DCFL-Chain: Digital-Twin-Based Collaborative FL-Integrated Energy Consumption Prediction for Smart Factory

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***Abstract*—This paper introduces DCFL-Chain, a digital twin-enabled collaborative federated learning framework designed to predict energy consumption in smart factories. By integrating a permissioned blockchain, the system ensures decentralized, tamper-resistant aggregation and secure client authentication. The model leverages federated learning to train local models using blockchain smart contracts to manage secure data transmission and network interactions. Simulation results demonstrate the framework's effectiveness, achieving an accuracy 99.04% across industrial datasets, highlighting its potential for scalable, secure, and efficient energy management in smart factory environments.**

***Index Terms*—Energy consumption prediction, blockchain, federated learning (FL), digital twin (DT), smart factory.**

I. Introduction

In Industry 4.0, industrial processes consume vast amounts of electricity, often from non-renewable sources, contributing to significant carbon emissions. Effective power management strategies are essential to reduce energy waste and optimize usage, requiring accurate electricity consumption predictions. Technologies such as AI, blockchain, and digital twins can enhance the efficiency and sustainability of industrial energy management.

Conventional energy prediction models [1]–[3] utilize centralized learning, where a large amount of energy consumption data is transmitted to a centralized server. This approach requires extensive network resources and poses significant security risks. Consequently, the literature [4] has adopted Federated Learning (FL) techniques for energy consumption prediction. However, traditional vanilla FL systems rely on a central server for aggregation, which increases the possibility of a single point of failure. To address this issue, blockchain technology is employed for decentralized aggregation. Additionally, blockchain-based client authentication and access control enhance the security of the overall power distribution system in smart factories. Moreover, the integration of Digital Twin (DT) technology serves as a bridge between cyber and physical systems, recreating a virtual replica using physical world data. This enables effective and cost-efficient model training and outcome prediction. Reflecting on the necessity of efficient energy consumption prediction in smart factories, this study proposes the following key contributions: (1) A blockchain-integrated collaborative learning framework is introduced for secure, decentralized, and distributed energy prediction. (2) A Digital Twin (DT) is deployed as a virtual replica of energy consumption to facilitate efficient energy management. (3) An optimized CNN-BiLSTM-GRU model for energy consumption prediction.

II. Proposed System

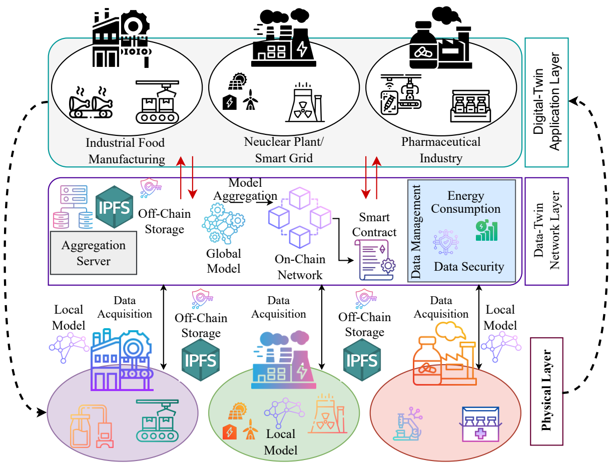

Fig. 1: Proposed blockchain-enabled collaborative power consumption model DCFL-Chain for DT integrated smart factory.

The DCFL-Chain system model integrates digital twin (DT), federated learning (FL), and blockchain to optimize energy consumption prediction for smart factories illustrated in Fig. 1. The model comprises three main layers: the Physical Layer, the Data-Twin Network Layer, and the Digital-Twin Application Layer, which interact to improve energy management efficiency while ensuring data security and transparency. Industrial sectors generate data through real-time sensors and devices in the Physical Layer. The data is collected via Data Acquisition modules and transferred securely to the Data-Twin Network Layer. In the Data-Twin Network Layer, blockchain ensures secure data transmission and decentralized model management. Each local node uses federated learning models to train on energy consumption data a CNN-BiLSTM-GRU architecture $\mathcal{M}$ was constructed, leveraging convolutional layers $(Conv1D(128,3)$ and $Conv1D(64,3))$ for initial feature extraction. These layers were followed by a bidirectional LSTM $BiLSTM(128)$, which learned temporal dependencies in both forward and backward directions, and a GRU layer

$GRU(64)$ to further refine sequential patterns. The model utilized the Stochastic Gradient Descent (SGD) optimizer with a learning rate $\eta = 0.01$, momentum $\mu = 0.9$, and Nesterov acceleration, aiming to enhance convergence speed and stability, while blockchain's smart contracts manage and authenticate interactions between nodes, preventing tampering and ensuring transparency. The formulation of the FL process can be described as follows: $\delta_i = \sum_{n_i}^{j=1}(x_j, y_j)$, where x_j is the input feature (e.g., time, machine state), and y_j is the energy consumption label. The local model updates its parameters ρ_i by minimizing the loss function $\imath_{\rho_i}$ over δ_i, expressed as: $\theta_i^{t+1} = \theta_i^t - \eta \nabla L_i(\theta_i^t)$, where η is the learning rate and $\nabla L_i(\theta_i^t)$ is the gradient of the local loss function. Once trained, the local models send their parameters to the Global Aggregation Server, which aggregates them using a weighted sum: $\theta^{t+1} = \sum_{i=1}^{N} \frac{n_i}{n} \theta_i^{t+1}$, where N is the total number of nodes, n_i is the size of the local dataset, and n is the total data size. The aggregated global model is distributed back to local nodes for the next training round, with blockchain storing model updates and metadata off-chain to minimize overhead, while on-chain verification ensures data integrity. The Digital-Twin Application Layer uses the global FL models for energy consumption predictions, and the On-Chain Network enhances security with decentralized storage and smart contract-based aggregation. This layer interacts with the Physical Layer to provide real-time insights, ensuring efficient energy consumption while maintaining privacy and integrity through the blockchain's tamper-proof system.

III. Performance Analysis

TABLE I: Energy Consumption Prediction on Different Companies of the Gumi Industrial Energy Consumption Dataset using the proposed DCFL-Chain Framework.

Company	Communication Round	Number of Clients	Accuracy (%)	MAPE (%)
Hanwha Main_data	125	10	99.04	0.96
B-dong Main_data			98.30	1.70
Building A cafeteria_data			98.21	1.79

The proposed DCFL-Chain system effectively predicts energy consumption across companies using the Gumi Industrial Dataset. Hanwha achieved 99.04% accuracy with a Mean Absolute Percentage Error (MAPE) of 0.96% over 125 communication rounds and 10 clients. Other companies, like B-dong and Building A cafeteria, showed an accuracy of 98.30% and 98.21%, respectively, with slightly higher MAPE values, the system demonstrates robust prediction performance shown in Table I.

Based on the evaluation results depicted in the Fig. 2, the aggregation time for decentralized processes increases from 5 to 20, the aggregation time also rises for both scenarios. However, the Non-IID distribution consistently requires more time than the independent and identically distributed (IID) distribution, reflecting the challenges posed by data heterogeneity. Specifically, with 20 clients, the IID setting records an aggregation time of 30 minutes, whereas the Non-IID setting extends to 35 minutes.

IV. Conclusion

The proposed DCFL-Chain framework combines digital twin technology, federated learning, and blockchain to predict energy consumption in smart factories. By decentralizing model aggregation and enhancing security with blockchain, the system achieves 99.04% accuracy, ensuring data integrity and privacy. Future work will focus on optimizing performance and exploring advanced security measures, such as quantum-based encryption, for smart grid operations.

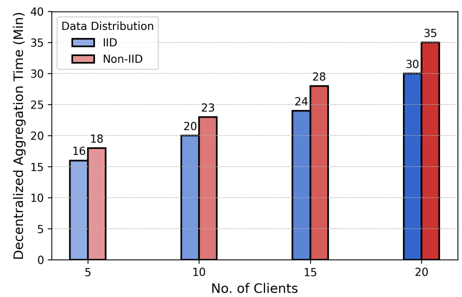

Fig. 2: DCFL-Chain Decentralized Aggregation Time for IID and Non-IID Data Distributions with increasing the Number of Clients.

V. Data Declaration

This research was conducted using data provided by the Energy Self-Sustaining Infrastructure Development Project, funded by Korea Industrial Complex Corporation (KICOX), Korea

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