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# Deep Learning Prediction of Methane Production in Mesophilic and Thermophilic Anaerobic Digestion

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## ABSTRACT

Anaerobic digestion (AD) converts organic waste into methane-rich biogas but forecasting methane yield is difficult due to nonlinear dynamics. This study compares Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Temporal Convolutional Network (TCN), and Temporal Fusion Transformer（TFT）models for predicting methane production rate (MPR, L/L/d) under mesophilic (37°C) and thermophilic (55°C) conditions. Lab-scale reactor data with features including hydraulic retention time (HRT), pH, chemical oxygen demand, volatile solids, and total solids were used. Results show LSTM achieved the best overall accuracy, followed by GRU and TCN. TFT performed lower, reflecting higher data demands. These results provide insights for model selection in biogas process optimization.

**Keywords:** Anaerobic digestion, methane prediction, biogas, time series, Deep Learning.

## INTRODUCTION

AD produces methane-rich biogas from organic waste, contributing to waste management and renewable energy (Inayat et al., 2021). Methane forecasting remains challenging due to nonlinear microbial dynamics and variable conditions (Rutland et al., 2023). Traditional models require large datasets yet often fail to capture such complexities (Le and Dong, 2024). Machine learning and deep learning provide alternatives capable of modeling nonlinear and temporal behaviors (Almomani, 2020). Recent reviews indicate machine learning generally surpass statistical approaches, with hybrid methods also demonstrating potential (Mendis et al., 2024). This study aims to compare four deep learning models for methane prediction under mesophilic and thermophilic conditions.

## MATERIALS AND METHODS

### Data Preprocessing

Time-series data were collected from lab-scale mesophilic and thermophilic AD reactors. Preprocessing included removal of missing and outlier values, followed by feature selection using a filter-based method to assess performance impact. Data were normalized and segmented by HRT (15, 10, 5 days). Sliding windows were applied without crossing HRT boundaries.

### Model Training and Evaluation

LSTM, GRU, TCN and TFT were trained separately for mesophilic and thermophilic datasets. Data were split into training, validation, and testing sets. Model performance was assessed using root mean square error (RMSE), which measures overall prediction deviation, and mean absolute percentage error (MAPE), which reflects relative accuracy across conditions.

Table 1 MAPE of four deep learning models under mesophilic and thermophilic conditions..

| Model / MAPE | Mesophilic | Thermophilic |
|---|---|---|
| GRU | 23.88% | 5.31% |
| LSTM | **16.31%** | **3.09%** |
| TCN | 30.57% | 6.33% |
| TFT | 26.37% | 6.44% |

## RESULTS & DISCUSSION

LSTM consistently achieved the lowest errors under both mesophilic and thermophilic conditions, as summarized in Table 1, followed by GRU and TCN, while TFT showed the lowest accuracy. These results suggest that recurrent models are more effective for methane forecasting in data-limited AD systems in this study.

## CONCLUSIONS

While LSTM achieved the best overall performance, further investigation by HRT segments may reveal conditions where other models perform better. Thus, HRT-specific evaluation is crucial, and future work should explore hybrid models and larger datasets to enhance AD methane forecasting.

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