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SIMULATING SMART CITY TRAFFIC WITH EDGE LEARNING AND GENERATIVE AI

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ABSTRACT

Novel models and methodologies are introduced to enable a simplified simulation framework for optimizing resource usage in edge-based Deep Learning (DL) traffic control systems of smart cities. An underexplored G/G/s queuing model is employed in simulation to measure stability, alongside using the Gamma distribution for traffic patterns. Beyond simulation, this G/G/s queuing can be embedded in a scheduler for real systems to predict network delays and node utility for adaptive job assignments. We develop a unique agent-based model and a simulation environment for edge training that captures network dynamics at the granularity of DL computational units. In addition to conventional ML experiments, this simulation enables the system-level evaluation of load-balancing scenarios for federated edge learning traffic monitoring systems in localized urban zones. In a comprehensive, data-driven simulation of scalability and resource management, the agent nodes undergo real training using synthetic video frames generated by the Wasserstein Generative Adversarial Network (WGAN).

1 INTRODUCTION

Advancements in building Smart Cities underscore the critical need for new optimization techniques and resource management of the systems running on top of edge and cloud, which are the backbones of the network's infrastructure. The challenge is that smart systems including the traffic monitoring applications extensively use Deep Learning (DL) artifacts, integral to network-based video analytics applications utilizing resources in edge and cloud computing. For smart urban traffic control, the sustainability and performance of DL solutions should be evaluated before deployment. It is difficult to use available simulators (e.g., SUMO, Veins and MATSim) to evaluate DL and predictive components of these systems.

In our previous work (Sharifi et al. 2021), different processing powers for edge devices, expressed in frames per second, were considered for a video traffic control application. A new queuing model based on Markovian processing was introduced for scalability testing of the system in the simulation of traffic in a smart city. Due to the complexity of the proposed queuing model, scalability simulation was only performed for 20 edge devices with variable service rates and a cloud system. The results showed the system was stable, having a 95% edge performance level (i.e., the percentage of node occupancy).

In the recent paper (Abhari 2024), the author used the collected real data from a prototype built for an edge-based traffic control system. The workload was measured in frames per second for a video streaming traffic surveillance camera application on an edge network. The developed prototype consists of object detection, motion detection, and movement tracking modules hosted on edge/fog nodes. After measuring the video frames' arrival rate to each module, the Gamma and Beta distributions were better models for the estimation of the arrival rates of the system. The processing capacity of edge nodes hosting these modules (i.e., service rates) is modeled by a Uniform distribution used in G/G/s queuing and compared with the traditional Markovian M/M/s model. Simulation was used to find system stability and network delay for variable edge nodes. Another contribution was the introduction of WGAN to generate numerical data for nodes' traffic patterns. In this work, WGAN will be extended to generate artificial videos.

2 SIMULATION OF FEDERATIVE EDGE LEARNING BY PROPOSED MODELS

In this work, we used a Gamma distribution for the arrival rate, with parameters estimated from a real dataset, and G/G/1 queuing modelling for each of the three edge nodes, which have processing powers of 10, 13.5, and 17 frames/sec, respectively. The utilization factor $\rho = \lambda/\mu$ shows that each of the three edge nodes is stable with theoretical local utilization factors of 0.72%, 0.55% and 0.42%, and negligible queuing delay, showing they are not congested. Agents used to simulate processing nodes where real DL training occurs on each edge node hosting a replica of a DL-ANN artifact using Python. Since producing artificial traffic video frames with WGAN is still a work in progress, each node is trained by an equal portion of the real image data set, CIPHAR-10, which contains 60K frames. The Gamma distribution (with the previous paper's measured parameters) was considered as the arrival rate λ, and its inverse $1/\lambda$ used to create a random delay of interarrival time between the batches of frames. In each round of federative learning, the replica models on edges (with the previous processing power differences) were trained, and after training, the model's parameters are sent to the central cloud, and all the edges' models were updated by the cloud for the next round. As shown in Table 1, the observed idle times of 25-40% of two faster edge nodes compared to the slowest one indicate that using a scheduler is helpful. The second simulation scenario is conducted by adding a load balancing scheduler that collects the local utility factors from nodes for job assignments. Figure 1 shows that the accuracy of 67% is reduced by 10% in trade-off, while expediting the training time in each round by almost 70% (45.5 sec average training time) with an equal load of 35% busy time for each node. The focus of this simulation is on evaluating the nodes' utility and load balancing, so a simple ANN with moderate accuracy is used. In the complete work, an advanced CNN with synthetic WGAN-generated frames will be used to achieve the high training accuracy needed for traffic control.

Table 1: Performance of Nodes in Edge Federated Learning Model in Round 100 without scheduler

Node	Proc. Ratio	Training Time(sec)	Transfer Model(sec)	Idle Time (sec)	Busy (%)	Idle (%)
A	1	158	0.1-0.9	0	100	0
B	1.35	117.04	0.1-0.9	40.96	73.96	25.93
C	1.7	92.94	0.1-0.9	65.06	58.96	41.18

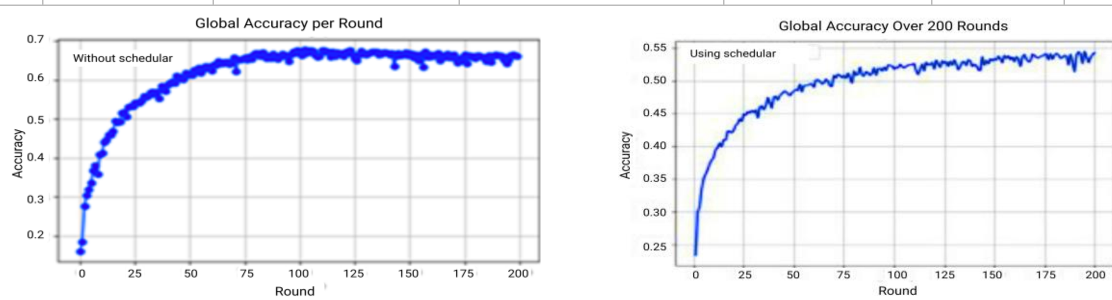

Figure 1: Accuracy of federative learning without scheduler (left) and with load balancing scheduler (right).

3 CONCLUSIONS AND NEXT DIRECTION

Two scenarios of federative edge learning for smart cities' traffic control are simulated with and without a load-balancing scheduler. A potential optimization for performance in large-scale systems can be achieved by adding the G/G/s queuing model to the scheduler to predict nodes' loads and delays for managing global traffic congestion through adaptive job assignments on edges trained by WGAN data.

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