RCT: Rewarding Clients Tool for Blockchain-based Decentralized Carbon Emission Classification

Paul Michael Custodio, Gifar Arif Haryadi, Jae-Min Lee, Dong-Seong Kim
Department of IT Convergence Engineering, Kumoh National Institute of Technology, Gumi, South Korea
(pmbcustodio, gieworld, ljmpaul, dskim)@kumoh.ac.kr

Abstract

This paper presents the implementation of the Reward Computation Tool (RCT) framework for carbon emission classification, addressing the increasing demand for environmental, social, and governance (ESG) responsibilities. Leveraging a decentralized learning setup, the RCT framework utilizes ERC721 tokens to incentivize active participation and performance across blockchain network nodes, achieving effective classification and robust blockchain performance. Key features include local training and global aggregation processes, with rewards structured to encourage best performance. Future work will focus on integrating privacy-preserving techniques and exploring additional reward methods to enhance data security and participant motivation. This approach highlights the potential for combining blockchain and federated learning to address critical environmental challenges.

***Index Terms*—Blockchain, carbon emission classification, decentralized learning, ERC721**

I. Introduction

With the demand of environmental, social and governance (ESG) responsibilities in corporate and government scenarios, carbon emission control has become a major point of focus. From international laws such as the Kyoto Protocol [1] and the Paris Agreement [2], carbon emission control is a global concern. As such, works on carbon emission estimation as well as classification of emission levels has been explored in order to provide adept decision making. Brought upon by the reliance on data of this motive, machine-learning (ML) models are utilized to create estimation and classification models of such systems. There exists however key problems in these types of ML-based approaches due to the nature in which data is centralized and gathered into a cloud server giving a single point of failure (SPoF). This opens up the use of federated learning (FL) [3] wherein various edge client devices which have data sensors and perform model training locally, so as not to send the data to a centralized server but rather send only the model parameters and then use an aggregation strategy to create a global model to be sent to each local device for the next round. Even with the solution provided by FL [4], the problem of SPoF still exists in the federated server, which is hence why a new architecture is introduced, a fully decentralized learning set-up [5]. This comparison is shown in Fig. 1, in a fully decentralized learning system, there is no direct communication between the local nodes and the aggregating node, but rather the model parameters are sent to the global client. In order to encourage more data involvement by participation and to incentivize the use of local model training devices resources, a rewarding clients tool, RCT, is proposed for carbon emission classification in a decentralized learning set-up.

II. System Methodology

The methods performed and the tools utilized in this study are discussed in this section, with the overall architecture shown in Fig. 2:

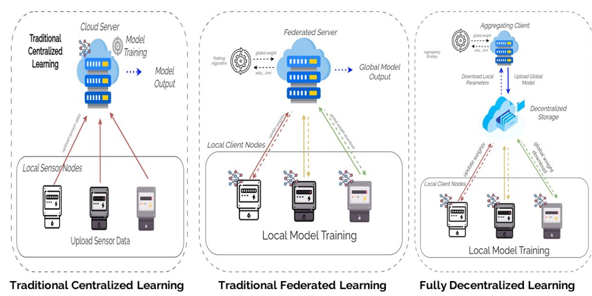

Fig. 1. Comparison of centralized and decentralized learning system

A. Fully Federated Classifier

In the RCT framework, the decentralized classifier performs local model training and global aggregation. During local training, clients process sensor data to train local models, storing parameters on the InterPlanetary File System (IPFS) to ensure decentralized storage and data privacy. Global aggregation uses the Federated Averaging (FedAvg) algorithm to combine model parameters from IPFS across rounds until performance targets or communication thresholds are met. The updated global model is then re-uploaded to IPFS, maintaining model accuracy and data privacy.

B. Client Incentive Algorithm

To motivate users to input their data and participate, the RCT framework uses ERC721 tokens to incentivize active participation and performance across blockchain network nodes involved in model training. Rewards are based on contributions and performance metrics, ensuring fairness and encouraging engagement. A total reward amount is set and distributed evenly across communication rounds, with rewards allocated based on node count and participation. The best-performing node receives double rewards, promoting higher performance.

TABLE I
AVERAGE LATENCY AND THROUGHPUT AT DIFFERENT SEND RATES

Send Rate (tx/s)	Average Latency (ms)				Throughput (tx/s)			
	Open	Query	mint (ERC721)	transfer (ERC721)	Open	Query	mint (ERC721)	transfer (ERC721)
50	1180.735	2.146	2026.693	1250.845	48	50	44	48
100	6499.561	2.332	6192.978	4902.293	48	100	44	53
200	7153.165	1.958	7987.817	6871.450	53	200	48	53

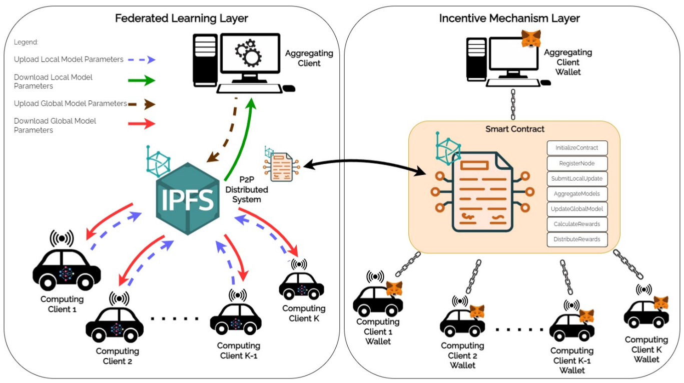

Fig. 2. RCT: Two-Layer System Architecture

This structured reward system drives active participation and incentivizes nodes to enhance their performance, boosting the RCT framework's efficiency and effectiveness.

III. RESULTS ANALYSIS AND EVALUATION

To simulate the proposed system, a blockchain system with eighteen nodes and ten validators has been set-up using the IBFT 2.0 consensus algorithm. The blockchain design shows the system in which it runs to model a vehicular network system in the decentralized and rewarding use case set-up. The results of the decentralized learning are compared with running it in a centralized set-up, the model is ran using the fuel consumption dataset of Canada, where vehicles have their carbon emission class. Blockchain performance is shown in Table I and classification results of the classifier in Table II.

TABLE II
COMPARISON OF PERFORMANCE METRICS BETWEEN CENTRALIZED AND RCT METHODS

	Accuracy	Precision	Recall	F1-Score
Centralized	0.7984	0.8122	0.7984	0.7903
RCT	0.8272	0.8312	0.8272	0.8265

The latency results indicate that as the send rate increases from 50 tx/s to 200 tx/s, the average latency for all operations also increases. Specifically, the latency for opening and querying operations rises significantly, with the minting and transfer operations (ERC721) showing even more pronounced increases. This trend highlights the system's growing delay in processing transactions under higher load conditions, suggesting potential bottlenecks or capacity limitations. The throughput results reveal that the system maintains consistent throughput for minting (ERC721) operations across different send rates, while there is a noticeable increase in throughput for querying operations as the send rate increases. The throughput for opening and transfer operations also shows slight improvements at higher send rates. These results suggest that while the system can handle higher transaction volumes effectively for certain operations, it may struggle with others, indicating areas for optimization.

IV. CONCLUSION

In conclusion, the implementation of the RCT framework not only achieved effective carbon emission classification but also demonstrated robust blockchain performance. The incentivization mechanism successfully motivated active participation and enhanced the overall efficiency of the decentralized learning setup. Future work will focus on integrating privacy-preserving techniques and exploring additional reward methods to further improve data security and participant engagement. This approach underscores the potential for integrating blockchain and federated learning to address critical environmental challenges while maintaining data privacy and security.

ACKNOWLEDGMENT

This work was partly supported by Innovative Human Resource Development for Local Intellectualization program through the Institute of IITP grant funded by the Korea government(MSIT) (IITP-2024-2020-0-01612, 50%) and by Priority Research Centers Program through the NRF funded by the MEST(2018R1A6A1A03024003, 50%)

REFERENCES

[1] United Nations, "Kyoto Protocol to the United Nations Framework Convention on Climate Change," United Nations Treaty Series, Vol. 2303, pp. 162-299, Dec. 1997.
[2] United Nations, "Paris Agreement to the United Nations Framework Convention on Climate Change," United Nations Treaty Series, Vol. 3156, pp. 3-28, Dec. 2015.
[3] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. Arcas, "Communication-efficient learning of deep networks from decentralized data," Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS), Fort Lauderdale, FL, USA, pp. 1273-1282, Apr. 2017.
[4] P. M. Custodio, M. A. Paramartha Putra, J. -M. Lee and D. -S. Kim, "TLFed: Federated Learning-based 1D-CNN-LSTM Transmission Line Fault Location and Classification in Smart Grids," 2024 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), Osaka, Japan, pp. 026-031, Feb. 2024.
[5] A. Zainudin, M. A. P. Putra, R. N. Alief, R. Akter, D. -S. Kim and J. -M. Lee, "Blockchain-Inspired Collaborative Cyber-Attacks Detection for Securing Metaverse," in IEEE Internet of Things Journal, Vol. 11, no. 10, pp. 18221-18236, May15, 2024