

Traffic Type Recognition in 6G Software-Defined Networking for Telepresence Services

Volkov Artem

Department of Telecommunication
Networks and Data Transmission,
Saint-Petersburg State University of
Telecommunications
Saint Petersburg, Russia
artemanv.work@gmail.com

Varvara Mineeva

Department of Telecommunication
Networks and Data Transmission,
Saint-Petersburg State University of
Telecommunications
Saint Petersburg, Russia
varvaramineyeva@gmail.com

Ammar Muthanna

Department of Telecommunication
Networks and Data Transmission,
Saint-Petersburg State University of
Telecommunications
Saint Petersburg, Russia
muthanna.asa@sut.ru

Andrey Koucheryavy

Department of Telecommunication
Networks and Data Transmission,
Saint-Petersburg State University of
Telecommunications
Saint Petersburg, Russia
akouch@mail.ru

Abstract— This paper deals with the problem of traffic typing and telepresence services, presents the results of analysis of existing methods based on DiffServ mechanisms such as Behavior Aggregate, Interface-based, MultiField. An extended traffic typing method based on LSTM networks is presented, a neural network for traffic recognition service in 6G networks is developed, promising directions such as the concept of 2030 networks and telepresence services are discussed, software-defined networking and virtualization of network functions are investigated. In this study, data obtained from an SDN flow table containing information about network traffic characteristics were used to train the ANN. To evaluate the effectiveness of the extended method, a special stand was developed to test and evaluate the quality of traffic typing. The stand includes the necessary hardware and software for conducting experiments and collecting data.

Keywords— 6G networks, traffic typing, telepresence services, SDN multicontroller, software-defined networking, artificial neural network.

I. INTRODUCTION

The Telepresence services are becoming one of the most important services of 6G networks [1,2]. It is worth noting that modern developments already allow the realization of such service models as "telepresence suits". In this regard, an important task of software-defined networking is to manage heterogeneous traffic transmitted over the network. Effective management requires classification of different types of traffic such as voice, video, data, etc. However, with the emergence of new traffic types, including telepresence services, haptic Internet traffic or M2M traffic, there is a need to develop and adapt classification methods for new data types [3,4].

Future networks should be able to provide high data density, more realistic communication and security with robust systems. It should also be noted that as the number of connected devices increases, the amount of data production will significantly increase, so the networks of 2030 will need to handle huge amounts of data. One prominent example is the model of humanoid robots, which are the direct nodes of the

network and implement network functions such as data transmission and processing.[5]

Therefore, traffic typing is necessary to ensure guaranteed throughput and congestion management in software-defined networking. This allows for a better user experience and improved data transfer. Typing techniques must be efficient and flexible to handle different types of traffic and adapt to changing network conditions.

Telepresence services are essential for next-generation networks to provide low latency and high data reliability. This is crucial for applications such as autonomous transportation systems, industrial automation, and real-time medical diagnostics. Proper classification and typing of telepresence traffic is essential in ensuring quality of service in these networks.

II. RELATED WORKS

As part of the MEGANET LAB 6G activities, a network architecture model is defined. It encompasses several functional segments, including robotic networks, fog computing, and holography.

A detailed functional diagram is shown in Figure 1.

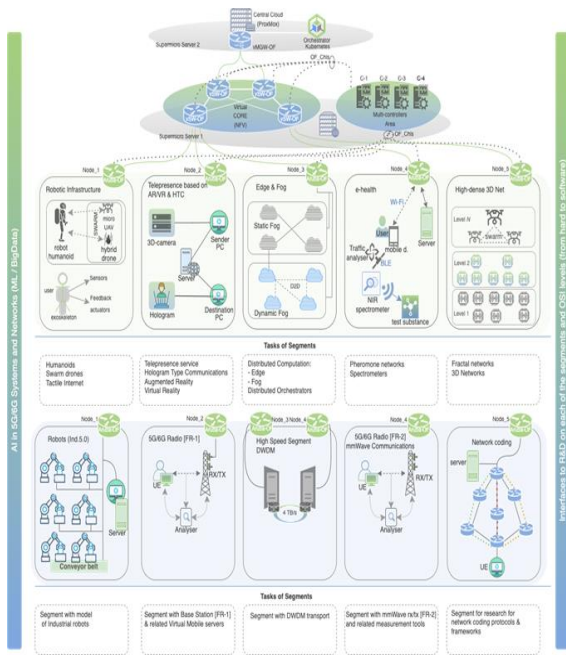


Fig. 1 - Architecture of the model network

According to ITU recommendations, this is a network of networks that provides seamless services regardless of the communication type, access technology, time, or user device. The network includes decentralized computing systems, integrated software-configurable environments represented by software-defined networking with virtual function virtualization, and a distributed software-controlled static and dynamic computing environment. This system operates as a self-evolving, self-regulating, and self-enhancing "living" intellectual entity.[6]

The 6G network will evolve from the 5G/IMT-2020 network, utilizing URLLC technology. Upgrading the 6G network will require point-to-point upgrades and advancements in all network layers, such as base stations, core networks, and end devices. It's crucial that these upgrades don't disrupt service availability, degrade quality, or alter service logic.[6]

Implementing telepresence services is a significant challenge. To manipulate objects in a remote environment, a telepresence system can control the device's movement. More complex alternatives, like reading hand and finger movements with special gloves or capturing body movements with a suit, are also possible. The device reproduces these actions, and the more accurate the movements, the stronger the immersion effect. Teleconferencing services provide new ways for users to interact over the network. Holographic communication has introduced innovative features. Numerous scientific studies, including ITU recommendations, have established a new form of communication known as holographic type communication (HTC).

To achieve this type of communication, the network requires easily configurable and maintainable facilities, which can be facilitated by SDN (Software-defined network) technology. Fig. 1 illustrates a model network that adopts a multi-controller network principle with a software-defined network. Refer to Fig. 2 for this segment.

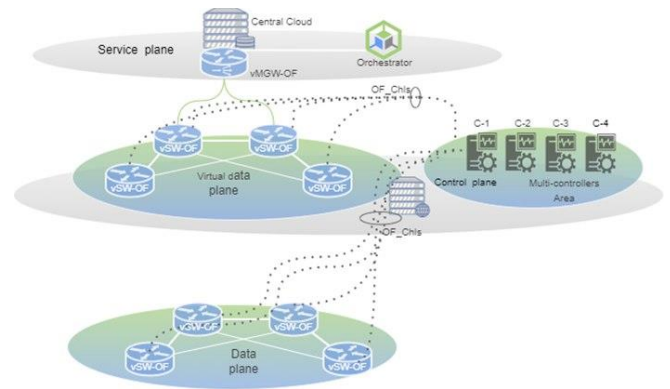


Fig. 2 - Structure of the stand with SDN multicontroller

Recognizing and classifying heterogeneous bulk traffic is a key challenge in designing 6G network traffic. This cannot be achieved using existing traditional methods. Instead, new robust artificial intelligence (AI) methods should be introduced. The algorithm developed to detect and recognize heterogeneous traffic in the underlying network serves as the basis for this approach, which is implemented at the control layer of the Software Defined Networking (SDN) network located in the core network. The algorithm is based on a neural network.[7]

III. PROBLEM STATEMENT

Software-defined networking (SDNs) centralize management and separate control functions from network devices, which allows for rapid and flexible network configuration and operation through software [8,9,10]. With the use of a centralized controller, network administrators can efficiently manage all network devices through software configuration and management, providing greater control and flexibility in network management.

The demand for telepresence services is on the rise. This type of traffic encompasses holographic replicas of individuals, robotic avatars, manipulation devices, and collaborative connections utilized within groups and communities. Telepresence services open up diverse opportunities for applications such as virtual reality, augmented reality, medical simulation, and beyond. High-speed data transfer, minimal delay, and consistent connectivity are essential for delivering an authentic and comprehensive user experience for this data type.

Various machine learning algorithms and methods for traffic typing in software-defined networking were studied in this paper. An investigation and extension of the traffic typing method using LSTM networks on a single SDN multicontroller responsible for network management was conducted. The ANN was trained using data from the SDN flow table containing network traffic information. To evaluate the effectiveness of the extended method, a dedicated stand was developed to test and assess traffic typing quality. The stand is equipped with necessary tools and software for conducting experiments and collecting relevant data.

The experiment produced data and ANN results for the traffic typing task. These results were evaluated based on the study's objectives, while also assessing the quality of traffic typing. Benefits and limitations of the machine learning technique were identified and the outcomes ultimately demonstrate the success of this approach for identifying promising traffic types.

IV. PROPOSED SYSTEM

Analysis of traffic typing methods

There are various methods to address traffic typing issues, and one such solution involves implementing DiffServ mechanisms. DiffServ, or Differentiated Services, is a Quality of Service (QoS) model that allows routers and switches to handle different types of traffic with varying priorities. By using the DiffServ approach, network traffic is classified into different classes based on their configurations, resulting in more efficient network transmission by offering different levels of service to various traffic types. DiffServ is a widely used technique for managing traffic in software-defined networking [11,12].

Based on this model, there are three methods for classifying network traffic:

Behavior Aggregate (BA) - This method utilizes a label in the packet header, such as the IP DSCP field.

Interface-Based - Traffic passing through a designated network interface is assigned to a particular traffic class.

MultiField (MF) is a packet analysis method that evaluates header fields, including IP addresses, ports, and MAC addresses, to attain a comprehensive understanding of network traffic and its behavior.

These traffic classification methods categorize traffic into different classes based on characteristics and labels. This enables network elements to effectively handle varied traffic classes in accordance with their priorities and requirements.

Several neural networks can address traffic typing problems, including recurrent neural networks (RNNs). RNNs analyze traffic with time dependencies and memorize data about past states to inform decisions based on current and previous features. LSTM (Long Short Term Memory) is a prevalent type of RNN that can memorize long-term dependencies in data. Recurrent neural networks with long short-term memory (LSTM) provide the best solution for the traffic typing problem. These networks demonstrate exceptional proficiency in handling time-dependent features. The advantages of using RNNs with LSTM include their ability to scrutinize the sequential structure of data, which is crucial for traffic typing, where packet arrival order holds significant importance. The LSTM cells within the RNN have the capacity to store information in long-term memory while also selecting what to transmit or forget, allowing for effective modeling of temporal dependencies and the capture of significant contextual features within the data. ITU Recommendation Y.3116 details this technique.

Therefore, using recurrent neural networks with LSTM for traffic classification results in high accuracy and robustness in

classification. Additionally, it enhances adaptability and processing of intricate temporal data structures, making it the preferred option for this task.

V. PROPOSED ARCHITECTURE

To perform a comprehensive experiment, we developed a testbed architecture that includes the essential equipment and components for collecting and analyzing traffic data. This architecture enables the replication of realistic network conditions and experimentation with various types of traffic.

The booth architecture includes the following major components:

SDN Controller: This component is the centerpiece of the stand and is responsible for network management. The SDN controller is used to manage the switches and collect traffic data.

SDN Switch: There is an SDN switch present in the booth, which performs the function of forwarding traffic in the network. The switch is connected to and receives instructions from the SDN controller.

Data Collection Software: A special software has been used to collect traffic data which makes queries on the north interface of the SDN controller. This software can access the flow table of the SDN switch and extract the necessary information such as byte-count, packet-count and TimeStamp.

The components allow for creating a realistic environment and collecting traffic data within the SDN network. This data will be used to train the neural network and categorize traffic in the future. Refer to Figure 3 for the stand architecture.

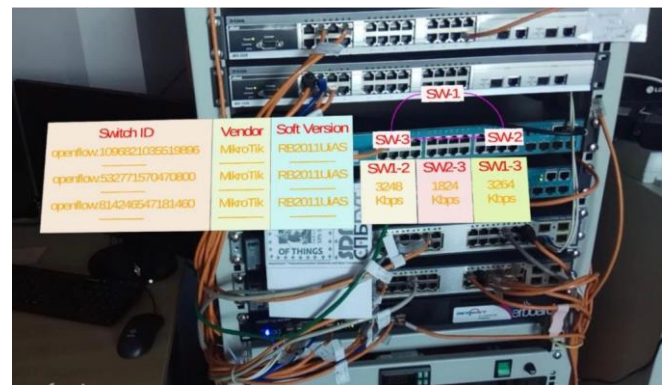


Fig 3 - Stand architecture

The revised version of the testbed architecture, shown in Figure 4, records data on all four traffic types used in this experiment. The equipment utilized for conducting the field experiment and gathering data is listed below:

Aruba Switch 2930F (JL259A) is an L3 switch that facilitates network traffic switching with support for the OpenFlow protocol, enabling its utilization in SDN-networks. The experiment employed the Aruba Switch 2930F (JL259A) to handle traffic and accumulate statistical data about SDN-network flows.

The Mikrotik CRS109-8G-1S-2HnD-IN is a versatile network device that combines router and switch functionalities,

providing various options for routing and traffic switching on the network. It features Ethernet ports for device connectivity and a built-in wireless module for creating wireless networks. During the study, we used the Mikrotik Cloud Router Switch CRS109-8G-1S-2HnD-IN to establish a wireless network segment and connect devices via Wi-Fi.

TP-Link TL-MR100 is a wireless router that enables internet access through cellular networks. It supports high-speed internet access with 4G LTE standards, making it ideal for locations without a wired connection or requiring mobile communication. The router was used in the experiment to create an isolated network segment for devices to access the internet.

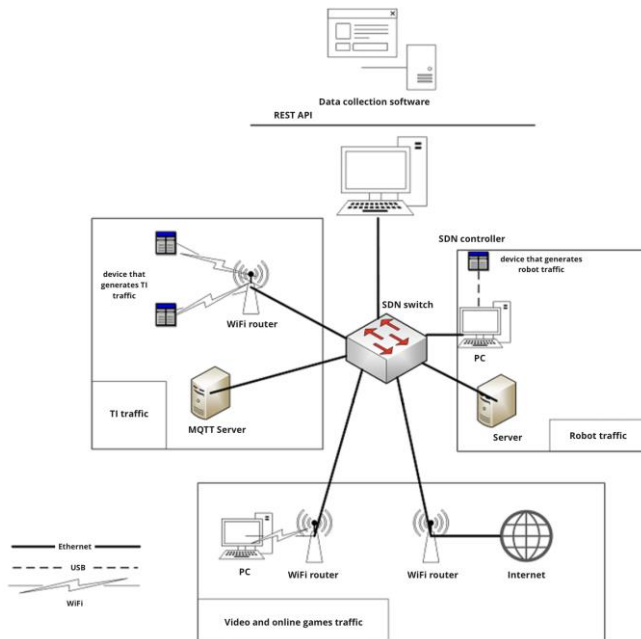


Fig. 4 - General stand architecture

The generators connected to the router through Wi-Fi. Two traffic generators gathered data by sending messages using the Message Queuing Telemetry Transport (MQTT) protocol to an MQTT server running on a personal computer. An SDN switch was vital in the network infrastructure by linking the router and the SDN controller.

VI. EXPERIMENTAL RESULTS

As part of our experiment, we carefully chose the size of the training batch (batch size). Increasing the batch size results in a significant improvement in learning speed, but it also leads to a decrease in accuracy. Similarly, increasing the batch size beyond 128 leads to a decrease in accuracy that falls short of 90%. Conversely, decreasing the batch size below 32 results in longer epoch times, taking more than 10 seconds to complete. To maintain a balanced outcome, we recommend a batch size between 32 and 128. Ultimately, we selected a training packet size of 128 since it achieves 95% accuracy and reduces training time by a factor of 2.6.

A neural network model with 256 neurons in the first hidden layer and 128 neurons in the second hidden layer was selected. These parameters resulted in high classification

accuracy and sufficient training efficiency. Figure 5 depicts the neural network model for the traffic recognition service in the 6G network.

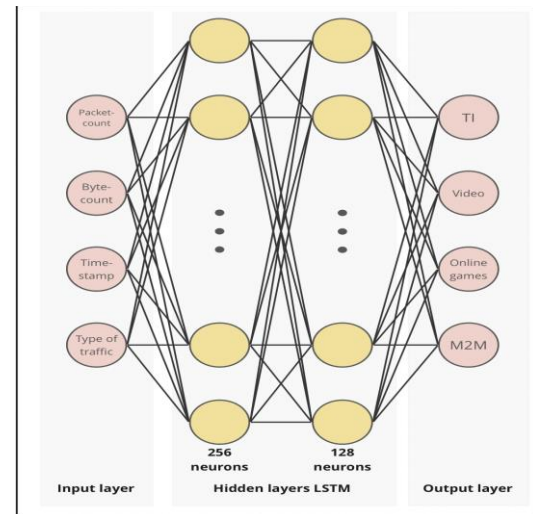


Fig 5 - ANN architecture

After training and testing the artificial neural network, we generated an error matrix, also referred to as a confusion matrix. This table helps us assess the model's performance by listing the number of examples that were correctly and incorrectly classified. Please refer to Figure 6 for the matrix.

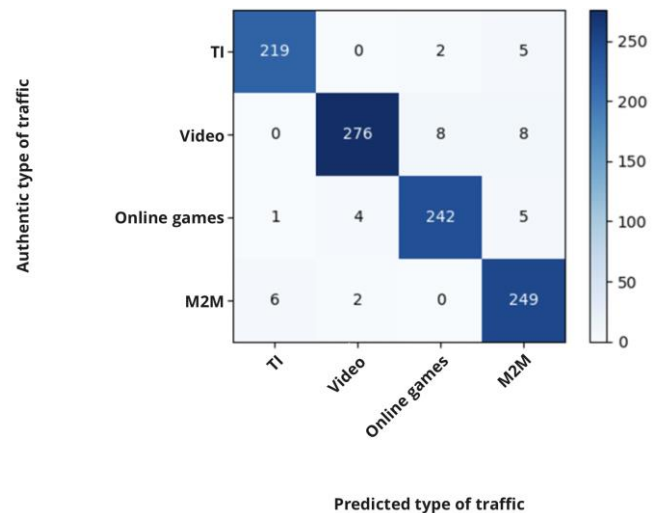


Fig. 6 - Error matrix

By analyzing the error matrix, we can draw conclusions regarding the model's performance:

The model accurately classifies haptic internet traffic and M2M traffic due to the values in the matrix cells being close to the diagonal.

The model struggles with categorizing both video and online game traffic due to non-zero values in the corresponding cells.

The total number of errors is small, indicating good performance of the model.

We examined the loss function, a metric that gauges the difference between the model's forecasted values and the actual values of the target variable. For an ANN, the loss function is its RMS error at every epoch. Figure 7 displays the loss function graph.

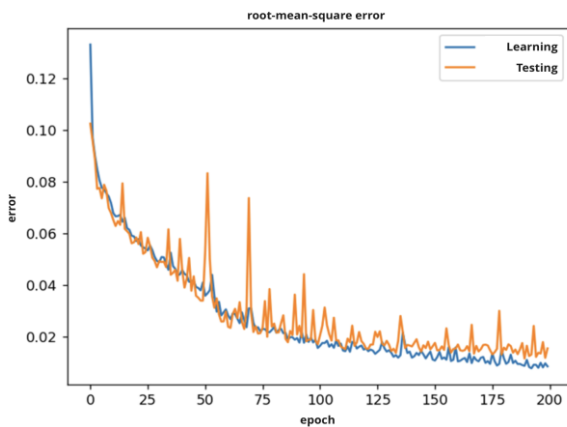


Fig. 7 - Loss graph

Analyzing the loss graph leads to the following conclusion:

The reduction in loss values with increasing epochs demonstrates the model's enhancements in its predictions and ability to typify traffic.

The final loss values are between 0.015 and 0.020, indicating effective model training.

After the ANN was trained, a diagram displaying the accurately identified traffic types and their corresponding probabilities was generated and presented in Figure 8.

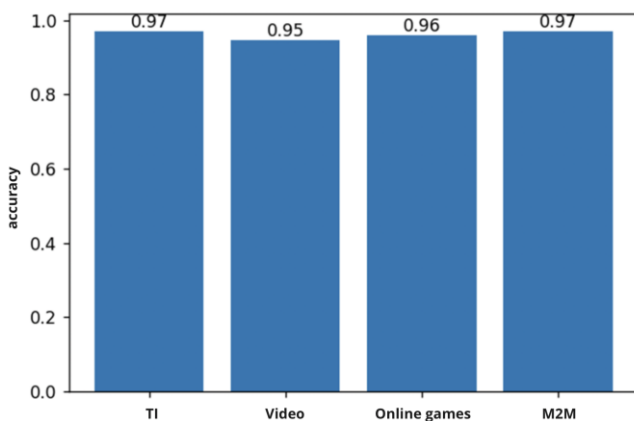


Fig. 8 - Probability of recognizing traffic types

The analysis indicates that the model accurately identifies and categorizes all four traffic types with high precision. Tactile Internet and M2M exhibit greater accuracy and fewer errors, whereas video traffic and online game traffic have slightly lower accuracy yet remain at a reasonably high level. Based on the column chart results and error matrix, it seems that the second and third traffic types share similar characteristics, causing the model to struggle when differentiating between

them. This assumption is supported by the fact that the recognition accuracy for these two traffic types (0.96 and 0.92 respectively) are closer to each other compared to the other types. In the error matrix, the off-diagonal feature values (misclassified samples) for the second and third traffic types are more similar to each other than to the other traffic types. This may indicate that there are common features or similar characteristics in the data that cause difficulty in classification.

VII. CONCLUSION

This study is a part of a larger project - researching the extensive application of artificial intelligence for 6G networks, specifically focused on ultra-low latency and ultra-high density networking technologies. The study results show that the developed model attained high accuracy on the validation data, and during the testing process, the oscillation and RMS loss were minimized while accuracy was enhanced.

The model effectively detects haptic Internet and M2M traffic with high probability values. These outcomes indicate that the model achieved high accuracy and successful recognition of promising traffic types. The empirical method of training parameter selection also proved effective, confirming the significance of the model for analyzing and classifying network traffic.

VIII. REFERENCES

- [1] Qiao, L.; Li, Y.; Chen, D.; Serikawa, S.; Guizani, M.; Lv, Z. A survey on 5G/6G, AI, and Robotics. *Comput. Electr. Eng.* 2021,95, 107372.
- [2] Dogra, A.; Jha, R.K.; Jain, S. A survey on beyond 5G network with the advent of 6G: Architecture and emerging technologies. *IEEE Access* 2020, 9, 67512–67547.
- [3] Muthanna, A., Ateya, A.A., Al Balushi, M. and Kirichek, R., 2018, May. D2D enabled communication system structure based on software defined networking for 5G network. In 2018 International Symposium on Consumer Technologies (ISCT) (pp. 41-44). IEEE.
- [4] Duo, R.; Wu, C.; Yoshinaga, T.; Ji, Y. SDN-based handover approach in IEEE 802.11 p and LTE hybrid vehicular networks. In *Proceedings of the 2018 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scal-able Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCOM/IOP/SCI)*, Guangzhou, China, 8–12 October 2018; IEEE: Manhattan, NY, USA, 2018;pp. 1870–1875.
- [5] FG-NET2030 – Focus Group on Technologies for Network 2030. Network 2030 Architecture Framework. – Geneva: ITU-T, 2020.
- [6] Artem, V., Ateya, A.A., Koucheryavy, A., 2019. Novel AI-Based Scheme for Traffic Detection and Recognition in 5G Based Networks, in: *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Springer Verlag, pp. 243–255. doi:10.1007/978-3-030-30859-9_21
- [7] Akyildiz, I.F. Holographic-type communication: A new challenge for the next decade / I.F. Akyildiz, H. Gu // *ITU Journal on Future and Evolving Technologies*. – 2022.
- [8] Long, Q.; Chen, Y.; Zhang, H.; Lei, X. Software defined 5G and 6G networks: A survey. *Mob. Netw. Appl.* 2019, 1–21.
- [9] Navarro-Ortiz, J.; Romero-Diaz, P.; Sendra, S.; Ameigeiras, P.; Ramos-Munoz, J.J.; Lopez-Soler, J.M. A survey on 5G usagescenarios and traffic models. *IEEE Commun. Surv. Tutor.* 2020, 22, 905–929 (10)
- [10] Ateya, A.A., Muthanna, A., Vybornova, A., Algami, A.D., Abuarqoub, A., Koucheryavy, Y. and Koucheryavy, A., 2019. Chaotic salp swarm

algorithm for SDN multi-controller networks. Engineering Science and Technology, an International Journal, 22(4), pp.1001-1012.

definednetworking-enabled architecture for vehicular networks. Internet Technol. Lett. 2020, 3, e10 (10)

- [11] Ge, X.; Li, Z.; Li, S. 5G software defined vehicular networks. IEEE Commun. Mag. 2017, 55, 87–93.
- [12] Muthanna, A.; Shamilova, R.; Ateya, A.A.; Paramonov, A.; Hammoudeh, M. A mobile edge computing/software-