Machine Learning for Predicting and Optimizing the Performance of an Anaerobic Digester with Diverse Feedstocks and Operating Conditions

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Anaerobic digestion (AD) plays a vital role in converting organic waste into renewable energy, reducing greenhouse gas emissions, and supporting sustainable waste management. However, AD encounters challenges such as feedstock variability, seasonal fluctuations, and operational complexity, which hinder its efficiency and reliability (Rasapoor et al., 2020). Recently, Machine learning (ML) has demonstrated potential in addressing some of these AD challenges by enabling predictive modelling and process optimization (Cruz et al., 2022).

In this study, we assessed the six years performance of Michigan State University's South Campus Anaerobic Digester using a dataset of 18 manure and food waste types, operational parameters (temperature, pH, HRT), and time-series data. After data pretreatment and normalization, 1,942 days of data were retained. ML models, including Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN), were developed to predict key AD performance metrics, including methane content, gas production, H_2S concentration, and electricity generation with performance evaluated using RMSE, r^2, and accuracy. Optimization models, including Simulated Annealing (SA) and Particle Swarm Optimization (PSO), were applied to minimize H_2S content or maximize biogas and electricity production. A representative day was chosen for optimization, with operational parameters adjusted to assess potential performance improvements under realistic conditions.

The RF model achieved the highest prediction accuracy across all target outputs, with an accuracy of accuracy of 89%–93% and R^2 values ranging from 0.60 to 0.71. Feature importance analysis revealed that year (20.4%), temperature (19.4%), and pH (13.2%) played dominant roles in gas production. Grouped feature analysis showed that time contributed 33%, operational parameters 37%, and feedstock 30% to overall gas production, underscoring the complex interactions between reactor conditions, seasonal effects, and feedstock composition (Fig. 1a). Feature importance analysis for H_2S revealed that time-related factors (month: 20.9%, year: 15.0%) had the greatest influence, highlighting the strong seasonal dependence of H_2S emissions, with higher levels of H_2S observed in winter possibly due to lower reactor temperatures favoring sulfate-reducing bacteria (Jung et al., 2019). pH fluctuations also played a key role possibly due to its impact on sulfur compound transformations and microbial competition (Yan et al., 2018). These findings emphasize the importance of stable temperature and pH conditions to minimize H_2S emissions and improve biogas quality. Grouped feature analysis revealed that time (43%) and operational parameters (37%) had the most significant impact on H_2S content, while feedstock contributed 20%, with dairy manure emerging as a key factor (Fig. 1b). For methane content, time-related factors accounted for 50% of feature importance, followed by operational parameters (32%) and feedstock (18%), suggesting that seasonal and temporal variations significantly affect methane percentage. Unlike H_2S prediction, food waste (10.1%) played a more significant role for methane percentage, with pineapple waste emerging as a key contributor (Fig. 1c). Compared to biogas production, seasonal influences were less significant for electricity generation, with manure (21.2%), temperature (17.7%), and year (17.0%) emerging as the most influential factors. Manure filtrate played a key role (7.0%) and could serve as an indicator (Fig. 1d).

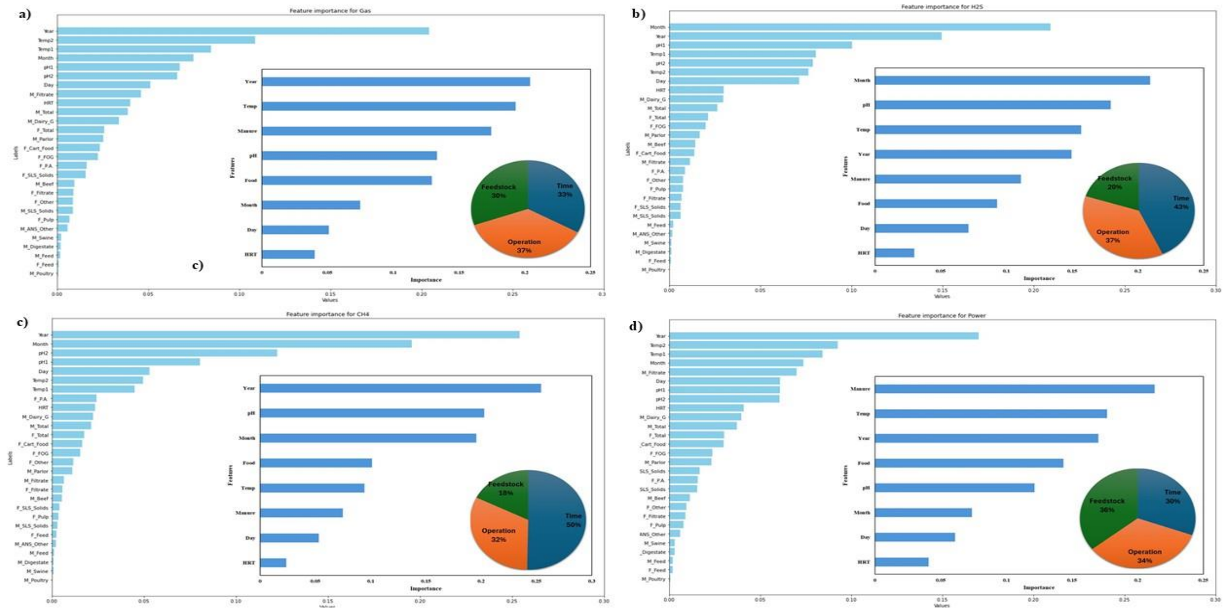

Figure 1. Key features identified by the ML model for gas production (a), H_2S content (b), methane percentage (c) and electricity production (d).

Based on feature importance analysis, five operational parameters were optimized to reduce H_2S content, maximize gas production, or increase electricity generation (Table 1). Optimization results demonstrated a 50.4% reduction in H_2S content and a 12% increase in both biogas and electricity production, showcasing the potential of ML-driven optimization to enhance AD system performance and inform real-time operational adjustments. By integrating long-term commercial data with ML, this study demonstrates ML's potential as a scalable, data-driven approach to enhancing AD efficiency, laying the groundwork for adopting advanced AI-driven tools in renewable energy production and waste management.

Table 1: Comparison of optimal operational conditions identified by ML for minimum H_2S, maximum biogas production, and maximum electricity generation with the actual operating conditions on 2018-12-08 (HRT = 17, Temp1 = 102.7°F, pH1 = 8.07, Temp2 = 102.6°F, pH2 = 7.98).

	HRT (days)	Temp1 (°F)	pH1	Temp2 (°F)	pH2	Optimized Result (% improvement)
H_2S	14.1	100.9	6.93	95.8	6.85	222.0 ppm (-50.4%)
Gas	24.0	95.3	6.86	106.3	6.52	138600 SCF (12%)
Electricity	24.2	101.6	8.43	103.5	6.72	7564 kWh (12%)

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