Abstract

Software-defined Internet of Things (SD-IoT) enables centralized control, programmability, and adaptability for managing the complexity of Internet of Things (IoT) networks. As these networks expand with the increase in the number of IoT devices, efficiently routing time-critical data—characterized by their sensitivity to latency and high-priority nature—becomes increasingly critical. Time-critical IoT applications, including healthcare, intelligent transportation systems, and industrial automation, often rely on the timely delivery of such data. Although SD-IoT helps to address these challenges to a certain extent, it, too, has lacunae in terms of mitigating IoT traffic congestion, the presence of resource-constrained devices, and heterogeneity of IoT traffic, which limit its ability to handle time-critical traffic effectively. The conventional techniques, including static routing and packet analysis techniques, often fail to adapt to the dynamic and heterogeneous nature of SD-IoT networks.

This Thesis addresses some of these challenges through the adoption of Machine Learning (ML) algorithms into SD-IoT networks. ML-based approaches offer predictive mechanisms to improve network performance by classifying and prioritizing time-critical packets, allocating resources dynamically, and optimizing routing paths based on real-time network behavior, thereby rendering Quality-of-Service (QoS) to the time-critical packets.

Addressing time-sensitive packet routing in SD-IoT networks necessitates the efficient management of congestion and latency while guaranteeing QoS for latency-critical IoT applications. Accurate prediction of the mobility of the device, as well as assessing the incoming traffic, helps to determine the points at which flow-rules can be introduced most effectively to avoid delays. Furthermore, SD-IoT networks, by deploying ML algorithms for predicting time-sensitive traffic and bandwidth demands, ensure the unrestricted flow of time-critical packets under congested conditions.

Despite congestion-aware IoT traffic forwarding, the growing complexity of IoT applications demands an architecture capable of simultaneously managing diverse time-critical IoT applications. Integrating heterogeneous fog computing architecture into the SD-IoT network enhances flexibility and adaptability in the time-critical traffic forwarding process. Fog nodes, which are capable of selecting ML algorithms dynamically, allow real-time modifications to predictive policies and dynamic flow-rule allocation. This method reduces latency as well as energy usage, thereby addressing the difficulties introduced by time-critical IoT applications. Dynamic traffic management at the fog layer guarantees that essential computations are executed locally, thereby minimizing reliability on centralized systems and rendering QoS for time-sensitive data.

Although the aforementioned fog-enabled SD-IoT architecture renders faster time-critical traffic forwarding, the flow diversity in resource-constrained SD-IoT networks necessitates scalable flow-rule design and replacement mechanisms. Virtualizing the storage space for flow-rules and reallocating unused flow-rules among the adjacent SDN switches or local controllers enhances flow-rule accommodation efficiency and mitigates memory overflow in the limited storage of SDN switches. This distributed method guarantees continuous routing of time-sensitive packets, even during high-traffic conditions, hence preserving network performance and dependability.

Finally, employing the Federated Learning (FL)--based decentralized learning model reduces the heterogeneity of IoT traffic, preserves privacy, and enables QoS. In addition, introducing network slicing provides service differentiation and QoS control for different slices, which supports time-sensitive traffic and achieves better performance in the overall network. Altogether, FL and network slicing propose a comprehensive solution for delivering time-sensitive packets in diversified and dynamic SD-IoT networks.

Smart healthcare and smart transportation traffic are time-sensitive in a way that the delaying of instant health alerts or vehicle safety messages would lead to fatalities. Thus, this Thesis further presents an SDN-enabled fog design for smart healthcare in which the ML models determine the time-criticality of the data collected and direct it to the respective fog or cloud nodes. The fog layer carries out the processing of high-criticality data to minimize delay and power usage and enhance the patients' experiences. Additionally, this Thesis also intertwines ML and SD-IoT for intelligent transportation systems, allowing edge nodes to analyze the road scenario and effectively control traffic flow through dynamic flow-rule placements.

The study demonstrated in this Thesis shows significant improvements in reducing delay and energy consumption and increased packet delivery ratio compared to existing methods. Thus, the suggested architecture advances the development of SD-IoT as a reliable paradigm for managing time-sensitive traffic within SD-IoT networks.

Keywords: Software-Defined Networking, Internet of Things, Machine Learning, Federated Learning, Convolutional Neural Network, Transfer Learning, Augmented Reality, Time-critical Data, Network Slicing, Heterogeneous Traffic Classification, Smart Healthcare, Smart Transportation.