Privacy-Preserving Remaining Ready Queue Processing Time Prediction Using Federated Learning and Lottery Scheduling

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Abstract: Sudden system failure, cyber-attacks, discrepancies in communication while process execution are been observed very frequently in cloud-edge infrastructure been operated by distributed multiprocessor systems. The purpose is to estimate the ready queue processing remaining time for recovery from any type of disaster, resource allocation backup, and management of service level agreement, in the distributed multiprocessor's environment. The traditional approach is having some loopholes such as the privacy concerns arises due to centralized data collection and the lottery scheduling approach which was the very basic classical way of dealing in a recent distributed multiprocessors system. The proposed research provides a novelty by presenting privacy preserving remaining ready queue processing time prediction (PPRRQPTP) framework which consists of the federated learning with support of lottery scheduling for the distributed multiprocessor environments. The model proposes a federated sampled ready queue framework by which independently the local nodes estimate the remaining processes times using statistics of the sampled queue, i.e without sharing the raw scheduled data estimates the partially processed jobs and imputed blocked processes. The federated server will be communicated about the aggregated learning updates and the encrypted parameters of the proposed model. The framework includes the Privacy-preserving distributed estimation, Federated Lottery Scheduling (FLS), Adaptive confidence interval prediction, Federated imputation of blocked jobs, and Failure-aware queue analytics. The proposed novel federated estimation strategy for predicting the remaining processing time after system breakdown while minimizing estimation variance and preserving node-level scheduling privacy, which is expected to outperform centralized scheduling estimation methods in terms of scalability, privacy preservation, estimation accuracy, and communication efficiency.

Keywords: Privacy-preserving distributed estimation; Federated Lottery Scheduling (FLS); Adaptive confidence interval prediction; Federated imputation of blocked jobs; Failure-aware queue analytics

Introduction

Geographically distributed multiprocessor nodes are used for modern computing systems like edge-cloud infrastructures, distributed datacenters, autonomous vehicle networks, smart factories and drone swarms, IoT scheduling systems. There are ready queues and scheduling mechanisms at each node for execution of processes. Lottery Scheduling is a scheduling technique for proportional resource allocation which is proposed and proven to be effective by Carl A. Waldspurger. The existing ready queue estimation methods rely on centralized scheduling information and local queue availability assumed by lottery scheduling. Distributed environments pose a number of challenges, however: Scheduling information that is sensitive to privacy – Scheduling information, including task priorities, deadlines, and resource usage patterns, should be kept private from unauthorized access, particularly in multi-tenant or cloud scheduling systems.

Decentralized queue structures: In distributed systems, ready queues are stored locally on each node instead using a global structure which will help to avoid bottlenecks and make the system more difficult to load balance.

Heterogeneous processors — Modern systems may have CPUs of different speeds, architectures, or capabilities (such as ARM big). Schedulers need to match the tasks to the most appropriate core when using LITTLE.

Asynchronous failures: Processes/Nodes may crash or go unresponsive at random times without informing the scheduler; fault detection/recovery can be a non-trivial problem.

Communication restrictions — Nodes in a distributed system may be bandwidth constrained, have high latency or poor-quality links and therefore need to keep the amount of co-ordination between nodes to a minimum.

Suspended processes — The process could be missing from the schedule because it is suspended or waiting for I/O. Waiting on I/O; A process that is waiting for I/O may be temporarily missing from the schedule. In Federated Learning, models are trained collaboratively without sharing of raw local data, suitable for privacy-sensitive scheduling systems. Although FL has been applied in various fields, such as the healthcare system, IoT, and mobile systems, it has not been applied to the integration of ready queue estimation and lottery scheduling. This work proposes a federated approach for remaining queue time prediction in a privacy preserving manner during sudden system breakdown condition.

Problem Definition

Assume that the distributed computing infrastructure has a number of edge and cloud nodes, each of which has multiple processors, local ready queues and local scheduling policies to define how tasks are prioritized and executed. Upon a failure at a specific moment, the system is in a state that has a mixture of jobs that have been fully completed and the results are ready to return, jobs that have not been fully completed but have an intermediate state that may or may not be recoverable, and jobs that have not been executed at all, waiting in local queues. The recovery estimation is more complicated due to the fact that the system administrator must determine how long the remaining work will take on all the nodes that are not fully up, how much backup resource will be required to resume or restart affected jobs, cost of the disaster recovery, which includes recompilation, data transfer, and restoring nodes, and the total disaster recovery time before the system is fully restored and functioning. None of these estimates can be done directly from the raw scheduling data stored on each local node, for privacy reasons, because the nodes are inaccessible, or due to the nature of the failure itself, and all of the above must be determined before the system can be restored and fully functional.

Research Objectives

This work focuses on the key goals of developing scalable, privacy-preserving, fault-tolerant scheduling estimation in distributed computing systems. The first target is to propose a Federated Lottery Scheduling framework that can be an extension of the classical lottery scheduling model in a distributed, privacy-aware environment where decisions can be made in a cooperative but decentralized manner between the edge and cloud nodes. On top of this, the second is to estimate remaining time to process the queue at all nodes without having to rely on centralized data collection, so that the local scheduling states are never reached outside of the node from where they originated. To support this rule, the third goal is to maintain scheduling privacy at every distributed node during the estimation process: raw queue data, ticket allocations and process priorities are all locally private data and should not be transmitted if identifiable. Because of failures, some processes may be unreachable or may be blocked forever, the fourth objective is to be able to infer the unreachable state and processing demand of blocked and unreachable processes from aggregated statistical signals rather than actual observation. The fifth objective is to minimize estimation variance, so that such inferences will be reliable and consistent across heterogeneous nodes, using federated optimization techniques to coordinate model updates without centralizing sensitive data. The sixth objective is to estimate adaptive confidence intervals with distributed failure conditions, giving system administrators statistically sound limits for the recovery time that adapt based on failure severity and distribution throughout the infrastructure. Finally, the practical communication limitations of multiprocessor systems are handled by designing the whole system in such a way that the inter-node communication overhead is minimized so that the federated approach is computationally feasible and scalable even for degraded network conditions.

Proposed System Architecture

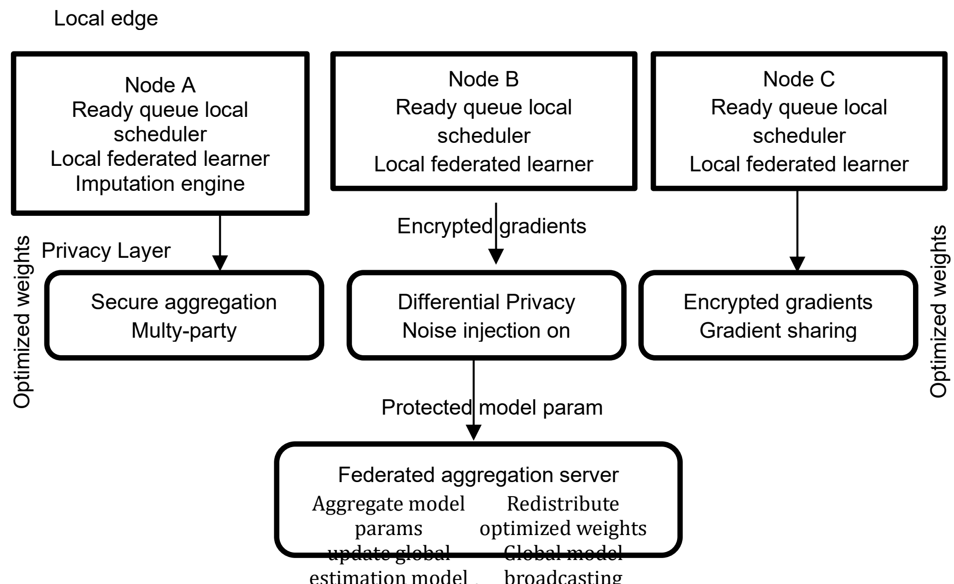

Figure 1. The Federated System Architecture

Proposed Federated Lottery Scheduling Model

Local Queue Sampling

Suppose:

- node $h$contains ready queue Q_h,
- sample size k_h,
- processors r_h.

Each processor selects jobs using lottery scheduling probabilities:

$$p_i = \frac{m_i}{\sum_{j=1}^{N} m_j}$$

where:

- m_i= tickets assigned to process i,
- p_i= winning probability.

Federated Remaining Time Estimator

Local Estimator

Each node computes:

$$\hat{t}_h = \phi_1 \bar{t}_{complete} + \phi_2 \bar{t}_{partial} + \phi_3 \bar{t}_{imputed}$$

subject to:

$$\phi_1 + \phi_2 + \phi_3 = 1$$

where:

- completed jobs,
- partially processed jobs,
- blocked/imputed jobs

are jointly incorporated.

Global Federated Estimator

The federated server aggregates local estimates:

$$\hat{T}_{FL} = \sum_{h=1}^{H} w_h \, \hat{t}_h$$

where:

- w_h= aggregation weight,
- H= number of distributed nodes.

Federated Imputation Strategy

The traditional way of replacing the random imputation is now replaced by the AI Based federated imputation where the prediction of blocked process time is done using the federated regression, federated neural networks and federated LSTM models. The input features are process priority, burst time, queue waiting time, processor speed, CPU utilization, ticket distribution and historical execution patterns.

Privacy-Preserving Mechanism

In the privacy layer, the framework consists of the secure aggregation, differential privacy and local parameter encryption. There is no raw processed data for the local nodes, only the gradients, model weights and aggregated statistics are transmitted.

Federated Optimization Function

The proposed optimization objective is:

$$L = \alpha E_{est} + \beta E_{imp} + \gamma C_{comm} + \delta P_{priv}$$

where:

E_{est}= estimation error,
E_{imp}= imputation error,
C_{comm}= communication cost,
P_{priv}= privacy leakage risk.

Objective:

$$\min L$$

Confidence Interval Estimation

The proposed federated confidence interval is:

$$P\left[\hat{T}_{FL} \pm 1.96\sqrt{V(\hat{T}_{FL})}\right] = 0.95$$

This interval predicts:

- minimum backup recovery time,
- maximum expected processing delay.

In the proposed Novel Contributions, there are federated lottery scheduling which is a distributed scheduling integrated FL with lottery scheduling, privacy preserving queue analytics which consists of no raw scheduling data shared between nodes, federated imputation for the AI driven prediction for blocked process times and the distributed confidence intervals for the adaptive uncertainty estimation in distributed systems.

Table 1. Expected Advantages

Parameter	Existing Methods	Proposed Method
Privacy	Low	High
Scalability	Moderate	High
Communication Cost	High	Reduced
Estimation Accuracy	Moderate	Improved
Distributed Support	Limited	Full
Failure Adaptation	Partial	Dynamic

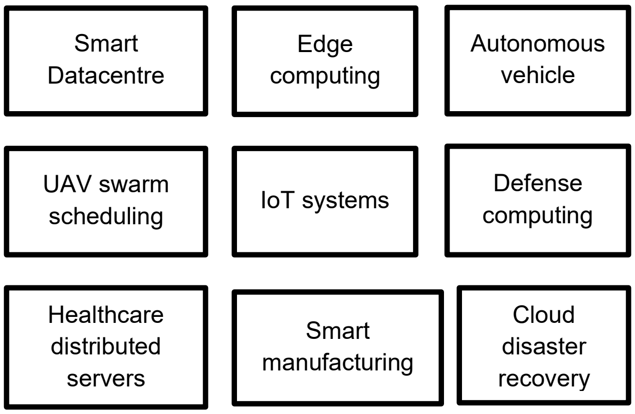

Figure 2. Real-world Applications

The proposed framework can be implemented using:

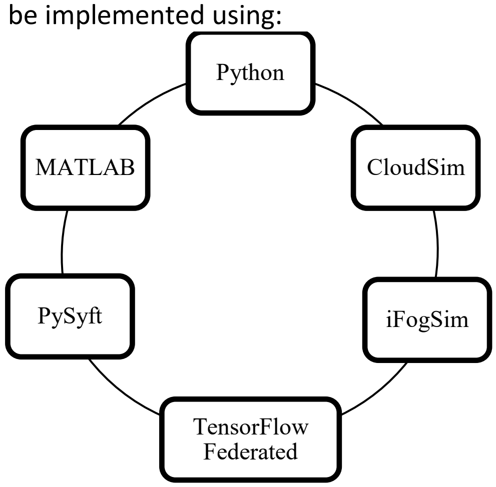

Figure 3. Simulation Environment

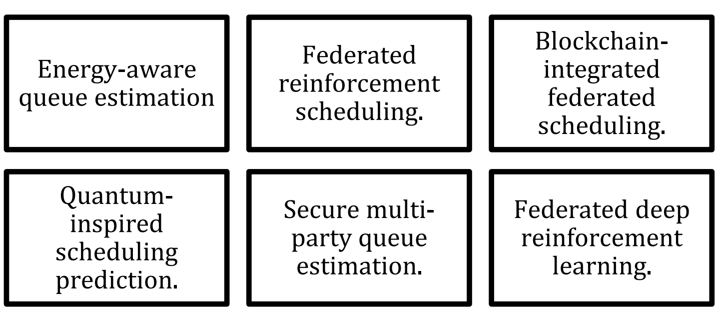

Figure 4. Future Research Directions

Conclusion

1. Traditional queue estimation exposes sensitive scheduling data; no privacy-preserving, distributed solution existed for remaining queue time prediction in multiprocessor systems.
2. Federated Learning + Lottery Scheduling + Distributed Imputation — collaborative prediction without sharing raw local data.
3. Accurate remaining queue time prediction is achievable across distributed nodes while preserving privacy, applicable to edge-cloud infrastructures.
4. Communication overhead in edge environments, non-IID data skew across nodes, Adversarial/poisoning attack vulnerability, Needs real-world scheduler integration (Linux CFS, YARN)

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