RL training approaches with parallel Multi-Agent Deep Reinforcement Learning to accomplish the three steps simultaneously in a coordinated way.According to the comprehensive testing results, OCRA is significantly more time-efficient than the state-of-the-art solutions, improving resource overhead and acceptance ratio by up to 50% and 10.8%, respectively.

[8]L. Wang, Z. Lu, X. Wen, R. Knopp, and R. Gupta developed a coordinated strategy to cooperatively optimize NFV resource allocation in these three stages. It takes into account both network expenses and service performance using a general cost model. A heuristic-based technique called JoranNFV is suggested to provide the nearly optimal solution for the coordinate NFV-RA, which is described as a mixed-integer linear programming. In order to simplify the coordinated NFV-RA, JoraNFV is separated into two sub-algorithms: a multi-path greedy algorithm for VNF chain composition and VNF forwarding graph embedding, and one-hop optimum traffic scheduling. Finally, in-depth simulations are run to assess JoraNFV's performance. The findings demonstrate that JoraN can obtain a solution within 1.25 times of the ideal solution with a respectable execution time, suggesting that JoraNFV can be employed.

[9]R.Mijumbi,S.Hasija,S. Davy, A. Davy, B. Jennings, and R. Boutaba, forecasted future resource needs for every VNF component (VNFC), and suggested a graph neural network-based approach that takes advantage of VNF forwarding graph topology information. Each VNFC's topological information is obtained by integrating its historical resource usage with the predicted impact on the same from neighboring VNFCs. A virtualized IP multimedia subsystem deployment and actual VoIP traffic traces were used to test our approach. The results showed an average prediction accuracy of 90%, as opposed to 85% with typical feed-forward neural networks. Furthermore,this method decreases call setup latency by more than 29% and lowers the average number of dropped calls by at least 27% when compared to a scenario where resources are allocated manually and/or statically.

[10]Stefan Schneider,Narayanan Puthenpurayil Satheeschandran,ManuelPeuster and Holger Karl, explained machine learning models are trained using actual VNF data, which includes resource and performance metrics. Every VNF's trained models can subsequently precisely forecast the resources needed to manage a specific traffic load. It assesses the influence of machine learning models on the final VNF placements after integrating them into an algorithm for joint VNF scaling and placement. This analysis using real-world data demonstrates that, in comparison to standard fixed resource allocation, the use of appropriate machine learning models effectively prevents over- and underallocation of resources, resulting in up to 12 times lower resource consumption and better service quality with up to 4.5 times lower total delay.

[11]MOHAMMAD BANY TAHA,etc designed strategy for the Cloud platform is auto-scaling, which is an essential management activity.However, in order to handle various normal and abnormal features, the Cloud platform's fluctuation and intense workload demand require appropriate and intelligent techniques. This research proposes a deep learning algorithm-based real-time proactive auto-scalar system. First, a real dataset of VNF in SFC for a data center is used to test a number of deep learning techniques. Then, to forecast the demand on VNF of SFC components including CPU, memory, and bandwidth, a hybrid model based on the MLP-LSTM algorithm for an online model is created.The online model's autocorrelation (ACF function) and a correction technique are employed in the suggested model to identify the abnormal events using regression model.

[12]Hurmat Ali Shah and Lian Zhao,provided a challenge of optimizations possible to formulate the Markovian decision process (MDP) of SFC placement within the system restrictions of IoT networks. A multi-agent DRL algorithm, in which each agent serves an SFC, is used to solve the MDP problem. Two Q-networks are examined, one of which resolves the SFC placement issue and the other modifies the Q-network's weights by monitoring long-term policy changes. Serving SFCs, the virtual agents engage with the environment, share rewards, and use their aggregate learnings to update the policy.With proper incentive design, state, and action space formulation, this system can resolve the SFC placement optimization problem. According to simulation data, the multiagent DRL scheme performs better than the reference systems in terms of utility obtained as determined by various network parameters.

[13]Hang Li, Luhan Wang, Xiangming Wen∗, Zhaoming Lu, Jinyan Li,examined The iterative deployment approach, which is frequently employed in existing solutions, is not required by MSV, which can automatically calculate the proper number of VNF instances without a specified maximum number threshold. MSV's primary concept is to identify a global basic solution first, then refine it through various improvement processes to prevent it from becoming easily stuck in local optimality and to steer clear of intricate anti-local-optimal methods. In comparison to the MIP approach, extensive testing showed that MSV may obtain solutions in the global range with a tolerable execution time and achieve a total cost ratio of less than 115%.

[14]Zhiwei Liu, Zhaogang Shu, Shuwu Chen, Yiwen Zhong, Jiaxiang Lin,explained the challenge of scheduling, routing, and mapping latency-sensitive virtual network functions (VNF) on a service function chain (SFC) on a virtual network. A VNF scheduling algorithm is put forth that considers VNF mapping, scheduling, and traffic routing during the scheduling process with the goal of minimizing the SFC rejection rate.A Markov decision process (MDP)-based VNF scheduling model that ensures SFC resource requirements are satisfied is developed in order to accomplish this goal. At each scheduling time point, the model chooses the SFC using the D3QN (Dueling Double DQN) algorithm based on composite rules. To reduce the SFC rejection rate, it uses a routing optimization technique to choose virtual nodes and routes.It evaluated algorithm against the DQN single rule and genetic algorithm can decrease the rejection rate of SFC by approximately 8% compared to genetic algorithms.

[15]Haojun Huang , Jialin Tian, Geyong Min using Federated Deep Reinforcement Learning (FDRL) model, a unique Parallel VNF Placement (PVFP) method is suggested for real-world networks.It has been designed to execute optimal VNF orchestration in networks under resource constraints.There are four finding had analysed as loss function ,local reward,average and end to end latency and resource overhead.According to simulation results in various scenarios the local training rate is to be either 0.0001 (0r) 0.001 for the small scale networks.Next PVFP reduced more network cost after 1100 training epochs for the large -scale networks.The end-to-end latency of SFCs can be considerably decreased using PVFP at medium resource expenditures.Through its VNF relationships and local DRL optimization, it effectively strikes a balance between resource usage and latency optimization, beating ParaSFC, GSS, NCO, and Gecode.

Table 2.1: SUMMARY OF RELATED WORKS

Ref.No	Problem	Approaches	Technology used	Topology used	Solutions	Operational criterion
[3]	VNF Scheduling and Service chain	Heuristic	Chromosome decoding algorithm Mixed Integer Linear Programme(MILP)	fully connected network topology	Network size increased,Transmission delay and schedule delay reduced	Schedule time=84(ms) Cpu Time=0.45,optimality gap=0.
[7]	NP-hard,NFV-RA	Deep Reinforcement Learning	Bi-Component Graph Convolution, Feature Extraction Based on Self-Attention [36]	Abilene /GEANT	Resource Allocation done effectively	Edge=12*12 node=12*12
[8]	NFV SFC	Dynamic	OneHop-SCH Multi-Path Greedy	Random /Flat free /Internet topology	Calculate no. Of flow created	Represented as graphically
[12]	SFC Placement	Deep RL	Multi Agent DQL Myopic Action Through Cost Calculation	fully connected network topology	Network capacity increased	Represented as graphically
[13]	NFV-RA	Heuristic	Merge Split viterbi Spilit chain viterbi	Abilene /GEANT	Easily trapped optimality,avoid anti-local -optimal measures.	Parameter in terms of mean and var node resources=10 & 8.33,transmission delay=2.5 & 0.0833,intra node delay=1.5 & 0.0833

[14]	VNF Low Latency	Deep RL	D3QN(Dueling Double DQN)	fully connected network topology	SFC Rejection Variation performance	Represented as graphically
[15]	VNF Placement	Federated Deep RL	SFC Decomposition FDRL -Based Training Framework	Abilene /GEANT	Maintain resource allocation in End to end and real world Scenarios.	capacity=64(or)128 Learning rate=0.001 (or) Learning rate=0.0001
[16]	VNF Placement	Heuristic	Integer Linear Programming(ILP)	Fat-Tree	minimize link bandwidth consumption, energy consumption, and SFC placement cost	Load Balance=80% Energy reduction=54% Cost reduced=67%
[17]	VNF placement	Clustering Heuristic	Clustering VNF Heuristic placement based on MOClusVNF	Sprint	Maximizing the number of flows admitted to the network, minimizing the path stretch, balancing the load among VNFIs.	No. of nodes=24, Links=43 Node capacity={0.1,0.2,0.3 }
[18]	VNF Architectur e	Mathematical	Mixed integer linear programming	Data center network, test network,random,sma ll and scale free network	Increase no. of flow accepted ,reduce resource cost,	Parameter value =1000 mbps

III. PERFORMANCE ANALYSIS

The following table represents execution time, CPU Utilization and memory utilization of a sample of RL, DRL.OCRA and PVFP Algorithms.

Sample Approaches	Execution Time	CPU Utilization	Memory Utilization
RL Coordination[12]	0.0000 seconds	63.58%	38.49%
DRL-Based Allocation[14]	0.0000 seconds	83.44%	38.49%
OCRA[7]	0.0000 seconds	63.58%	38.49%
PVFP[15]	0.0012 seconds	63.58%	38.49%

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IV. CONCLUSION

In this paper, a comprehensive review was conducted to examine resource allocation problems in NFV with various approaches. The implementation is carried out between RL, DRL, OCRA and PVFP algorithms for Virtual network functions across Multiple servers, to pivot on Memory, CPU and execution Time synthetic dataset featuring 5 servers and 10 VNFs is utilized, creating a controlled environment for testing. The dataset encompasses a range of resource needs for the VNFs and differing capacities for the servers, replicating real-world situations with diverse resources. The variety in the dataset ensures that each algorithm's strengths and weaknesses are highlighted.RL Coordination offers a compromise between efficiency and resource use, making it ideal for typical tasks. Optimal for Maximizing Resource Use: The DRL-Based Allocation ensures peak CPU utilization, making it suitable for tasks that require significant resources. Optimal for Simplicity: OCRA is efficient for basic allocation, but it may not fully utilize resources. Ideal for Parallelism: PVFP performs exceptionally well in parallel execution situations, although it tends to have longer execution durations. Choosing an algorithm must take into account the nature of the workload, the availability of resources, and the particular needs of the application setting.

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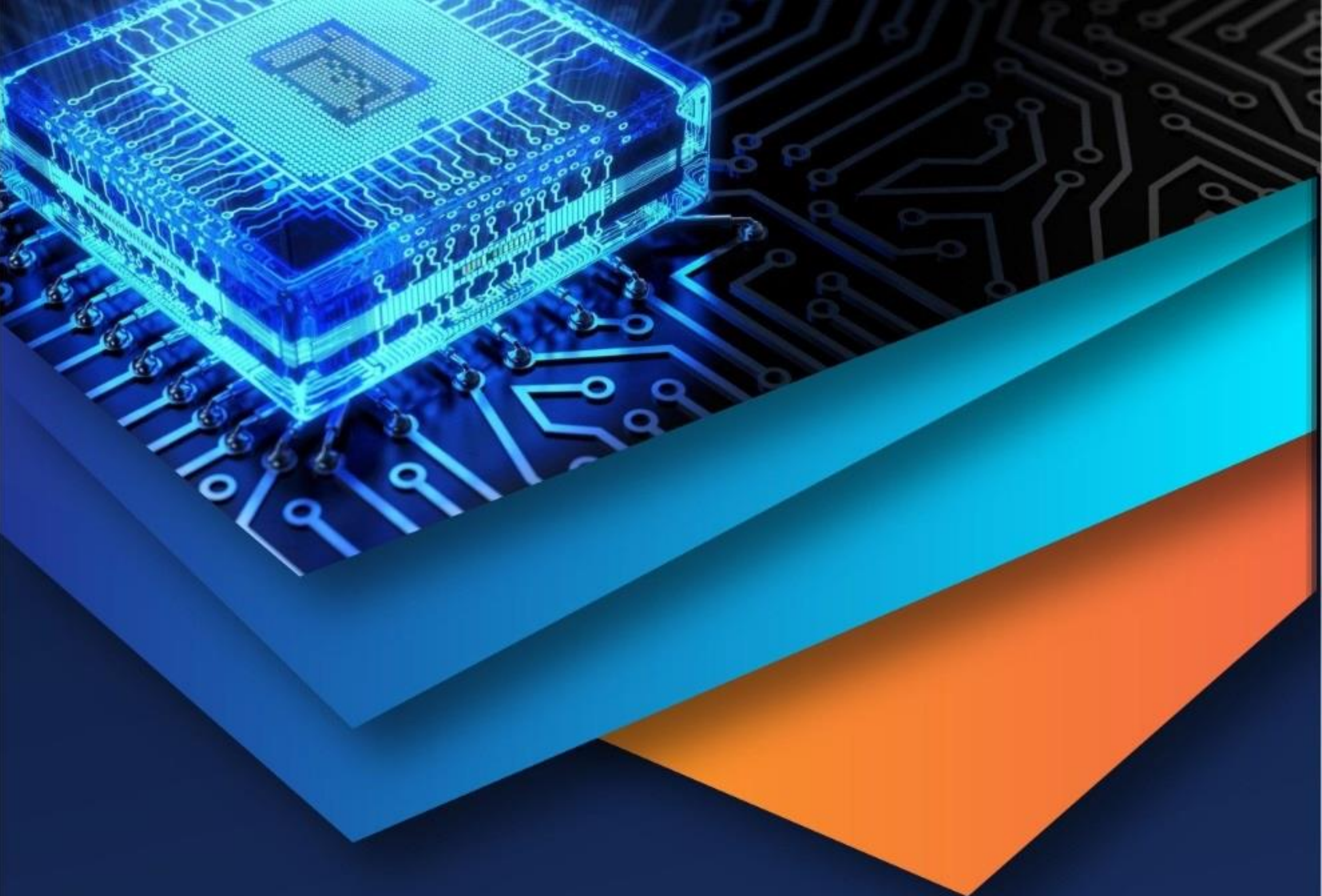

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