Batch Network Slicing for OTT Services in a Demand-Aware SDN Environment

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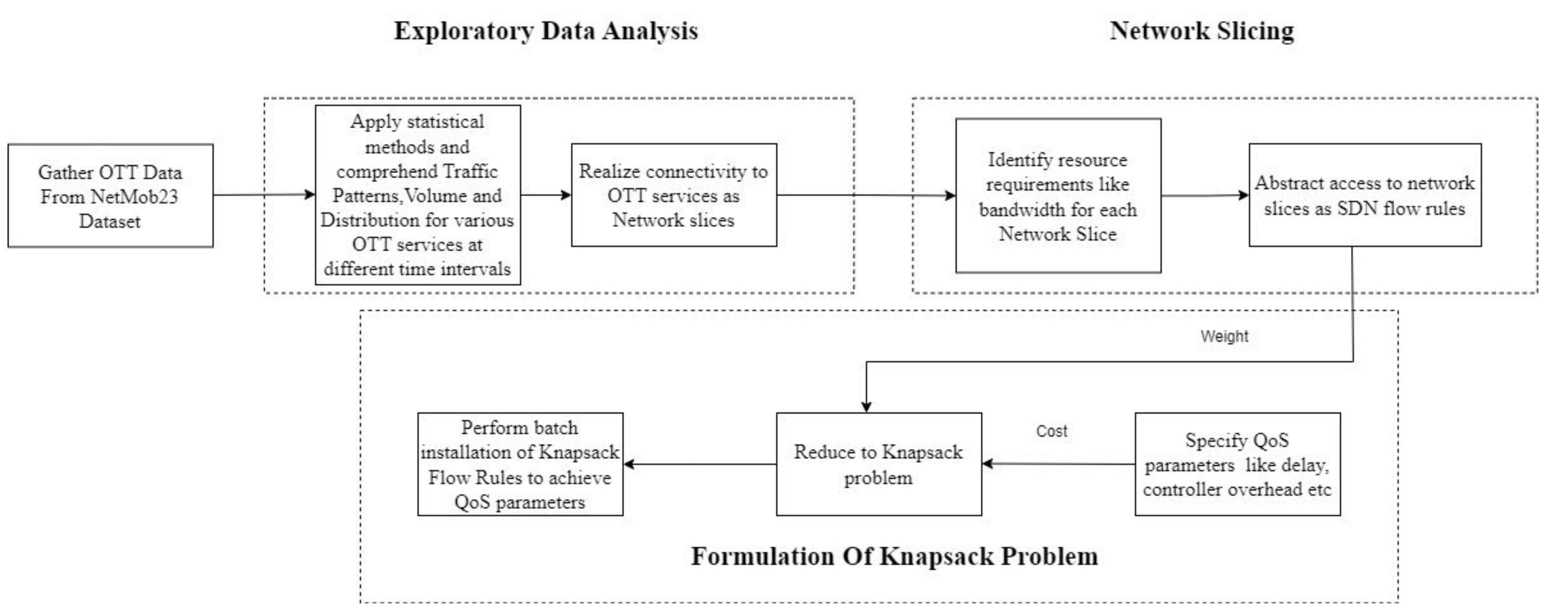
Background

- **Software Defined Networking (SDN)** is the networking paradigm of this era that has centralized control over the network and enables data driven networking.
- Network slicing is considered a powerful technique for efficient network resource management and provision of differentiated services in modern networks. It enables the partitioning of network infrastructure into virtual slices, each customized for specific applications or services. It allows for efficient resource allocation, flexibility, and improved service quality by providing dedicated resources to each slice.

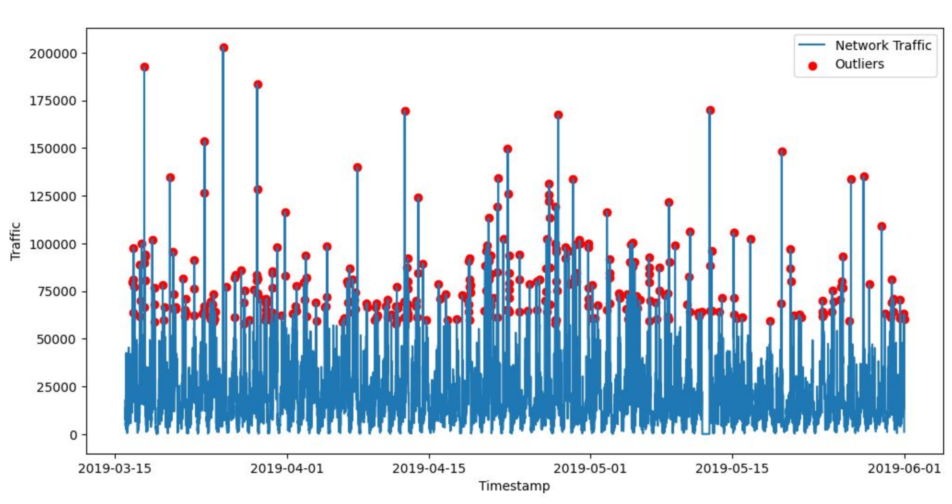
Problem Statement

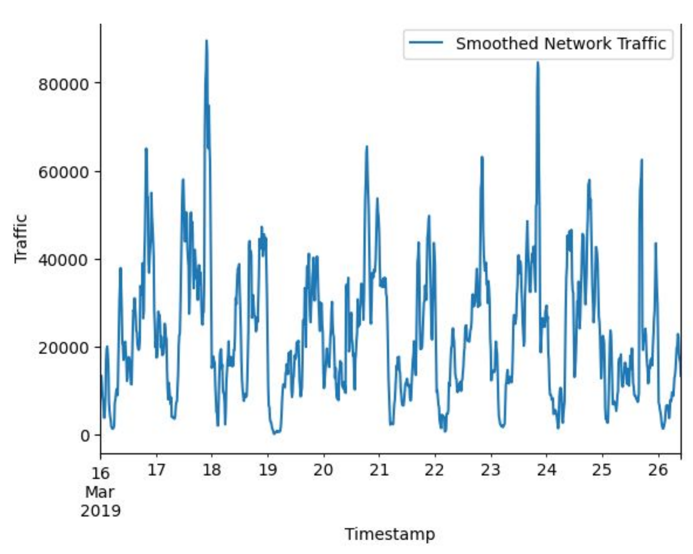
- This paper presents a solution for network slicing, facilitated by Software-Defined Networking (SDN) techniques to efficiently manage network resources, and deliver differentiated services, with a specific focus on addressing the challenges posed by Over-the-Top (OTT) services and their data-intensive flows.
- OTT services exhibit distinctive characteristics, particularly in terms of traffic patterns and data flow. These services typically involve the transmission of data-intensive content, such as video streaming, large file downloads, and real-time communication applications.
- By formulating the problem as a knapsack optimization, this paper aims to maximize the QoS parameters, while meeting the unique demands of OTT traffic.
- An LSTM model is used to predict the traffic demands of OTT services.
- Picking the right slice for the predicted demand is considered as a cost function of the knapsack formulation and, the reduction of delay has been framed as a profit function.

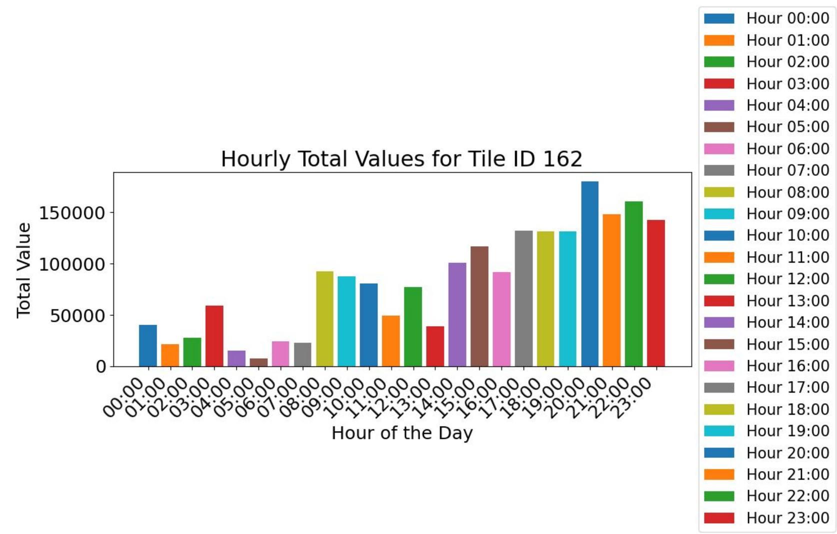


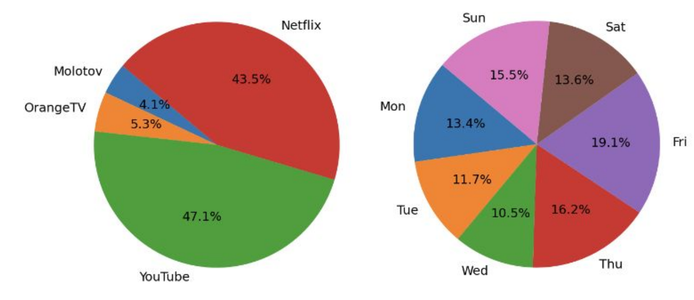
Data Analysis

- The NetMob 2023 dataset encompasses 68 mobile services across 20 regions in France for 77 days in 2019.
- The OTT services used include OrangeTV, YouTube, Netflix, and Molotov. Missing values were handled through forward-fill and backward-fill techniques, and outliers are detected using the Isolation Forest algorithm. Smoothing was applied to mitigate high-frequency noise.
- Traffic patterns were analyzed, revealing the influence of time and day of the week on traffic flow.





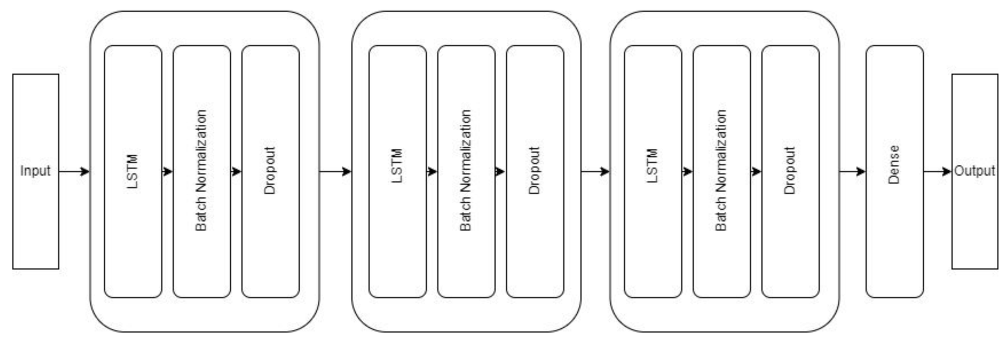


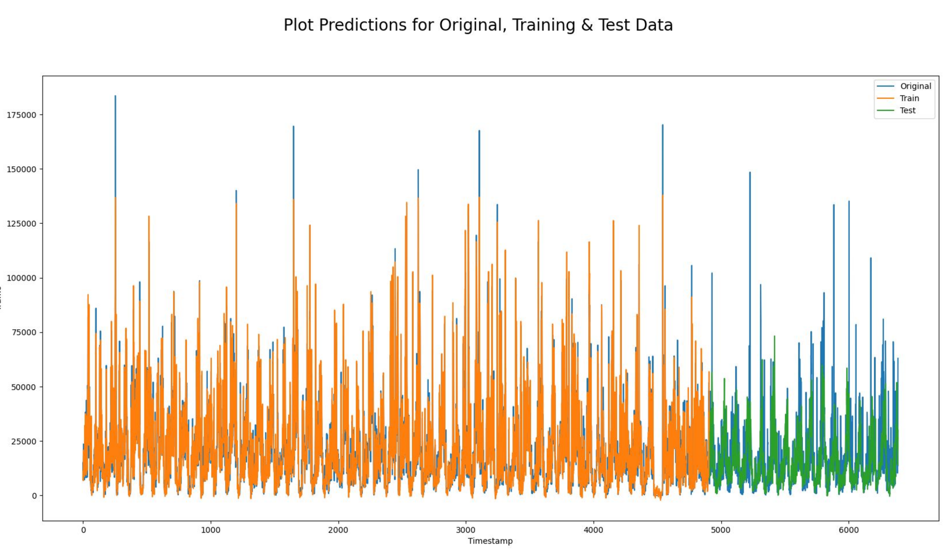


(a) Proportional Share of OTT Services (b) Traffic Flow by Day of the Week

Utilizing RNNs and LSTM for Traffic Prediction

- RNNs and LSTM networks are used to model temporal dependencies in traffic data for precise bandwidth allocation to OTT services, with LSTM configured for sequence-to-sequence prediction based on historical data.
- The LSTM model includes key architectural elements like LSTM layers, Batch Normalization and Dropout Regularization, and undergoes training to achieve effective traffic predictions.





Knapsack Formulation

- A knapsack problem involves finding a subset from a set of objects such that sum of the object profits is maximized while not exceeding the knapsack or violating other constraints.
- The aim is to **minimize overall round-trip delay**, that is inversely proportional to the traffic demand. The total traffic demand is bounded by the maximum bandwidth.

Let **S={ s_1, s_2,…, s_k}** be the k **OTT services**. For each time slot i ∈ T, assume a **cost vector c= {c_1, c_2, …, c_k}** representing the predicted traffic generated by each OTT service. **B** denotes the **maximum bandwidth**. Let **D= { d_1, d_2, …, d_k}** be the **delays** incurred by the k OTT services. Define **D' = {d_1', d_2', …, d_k'}** as the **profit vector**, where $d_i' = -d_i$.

Maximize:

$$\sum_{i \in [k]} d_i' * x_i$$

$$\sum_{i \in [k]} c_i \cdot x_i \leq B$$

Constraints: $0 \leq x_i \leq 1$ for i ∈ {1,2, …, k}

Solution Vector: x = {x_1, x_2, …, x_k} represents the solution for flow rule allocation in each time slot.

The **fractional knapsack problem formulation** allows allocating fractions of the traffic demand request, ensuring efficient bandwidth usage for each OTT service. **Each 15-minutes time slot and geospatial ID requires a separate knapsack instance for solution.**

Conclusion

- The access to OTT services has been realized as the placement of flow rules at the SDN switches. Models built using LSTM predict the traffic demands for the OTT services on the specified timeslots. Knapsack formulation uses the predicted value as input to cost function and QoS attainment as profit function. The **Mean Squared Error** of the model is measured as **0.62** and **R^2** value is measured as **0.79**.
- Future work includes integrating machine learning into SDN and investigating batch installation overhead and fine-tuning the knapsack formulation with additional parameters and revenue considerations.

References

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