Research On The Optimization Of Agricultural Waste Gasification Process By Integrating DoE, SVR, GA, PSO Machine Learning Technologies

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Agricultural waste is increasingly recognized as a sustainable feedstock for clean energy generation through thermochemical gasification. This study develops a comprehensive AI-driven simulation and optimization framework to improve the efficiency of a fixed-bed gasification system. Support Vector Regression (SVR) was employed to construct a robust predictive model with high accuracy ($R^2 > 0.90$), while the Taguchi method was applied to identify and optimize critical operational factors. Key variables, including reactor temperature, air flow rate, feedstock moisture content, and catalyst ratio, were systematically evaluated for their effects on syngas yield and overall efficiency. The integrated model not only demonstrated excellent predictive performance but also revealed strong nonlinear interactions among parameters influencing gasification outcomes. Results indicate that optimal efficiency can be achieved by carefully balancing reactor temperature and feedstock moisture, in conjunction with appropriate catalyst dosing. This research provides a data-driven pathway toward intelligent optimization of biomass gasification, contributing to sustainable energy production and practical deployment of Taguchi–SVR–GA/PSO enabled clean energy technologies.

Keywords: agricultural waste; gasification; support vector regression (SVR); genetic algorithm (GA); particle swarm optimization (PSO); design of experiments (Taguchi method).

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1. Introduction

As the world seeks sustainable and low-carbon energy alternatives, the valorization of agricultural waste through thermochemical conversion has gained increasing attention [1, 2]. Gasification enables the transformation of biomass into syngas-a valuable fuel for heat and power applications [3]. Unlike direct combustion, gasification offers higher thermal efficiency and cleaner emissions, making it suitable for decentralized energy production [4, 5]. However, gasifier performance is highly sensitive to operating parameters such as feedstock composition, reactor temperature, air ratio, and moisture content [6, 7]. Inconsistent control of these factors can lead to unstable syngas quality and reduced efficiency, while conventional optimization approaches often lack the flexibility to capture nonlinear and interacting effects among variables [8].

From a broader perspective, recent advances in statistical learning and AIoT-enabled energy systems provide new opportunities for optimizing biomass gasification. Foundational work in statistical learning theory offers robust strategies for regularization and model selection in high-dimensional, nonlinear regression problems [9]. Hybrid machine-learning and optimization schemes, such as SVR-PSO and SVRGA, have been successfully applied to energy forecasting and bioenergy process optimization, demonstrating the advantages of combining data-driven models with evolutionary algorithms [10–12]. In parallel, AIoT-based sensing and control frameworks are increasingly deployed to couple data-driven models with real-time monitoring in advanced biomass gasification systems [13, 14], while gasification studies highlight the importance of operating conditions and formulation for enhancing hydrogen yield and syngas quality [15]. These trends underscore the need for integrated, data-driven optimization frameworks. In this context, the present study develops a Taguchi-SVR-GA/PSO approach to predict cold gas efficiency (CGE) and identify optimal operating conditions for agricultural waste gasification [9–24].

2. Theory and formula

2.1. Gasification Process Fundamentals

Biomass gasification is a thermochemical conversion process that transforms agricultural residues into syngas, primarily composed of H_2, CO, CO_2, and CH_4 [1, 2]. The general overall reaction of biomass gasification can be represented as: Biomass $(CH_xO_\gamma) + O_2 + H_2O \rightarrow aCO + bCO_2 + cH_2 + dCH_4 +$ Tar + Char The cold gas efficiency (CGE) is often used to evaluate the performance of the gasifier: η_CGE = (ṁ_syngas ×LHV_syngas)/ (ṁ_biomass× LHV_biomass) × 100%

$$\eta_{CGE} = \frac{\dot{m}_{\text{syngas}} \cdot LHV_{\text{syngas}}}{\dot{m}_{\text{biomass}} \cdot LHV_{\text{biomass}}} \times 100\%$$

2.2. Taguchi Method for Experimental Design

The Taguchi method provides a systematic approach to reduce the number of experiments while maintaining statistical significance [6]. An orthogonal array (OA), such as L18 or L25, is used to design experiments by varying key factors. The signal-to-noise (S/N) ratio for the "larger-the-better" criterion is:

$$\text{S/N} = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2} \right)$$

2.3. Support Vector Regression (SVR)

SVR is a supervised machine learning algorithm used for nonlinear regression [3]. Given a training dataset $\{(x_i, y_i)\}$, SVR seeks to approximate the function:

$$f(x) = \langle w, \phi(x) \rangle + b \qquad \min_{w,b,\xi,\xi^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*)$$

2.4. Genetic Algorithm (GA)

GA is a population-based metaheuristic inspired by natural selection [4]. The optimization process involves initialization, fitness evaluation, selection, crossover, and mutation. The fitness function for efficiency optimization is:

$$F(x) = \max\left\{\eta_{CGE}(T, \dot{Q}, M, R, C)\right\}$$

2.5. Particle Swarm Optimization (PSO)

PSO is a swarm intelligence algorithm that models the social behavior of particles [5]. Each particle adjusts its velocity and position according to:

$$v_i^{t+1} = wv_i^t + c_1 r_1 \left(p_i^{\text{best}} - x_i^t\right) + c_2 r_2 \left(g^{\text{best}} - x_i^t\right)$$
$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

2.6. Integration Framework

The hybrid framework integrates Taguchi design → SVR modeling → GA/PSO optimization. Taguchi identifies the main factors and levels, SVR builds predictive models, and GA/PSO explores the solution space to find optimal parameter combinations that maximize CGE. The study investigates the efficiency of agriculturalwaste gasification by constructing a predictive Support Vector Regression (SVR) model and performing evolutionary optimization using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). To ensure the accuracy, robustness, and statistical completeness of the modeling process, a unified experimental design methodology was adopted.

3. Experimental setup

3.1. Gasification System

The experiments were conducted using a fixed-bed downdraft gasifier designed for small-scale agricultural residue utilization. The system consists of four main sections:
A. Feeding unit - Agricultural waste (e.g., corn stalks, rice straw, and rice husks...) was dried and ground into wood particles with a size of $5-8$ cm before feeding into the reactor. The prepared biomass was stored in a hopper and fed into the downdraft gasifier by a gravity-assisted feeding mechanism at a nearly constant rate. The actual feed rate (kg/hr) was monitored and adjusted based on the mass of biomass loaded over a given operating period to ensure stable operating conditions during each run.
B. Gasifier reactor - a cylindrical fixed-bed reactor equipped with electric heating elements for start-up and an air supply system for controlling the equivalence ratio.
C. Gas cleaning and conditioning - a cyclone separator and a water scrubber were used to remove particulates and tar.

D. Measurement and control system - included flow meters, thermocouples, and gas analyzers (CO, H_2, CO_2, CH_4) to measure syngas composition and temperature at different reactor zones.

3.2. Feedstock Preparation

Agricultural waste in the form of wood particles was selected as the feedstock due to its abundance and energy potential. Proximate and ultimate analyses were performed according to ASTM standards to determine the moisture, volatile matter, fixed carbon, and ash content. The lower heating value (LHV) of the feedstock was measured using a bomb calorimeter.

3.3. Control Factors and Levels

Five major operational factors were selected based on their proven influence on syngas production and gasification performance. These factors were chosen due to prior experimental evidence and their importance in biomass pyrolysis/gasification chemistry, as validated by previous gasification studies [2, 5, 7] and other related references.

3.4. Taguchi Experimental Design

Initially, an L18 orthogonal array was considered to screen the influence of the five control factors while reducing the number of experiments [6, 8]. However, for the final modeling and optimization framework, a standardized full factorial design was adopted to ensure complete coverage of all factor levels. The final design used throughout this study is:

- Full factorial design with 5 factors $\times 5$ levels (25 runs);
- Plus 5 center points at the mid-levels of all factors;
- For a total of 30 experimental/simulation points.

No random sampling or alternative sampling strategies were used. The L18 arrangement is mentioned only for historical comparison and is not included in the SVR training dataset.

3.5. Data Collection and Model Training

The 30-run full factorial design with center points, described in Section 3.4, was used as the unified dataset for training and validating the SVR model. All input variables were normalized to the range $[0, 1]$ before training. An SVR model with a radial basis function (RBF) kernel was adopted, and the hyperparameters (C, γ, ε) were tuned using 10-fold cross-validation to avoid overfitting.

The trained SVR model was then used as a surrogate objective function in the GA and PSO optimization procedures to search for the combination of operating parameters that maximizes cold gas efficiency (CGE).

4. Results and discussion

4.1. Taguchi Analysis of Gasification Efficiency

The main effects of reactor temperature and moisture content on cold gas efficiency (CGE) are shown in Fig. 1. CGE increases from about 70% at 700°C to a maximum of approximately 95% at 850°C, and then slightly decreases at 900°C, which is likely due to excessive tar cracking and additional thermal losses. In contrast, CGE decreases almost monotonically as the feedstock moisture content increases from 10% to 50%, reflecting the additional energy required for drying and the resulting reduction in energy available for gasification reactions.

The full main-effect trends for all five control factors—reactor temperature, air flow rate, moisture content, feed rate, and catalyst ratio-are summarized in Fig. 2. These plots confirm that moisture content is the most influential factor with a strong negative effect on CGE, while moderate levels of feed rate ($2-3$ kg/hr) and catalyst ratio (around $2-3\%$) are favorable for achieving high efficiency.

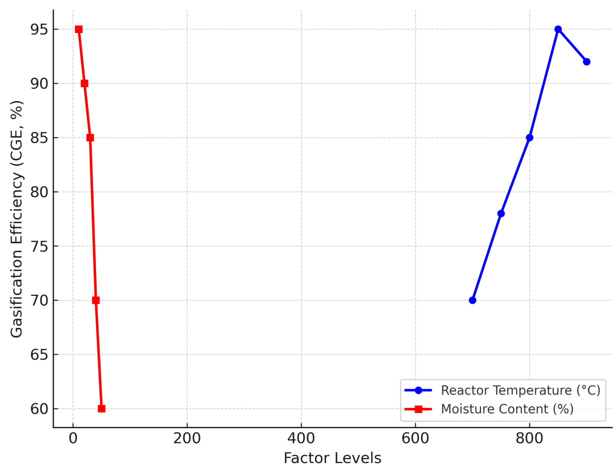

Fig. 1. Gasification efficiency vs. temperature and moisture

4.2. Interaction Effects

Interaction plots in Fig. 3 highlight the combined influence of the control factors on mean gasification efficiency (CGE). In Fig. 3(a), the interaction between catalyst ratio and moisture content shows that increasing catalyst loading significantly improves CGE at low to moderate moisture levels (10-30%). However, at higher moisture contents (40-50 %),

Table 1. The five primary control factors and their corresponding levels.

Factor	Level 1	Level 2	Level 3	Level 4	Level 5
Reactor Temperature (A)	700°C	750°C	800°C	850°C	900°C
Air Flow Rate (B)	5 L/min	10 L/ min	15 L/ min	20 L/ min	25 L/ min
Moisture Content (C)	10%	20%	30%	40%	50%
Feed Rate (D)	1 kg/hr	2 kg/hr	3 kg/hr	4 kg/hr	5 kg/hr
Catalyst Ratio (E)	0%	1%	2%	3%	4%

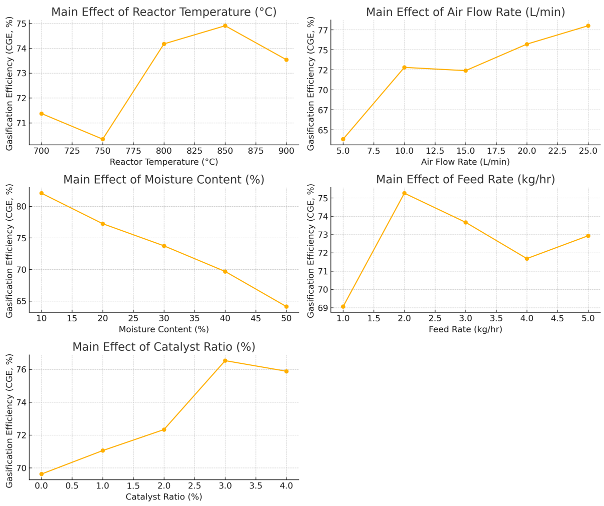

Fig. 2. Main effect plots of the five control factors

the benefit of additional catalyst becomes much smaller, because more heat is consumed to evaporate water, leaving less energy for gasification reactions.

Fig. 3(b) illustrates the interaction between reactor temperature and feed rate. Higher temperatures enhance CGE, especially when the feed rate is maintained at a moderate level ($2-3$ kg/hr). At higher feed rates ($4-5$ kg/hr), CGE tends to plateau or even decrease, suggesting that excessive biomass loading can hinder heat transfer and limit the completeness of gasification. These interactions emphasize the need to jointly tune temperature, moisture content, feed rate, and catalyst ratio rather than treating them as independent variables.

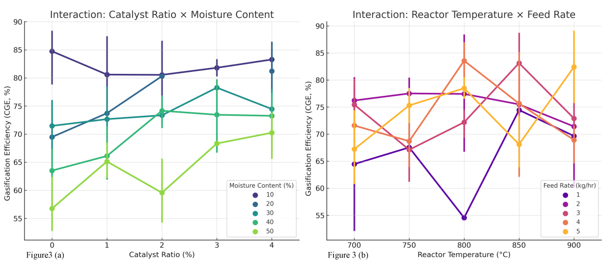

Fig. 3. Interaction effects on mean gasification efficiency (CGE)

4.3. SVR Model Performance

The SVR model with an RBF kernel was trained on the 30 -run full factorial dataset (including center points) described in Section 3.4. Hyperparameters (C, γ, ε) were optimized using 10 -fold cross-validation. The final model achieved excellent predictive performance, with a coefficient of determination $R^2 = 0.9445$, mean squared error (MSE) $= 2.3363$, mean absolute error (MAE) $= 1.2509$, and mean absolute percentage error (MAPE) $= 1.68\%$. These metrics are summarized in Fig. 4. The high R^2 and low error values indicate that the SVR model effectively captures the nonlinear relationships between the five operational factors and CGE, and provides a reliable surrogate for subsequent optimization.

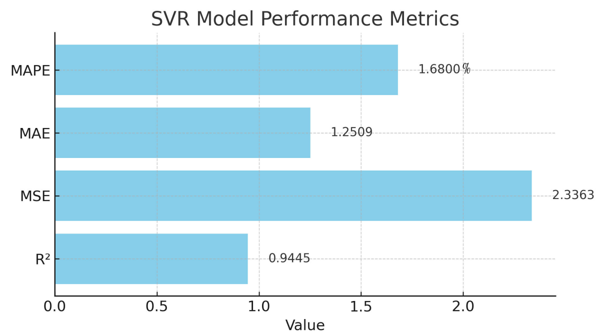

Fig. 4. Performance metrics of the SVR model trained on the 30-run full factorial dataset

Although the 30 -run full factorial design with center points provides reasonable coverage of the operating space, the resulting dataset is still modest in size compared with long-term, plant-scale databases. As a consequence, the statistical power and generalization capability of the SVR model remain constrained by the available sampling window. Future work will expand this dataset using extended operational campaigns and online monitoring data to further enhance model robustness and external validity.

4.4. Optimization by GA and PSO

Both Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) were employed to optimize the SVR-based surrogate model of CGE. Table 2 summarizes the best solutions found by GA and PSO. The GA search yielded an optimal configuration of 900°C reactor temperature, 23.65 L/min air flow, 10% moisture content, 2.87 kg/hr feed rate, and 1.56 % catalyst ratio, with a predicted CGE of 95.57%. The PSO search produced a comparable optimum of 900°C, 25 L/min, 10% moisture, 2.88 kg/hr feed rate, and 1.45% catalyst ratio, resulting in a predicted CGE of 95.39%.

The convergence behavior of both algorithms is shown in Fig. 5. GA and PSO rapidly approach the global optimum within about 30-40 iterations, with PSO converging slightly faster while reaching a similar final efficiency. These results confirm that coupling SVR with evolutionary algorithms is effective for identifying near-optimal operating conditions in a multi-factor gasification system.

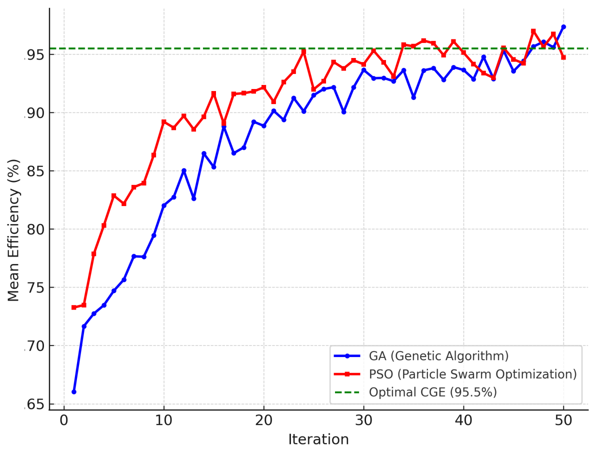

Fig. 5. Convergence curves of the GA and PSO algorithms

To put these optimized efficiencies into context, typical cold gas efficiencies reported for biomass fixed-bed gasifiers in the literature are around $70-85\%$ under comparable operating conditions. Achieving a predicted maximum CGE close to 95.5% therefore represents a substantial improvement over baseline operation and highlights the benefit of the proposed SVR-guided GA/PSO optimization framework.

4.5. Practical Implications

The AI-driven optimization framework provides superior accuracy and robustness compared with conventional statistical methods. The integration of Taguchi design, SVR modeling, and evolutionary algorithms offers:

A. Reliable prediction of nonlinear system performance.
B. Efficient exploration of multi-dimensional parameter space.
C. Practical operational guidelines for maximizing gasification efficiency under varying feedstock conditions.

These findings demonstrate the potential of AI-based digital twin frameworks for real-time process optimization in renewable energy systems.

5. Conclusions

This study presents an AI-driven optimization framework for improving the efficiency of agricultural residue gasification. By integrating Taguchi design of experiments (DoE), Support Vector Regression (SVR), and evolutionary algorithms (GA and PSO), the work provides a comprehensive methodology for both simulation and practical optimization of fixed-bed gasifiers.

The main findings are summarized as follows:

i. Taguchi-based analysis of the unified 30-run full factorial design demonstrated that reactor temperature and feedstock moisture are the most significant factors influencing cold gas efficiency (CGE). Interaction effects, particularly between reactor temperature and feed rate as well as between catalyst ratio and moisture content, were also identified as critical for optimizing syngas quality.
ii. The SVR model achieved excellent predictive accuracy ($R^2 = 0.9445$, MAPE $= 1.68\%$), outperforming traditional regression methods in capturing nonlinear and interactive effects among variables.
iii. GA and PSO optimization converged consistently to similar optimal operating conditions—reactor temperature $\approx$ 900°C, air flow rate $\approx 23-25$ L/min, moisture content $\approx$ 10%, feed rate $2-3$ kg/hr, and catalyst ratio below 2%-yielding a maximum predicted CGE of approximately 95.5%, which represents a substantial improvement over baseline operations.

Overall, the proposed Taguchi-SVR-GA/PSO framework enables reliable predictions, robust optimization, and scalable application for diverse agricultural waste feedstocks. These findings provide practical guidance for renewable energy system design and intelligent optimization in engineering applications.

6. Future works

To further enhance the applicability of this research, future studies should focus on:

i. Extending the model to include syngas composition, carbon conversion efficiency, and tar reduction.
ii. Developing hybrid models (e.g., SVR combined with deep neural networks) for improved generalization.
iii. Implementing real-time optimization with sensor feedback, paving the way for smart bioenergy systems.

Table 2. Optimal operating conditions obtained by GA and PSO.

Method	Temp. (°C)	Air Flow (L/min)	Moisture (%)	Feed Rate (kg/hr)	Catalyst (%)	Predicted Efficiency (%)
GA	900.00	23.65	10.00	2.87	1.56	95.57
PSO	900.00	25.00	10.00	2.88	1.45	95.39

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