Reliability Analysis of Edge Scenarios using Pedestrian Mobility

Kshitiz Goel, Abhishek Bhaumick, Deepika Kaushal, Saurabh Bagchi {goel46, abhaumic, dkaushal, sbagchi} @purdue.edu Purdue University, IN, USA

Abstract—Edge computing is actively being adopted by various organizations and applications owing to its bandwidth saving and faster response times. However, this is accompanied by its own set of reliability issues and serves as an excellent target for optimizations and analysis. Our work analyzes the effect of mobile clients on task failure rates and proposes a low overhead location and network congestion aware optimization. In this paper, we discuss our motivations, provide details about the dataset, present some statistical analysis, and propose an improved mobile-side edge selection policy.

Index Terms-edge computing, Edgecloudsim, task failure rate

I. INTRODUCTION

Today, mobile and personal devices are generating data at unprecedented volume, velocity, and variety. This, combined with emerging applications like (AR, VR, Object Detection) has resulted in an explosion in network bandwidth requirements and the number of different tasks executed on computing resources. Supporting computationally expensive applications on these devices requires augmenting them with some central or distributed computation resources. Edge computing is a distributed computing scheme that brings data storage and compute capability close to the *mobile device* In contrast to the centralized cloud, the edge computing infrastructure can provide increased bandwidth and reduced latency, significantly improving the Quality of Service.

While edge computing might be an answer to issues related to network over-crowding and computational requirements of an individual device, it has with its own set of problems: robustness, maintenance, dependability, privacy, and security.

A general edge infrastructure consists of a hybrid network [4] of multiple *edge devices* (can cater to mobile devices in a limited capacity) and a centralized Cloud. With increasing number of smartphones acting as mobile devices, it is important to capture the impact of their highly mobile nature on the edge infrastructure. Current available simulators employ random mobility models for mobile devices. While Nomadic Mobility captures random motion well, it is not representative of the real-life scenarios and might lead to misleading results. This work explores the effect of mobility on average task failure rate and proposes a mobile-side edge device selection heuristic that guarantees improved performance.

II. EDGE-CLOUD BASE STRUCTURE

We simulate a realistic infrastructure with a two-tier topology comprising of edge devices interconnected by a MAN, with individual connections to a central cloud over a WAN. Mobile devices traverse across a simulated area ($\sim 6000 \text{ m}^2$) based on Poisson arrival rates and allot compute tasks to nearby edge devices over WLAN. This selection of edge device is done via selection policies (b) and have a significant impact on network performance and congestion. These policies have been simulated for random mobility models (c) and a real-world mobility dataset (d). (e) discusses different strategies for offloading tasks to cloud when edge is overburdened.

a) Edge Device Distribution: To observe the effect of edge device placement on the network, we have distributed the edge devices over the entire movement space of mobile devices using both random and uniform (grid-like) distributions.

b) Edge Selection Policies: Two edge selection policies have been proposed consistent with the assumption that bandwidth degrades over distance. Closest policy simulates the real-world behavior of connecting to the access point (edges) with the strongest (WLAN) signal; modeled by computing the Euclidean distance from each edge device and selecting the closest edge device. It is used by Nomadic Mobility. Best K-Closest is a policy where given a measure of the workload of K nearest edge devices, the mobile device selects the least loaded edge device. This is expected to provide a good balance of mobile edge connection bandwidth and network decongestion.

c) Mobility Models: Improving upon the existing random models, the clients now move over a constrained 2D space. This movement is governed by a uniform random function and thereby this model is called Nomadic Mobility. To capture the non-random movement of client devices, we have used a mobility dataset from Crawdad [2] that is used to study Pedes-trian Mobility models for opportunistic communications. It is a high mobility scenario with fine granularity (position recorded every 0.6 seconds). The pedestrian arrival rates vary between 0.01 and 0.05 nodes/sec. Some pedestrians in the dataset are stationary for some periods of time, representing a real-world stationary mobile device and which translates to a constant load on the nearby edge device.

d) Edge Orchestration (EO) Strategies: When a task arrives at an edge device, different EO strategies are employed to decide which of the available platforms (Edge or Cloud) to use for processing. Utilization: Offload to Cloud if Edge Utilization exceeds certain percentage. Bandwidth: Offload to Cloud if the available WAN Bandwidth at that Edge device exceeds a certain threshold. Hybrid: This requires both the Utilization and Bandwidth conditions to be satisfied.

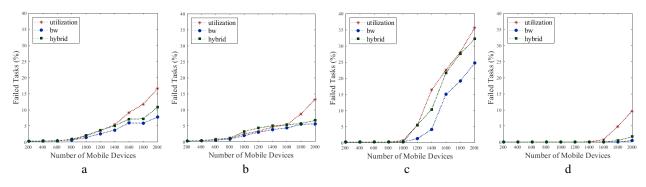


Fig. 1. Avg. Failed Task for **a**. Nomadic Mobility (Random Edge Distribution) **b**. Nomadic Mobility (Uniform Edge Distribution) **c**. Pedestrian Mobility (Closest Selection) **d**. Pedestrian Mobility (K-Closest Selection; K = 3) Note. *utilization, bw, hybrid* are EO Strategies [1]

The mobile devices send 4 types of workloads to the Edge and Cloud : *Health Apps, Augmented Reality, Infotainment, Heavy Comp*; in increasing order of computational requirements. If neither of the platforms are able to compute and relay the results back to the mobile device for any reason (Network, Mobility, or Compute Capacity), the task is dropped and classified as a failed task.

III. EDGE MOBILITY ANALYSIS

EdgeCloudSim [1] is a recent simulator platform for performance evaluation of edge computing systems.

A. Edge Distribution

The network performs better when the edge devices are distributed uniformly over the mobility space (fig.1(a),(b)). However, the random placement of edge devices causes only slightly higher rates of task failure even under high client load (worst case is 13% uniform-grid and 17% random) and exhibits similar trends. The pathological case of highly clustered edge devices (placed closely together, at some point in 2D space) will result in a huge number of mobile devices connecting to a single edge device based on least distance, resulting in congestion at that edge and subsequent high failure rates. In the following sections, we have selected a uniform random distribution of edge devices which represents a middle ground, resembling a realistic scenario.

B. Pedestrian Mobility Dataset

Pedestrian mobility exhibits significantly higher (35%) task failure rates compared to random mobility (16%) at higher mobile device population. In Pedestrian Mobility scenario, development of localized congested regions of mobile devices which leads to higher network-based failures in those areas. In other areas, the high mobility of certain other mobile devices causes mobility-based failures. Based on our experiment with a real-world movement dataset, it can be concluded that random placement of edge devices does not have a significant detrimental effect on the edge-cloud performance. Thus when placing edge devices without prior information about movement patterns, random placement will suffice as long as the total number of mobile devices is within the network's capacity and does not cause significant congestion.

C. Best K-Closest Selection Policy

Best K-Closest selection is a significant improvement over Closest selection fig.1 (c),(d),. Specifically, failures at edge devices have reduced considerably ($\approx 20\%$). We found that majority of failures are attributed to the overloaded Cloud and the remaining errors are caused by overloaded edge devices. In contrast, failure due to mobility and network congestion dropped to a mere 1% even for heavy workloads. The K-Closest heuristic is an effective means of distributing the workload and thereby improving the overall edge infrastructure performance. Better distribution of workloads results in better QoS far all mobile clients. We have open sourced our simulator and experimental traces [3].

IV. FUTURE WORK

The performance improvements of edge device placement strategies at potential hotspots based on mobility patterns has not been explored in this project but the models and techniques developed here can easily be utilized to conduct such experiments. The best K-closest edge selection technique requires that the mobile device be able to locate, collect and use information about the edge devices. This would in turn place additional demand on the network as well as processing resources at both edge devices and mobile device. Analysis and study of this metric for different network models is another potential study topic. We strongly believe our extension of EdgeCloudSim will enable simulation studies that closely resemble and promote a better understanding of real-world edge computing scenarios.

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