Optimizing Data Transfer in IoT: Strategies for Reducing Data Volume

Dora Kreković, Mario Kušek
University of Zagreb Faculty of Electrical Engineering and Computing
Zagreb, Croatia
dora.krekovic@fer.hr, mario.kusek@fer.hr

***Abstract*—The rapid proliferation of Internet of Things (IoT) devices has led to a significant increase in data generation and transmission. However, the limitations of IoT devices, including constrained processing power, memory, and battery capacity, along with restricted network technologies, necessitate effective data management. This study offers an overview of various techniques proposed to reduce the volume of data transferred within IoT contexts. These techniques encompass approaches like data compression, aggregation, and selective transmission. By exploring the advantages, constraints, and suitable deployment contexts of these methods, this research aims to contribute to the evolving field of data reduction in the IoT environment. This contribution aims to improve network efficiency, reduce energy consumption, and optimize data usage, thereby enhancing the overall landscape of data management in the IoT domain.**

***Index Terms*—Data reducion, IoT, Data Compression, Data Aggregation, Federated Learning, Edge Computing**

I. Introduction

In an era of remarkable connectivity and technological progress, the proliferation of Internet of Things (IoT) devices showcases the potential of interconnected technologies. Yet, this surge in data generation brings challenges. IoT devices, often compact and resource-constrained, contend with limited processing power, memory, and battery life [1]. Technological frameworks and connectivity methods introduce constraints, such as Narrowband IoT's (NB-IoT) bandwidth limits and LoRaWAN's confined spectrum. Amid these challenges, optimizing data transfer for IoT's potential is vital.

This research aims to explore a diverse techniques designed to tackle the issue of data reduction within IoT contexts. Examining methodologies such as data compression, aggregation, and selective transmission, we seek to decipher the strategies that mitigate the volume of data transferred within IoT networks. The goal of this research is to offer insight into the advantages, limitations, and scenarios suitable for the application of these techniques. In doing so, we aim to make a meaningful contribution to the evolving field of data reduction within the IoT domain, ultimately enriching the efficiency, sustainability, and optimization of data management strategies in this dynamic landscape.

II. Approaches for Minimizing Data Volume

As a response to challenges mentioned in a preceding chapter, a range of techniques have been developed to reduce the amount of data transferred within IoT systems. These techniques not only enhance network efficiency but also contribute to the sustainability and optimization of IoT ecosystems. The fundamental partition is illustrated in Figure 1.

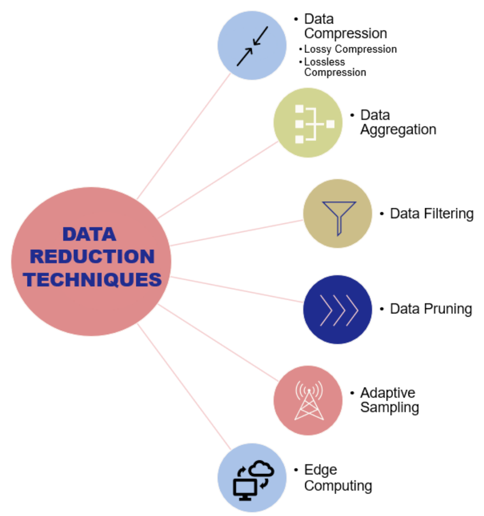

Fig. 1. Data reduction techniques

Data Compression. One of the fundamental approaches to data reduction involves compressing the data before transmission. Data compression techniques aim to decrease the size of the data by eliminating redundancies or using algorithms that represent the data more efficiently. This reduces the bandwidth required for transmission and minimizes the time and energy needed for data processing at both ends.

Data Aggregation. Aggregating data from multiple IoT devices before transmitting it to the network can significantly reduce the amount of data transferred. Instead of sending individual data points, devices send summarized or averaged data, thereby minimizing redundancy and lowering network traffic.

Edge Computing. Edge computing involves processing data closer to the source – at the ”edge” of the network. This technique enables filtering and processing of data locally, sending only relevant or condensed information to the central system. This not only reduces the data transferred but also mitigates latency issues and enhances real-time responsiveness.

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Data Filtering. IoT devices can implement data filtering mechanisms to determine which data is essential for transmission and which can be discarded. This selective approach reduces the volume of unnecessary data transferred, optimizing bandwidth usage and reducing network congestion [2].

Lossy vs. Lossless Compression. Techniques like lossy compression sacrifice some data accuracy for reduced file sizes, while lossless compression maintains data integrity. The choice between these approaches depends on the specific IoT application's requirements [3].

Data Pruning. In scenarios where historical data becomes less relevant, data pruning involves discarding older or less significant data. This ensures that only the most pertinent data is transferred, minimizing data load.

Adaptive Sampling. By intelligently adjusting the frequency at which data is sampled and transmitted based on varying conditions or events, adaptive sampling can greatly reduce the overall data transferred while retaining crucial insights.

III. Federated Learning for Data Reduction: Advancing IoT Efficiency

Conventional data reduction methods often involve centralized processing, which raises concerns about privacy, latency, and scalability. However, the emergence of Federated Learning (FL) introduces a transformative approach by distributing the data reduction process. FL disperses data processing responsibilities across devices and aggregates insights at the edge or a central server. This results in reduced raw data transmission, alleviated bandwidth congestion, and energy conservation.

In traditional machine learning, challenges arise from data centralization, leading to privacy concerns and significant data transfer overhead. FL addresses these issues by enabling collaborative model training across decentralized IoT devices while maintaining localized data. This not only mitigates privacy risks but also minimizes communication overhead and network traffic, proving beneficial in resource-constrained scenarios.

Employing federated learning for data reduction in IoT offers advantages such as enhanced data privacy through localized storage and processing, decreased network traffic, and potential for real-time decision-making. However, resolving challenges related to synchronization intricacies is crucial [4].

IV. Data reduction techniques based on location of procesing

Shifting data processing to the network edge involves transferring computation from the cloud – typically a high-capacity, storage-rich server – to a device in closer proximity to data sources or end devices. Edge devices can encompass diverse roles like data servers, routers, gateways, embedded systems, and even end nodes such as sensors or vehicles equipped with computing capabilities [5]. Processing can occur at the network edge in the following ways:

- **End Devices:** Here, processing occurs directly on the devices housing the sensors. These are usually microcontrollers with limited processing power and memory.
- **Network Gateways:** These are often single-board computers like Raspberry Pi, boasting more processing power and memory. They collect data, undertake simpler processing tasks, and facilitate swift communication with end devices [6].
- **Proximity Computers:** Positioned near end devices or network access points, these computers, found in settings like smart homes or factories, provide a platform for data processing.

V. Conclusion and Future work

With the objective of mitigating network congestion, conserving energy used for data processing, and reducing data storage demands, the need for minimizing transferred data has emerged as a critical priority. As a result, the prominent of implementing strategies for data reduction has grown progressively evident. To summarize, the variety of approaches aimed at decreasing data transmission within IoT systems accommodate diverse application requisites and resource limitations. Spanning from compression and aggregation to edge computing and federated learning, these methodologies collaboratively enhance the efficiency of network operations, diminish energy expenditure, and optimize data utilization within the intricate domain of the Internet of Things.

As part of the ongoing doctoral study, the forthcoming stage involves the development of a specific application scenario, informed by a comprehensive exploration of the domain's intricacies and potential trajectories. Additionally, there is a proposal to execute the solution and evaluate it within real-world contexts. Taking into account the emerging prospects in the domain of federated learning, the research direction inevitably gravitates towards subjects aligned with this growing field.

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