Optimizing Energy Consumption Patterns with PureChain-Based Federated Learning

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***Abstract*—This study examines energy-efficient machine learning models in PureChain-based federated learning, focusing on the energy challenges of communication overhead and extended training rounds. Enhanced spatiotemporal Bidirectional LSTM (ESTG-BiLSTM) demonstrates energy efficiency due to its rapid convergence. BiLSTM offers a balanced performance-energy trade-off, while LSTM, with slower convergence, leads to higher energy consumption. The study highlights the need to optimize blockchain throughput and latency to enhance energy efficiency in decentralized learning systems.**

***Index Terms*—Blockchain, BiLSTM. Energy consumption, ESTG-BiLSTM, LSTM, PoA^2, PureChain.**

I. Introduction

The transition to decentralized energy systems, driven by renewable sources like solar and wind, creates challenges in managing volatile demand influenced by weather, consumer behavior, and distributed energy resources [1], [2]. Traditional grids struggle with this variability, requiring decentralized solutions [3]. While Bidirectional LSTM (BiLSTM) networks promise to forecast energy demand, they face issues like handling complex spatial-temporal dependencies, fragmented data, and privacy concerns [4], [5].

This paper proposes integrating Blockchain-based Federated Learning with an enhanced spatiotemporal BiLSTM model (ESTG-BiLSTM) to predict energy consumption. PureChain, a custom blockchain with proof of authority and association (PoA^2) [6], employs smart contracts to record payments immutably, enforces access control based on on-chain data, allowing dynamic updates of payment rules, and securely manages funds. This hybrid approach captures temporal and spatial demand variability while ensuring privacy and scalability in decentralized systems by utilizing attention mechanisms to improve the accuracy and robustness.

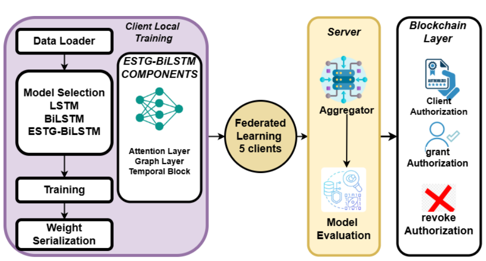

Fig. 1: Illustration of the proposed framework

II. Mathematical Formulation of the ESTG-BiLSTM in Federated learning framework

The **ESTG-BiLSTM with attention mechanisms** as shown in Figure 1 is for energy consumption prediction in a Federated learning architecture processes spatiotemporal input sequences $\mathbf{X} = \{\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_T\}$, where each input $\mathbf{X}_t$ consists of spatial and temporal features. The BiLSTM model computes forward and backward hidden states $\overrightarrow{h}_t$ and $\overleftarrow{h}_t$, and combines them as $h_t = \left[\overrightarrow{h}_t, \overleftarrow{h}_t\right]$. The attention mechanism assigns attention weights α_t to each hidden state as in Equation 1.

$$\alpha_t = \frac{\exp(\text{score}(h_t))}{\sum_{t=1}^{T} \exp(\text{score}(h_t))}, \tag{1}$$

where the score is $\text{score}(h_t) = w^T \tanh(W h_t + b)$, the vector c is obtained as the weighted sum of the hidden states in Equation 2.

$$c = \sum_{t=1}^{T} \alpha_t h_t, \tag{2}$$

and the local prediction in Equation 3.

$$\hat{Y}_t^{(i)} = W_{\text{out}}^{(i)} c + b_{\text{out}}^{(i)}. \tag{3}$$

Each client in the federated learning computes local updates based on its data and sends them to a central server. The server aggregates the model updates using federated averaging in Equation 4.

$$W_{\text{out}} = \frac{1}{N} \sum_{i=1}^{N} W_{\text{out}}^{(i)}, \quad b_{\text{out}} = \frac{1}{N} \sum_{i=1}^{N} b_{\text{out}}^{(i)}, \tag{4}$$

where N is the number of clients and the final prediction is $\hat{Y}_t = W_{\text{out}} c + b_{\text{out}}$. This approach efficiently learns from decentralized data while maintaining privacy and improves prediction accuracy by aggregating local updates. The FLPaymentContract uses PureChain to securely record and verify client payments, with a `makePayment()` function that accepts a specified amount, stores payment details, and marks it active. It emits a `PaymentReceived` event for off-chain tracking and uses `isClientAuthorized()` to validate payments based on amount and duration. The contract owner can adjust payment terms via `setPaymentAmount()` and `setPaymentDuration()`. The `withdraw()` function allows the owner to transfer funds. The contract is governed by

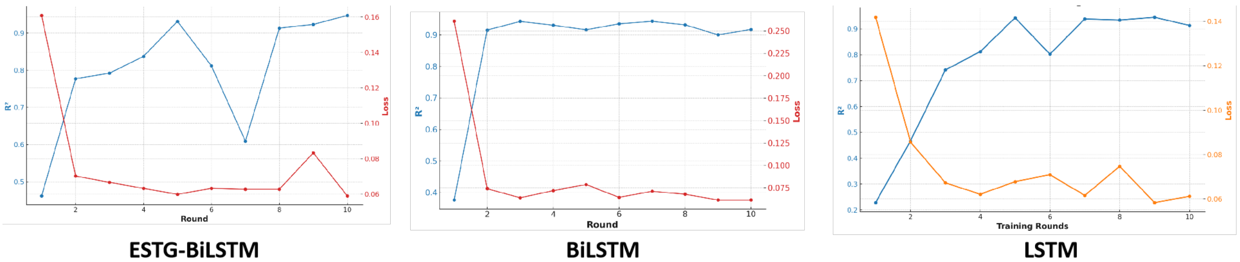

Fig. 2: Performance comparison of ESTG-LSTM, BiLSTM, and LSTM with 5 clients over 10 training rounds.

access control, with the `onlyOwner` modifier ensuring secure operations. It provides transparency, auditability, and secure fund management.

III. RESULTS DISCUSSION AND ANALYSIS

Figure 2 shows high R^2 ESTG-BiLSTM, stabilizing at 0.9 and rapid loss reduction, demonstrating energy-efficiency, ideal for blockchain-based federated learning. BiLSTM offers a balanced trade-off between performance (0.85 R^2) and energy use, but converges more slowly than ESTG-BiLSTM. LSTM shows slow convergence (R^2 0.6), with gradual loss reduction and higher energy consumption due to more training rounds. It suggests that ESTG-BiLSTM is the most energy-efficient, compared to BiLSTM and LSTM.

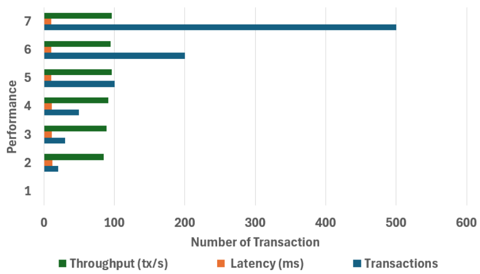

Fig. 3: PureChain Performance

Figure 3 compares the model performance regarding throughput, latency, and transactions. Throughput increases with the number of transactions, peaking at 500, while latency rises initially and stabilizes, correlates positively with the number of transactions. ESTG-BiLSTM benefits from rapid throughput stabilization, optimizing energy consumption. High throughput and low latency reduce communication costs, whereas higher latency increases energy usage due to more training rounds.

TABLE I: Model Computational Time

Model	Time (s)
LSTM	57
BiLSTM	55.62
ESTG-BiLSTM	53.99

Table I shows that the ESTG BiLSTM (53.99s), despite its advanced spatiotemporal features, is more computationally efficient than LSTM (57s) and BiLSTM (55.62s), due to architectural and training optimizations that reduce overhead while preserving performance.

IV. CONCLUSION

The study shows ESTG-BiLSTM as energy-efficient for blockchain-based federated learning due to its rapid convergence and high performance. BiLSTM offers a balanced trade-off between energy consumption and accuracy, while LSTM's slower convergence leads to higher energy use. Optimizing blockchain throughput and latency further improves energy efficiency. Future work will focus on optimizing federated learning models with techniques like adaptive learning rates to enhance the sustainability of decentralized AI systems.

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