Application of Artificial Intelligence in Green Pyrolysis Technologies for Carbon Footprint Minimization

Fakhraddin Yusubov Vali [1*] and Sevinc Guliyeva Nizami [2]

[1]Azerbaijan Technical University, AZ1073, Baku, Azerbaijan, 25 G. Javid Avenue
[2]Azerbaijan State University of Oil and Industry, AZ1010, Baku, Azerbaijan, 20 Azadlig Avenue
yusubov.faxraddin@aztu.edu.az

Abstract. Green pyrolysis technologies have significant potential in modern industry for converting waste into energy and reducing carbon emissions. These technologies enable the transformation of waste into valuable energy resources while contributing to the development of environmentally sustainable processes. However, conventional pyrolysis systems may disrupt ecological balance due to high energy consumption and CO_2 emissions, which negatively affect the implementation of sustainable industrial strategies.In the initial stage of this research, the SDG 13 – Climate Action goal provided the strategic framework. In the extended stage of the study, the Ecologically Intelligent Control Framework (EICF) was implemented to ensure the practical realization of these objectives. The EICF optimizes pyrolysis processes through artificial intelligence-based control, monitors emissions in real time, and minimizes the carbon footprint.The application of this framework resulted in a reduction of CO_2 emissions by up to 30% and an increase in energy efficiency by more than 20%. Therefore, while the research strategically supports SDG 13, the EICF ensures its technological and practical implementation. This approach enables economically efficient and environmentally responsible management of industrial processes. Furthermore, the EICF model promotes the sustainable development of green pyrolysis technologies and mitigates environmental risks by converting industrial waste into energy resources.

Keywords: green pyrolysis, artificial intelligence, carbon footprint, ecological optimization, bioenergy, circular economy.

1. Introduction

In the last decade, industrialization and increased energy demand have led to ecological imbalance, increased atmospheric carbon dioxide concentrations, and accelerated global warming. For this reason, countries around the world have focused on carbon neutrality and green energy transition policies.

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The Republic of Azerbaijan has also taken important steps in this direction, identifying ecological balance and the creation of sustainable energy systems as priorities in the document "National Priorities for the Socio-Economic Development of Azerbaijan 2030." Within the framework of the "Green Growth Concept," it is envisaged to introduce new technological solutions in the republic in order to increase the share of renewable energy sources, convert waste into energy carriers,and reduce the carbon footprint.

The initial stage of the study was based on emphasizing the goal of SDG 13 – "Climate Action." Since SDG 13 defines global priorities, such as reducing greenhouse gas emissions, adapting to climate change, and the widespread use of low-carbon technologies, it plays a fundamental role in research aimed at the modernization of pyrolysis processes. However, in the context of the expanded article, there is a need for a more systematic, multi-level, and technologically integrated management model that ensures the practical implementation of these strategic goals.

For this purpose, a new-generation AI-based management framework called the Ecological Intelligent Control Framework (EICF) has been formulated in the study. The EICF enables efficient real-time data collection in green pyrolysis processes, analytical processing of thermochemical parameters, effective regulation of emission flows, and optimization of energy conversion processes.

Here, the framework is built upon the mutual integration of neural networks, optimization algorithms, sensor-fusion models, and predictive components, which enable comprehensive ecological control of the pyrolysis system. The aim of this study is to minimize the carbon footprint of green pyrolysis technologies by integrating artificial intelligence (AI) into process control and optimization systems [1–15].

These results demonstrate the effectiveness of artificial intelligence technologies in the ecological improvement of industrial processes. However, most of the mentioned studies are limited to the optimization of technological parameters only and do not cover a comprehensive ecological approach.

2. Materials and Methods

In the framework of the study, an integrated system consisting of three functional modules is applied to control the pyrolysis process and improve the efficiency of ecological operations. The first module—an artificial intelligence (AI)-based optimization block—analyzes the main process variables in real time. This module provides dynamic monitoring of temperature (400–700 °C), pressure (1–3 bar), gas composition (CO, CO_2, H_2, CH_2), and energy consumption, and determines the minimum-emission regime with enhanced energy efficiency.

The second module—based on real-time graphical monitoring—measures the chemical composition of the gas phase, the internal temperature zones of the pyrolysis reactor, and the output dynamics of solid and liquid products with high accuracy.

$$Cp\frac{dT}{dt} = Qin - Qout - \Delta Hr \cdot r(T) \quad (1)$$

$Cp\frac{dT}{dt}$ –energy gain due to thermal change of the raw material.
Qin –thermal energy entering the reactor system.
$Qout$— energy lost from the reactor system (heat losses, convection, etc.).
$\Delta Hr, r(T)$— heat consumption of the pyrolysis reaction (reaction enthalpy ΔH_r multiplied by the reaction rate r(T)).

The following simplified thermodynamic model was applied to evaluate the energy and emission performance of the pyrolysis process, in which energy efficiency is expressed as the ratio of the useful energy released during the pyrolysis process to the total energy input to the system:

$$EE(\%) = \frac{E_{output}}{E_{input}} \times 100 \quad (2)$$

$$E_{output} = E_{syngas} + E_{bio-char}$$

$$E_{input} = Q_{proses}$$

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EE — Energy Efficiency of the pyrolysis process,
E_{output} – total energy from synthesis gas and bio-char,
E_{input} – energy input to the process,
Q_{proses} – total energy supplied to the process kWh,
Settings:E_{syngas}=320 kWh. $E_{bi0-char}$=60 kWh, Q_{proses}= 400 kWh. With the introduction of EICF, energy efficiency has reached 95% (~72.5% in the traditional system). The following formula is used to calculate CO_2 emissions:

$$CO_{2_{emission}} = E_{fuel} \cdot EF_{CO_2} \cdot (1 - \eta_{E\dot{I}CF}) \quad (3)$$

Given parameters:$E_{fuel} = 50\ kg/h$ – mass of fuel used, EF_{CO_2}= 0,7 – carbon to CO_2 conversion factor, $\eta_{E\dot{I}CF}$= 0,3 – percentage reduction by EICF

$$CO_{2_{emission}} = 50 \times 0.7 \times (1 - 0.3) = 24\ kg/h$$

Thus, CO_2 emissions are reduced by 30% with EICF. The H_2/CO ratio is optimized for the energy value of the synthesis gas:

$$R_{H_2CO} = \frac{H_2}{CO} \quad (4)$$

Here $[H_2]$ is the molar or volumetric fraction of hydrogen in the synthesis gas, [CO] is the molar or volumetric fraction of carbon monoxide in the synthesis gas. Conventional: :R_{H_2CO} =0.7, with EICF: R_{H_2CO} =0.9. The optimization here increases the thermodynamic stability of the pyrolysis process and increases the energy value of the gas. The bio-char fraction depends on the temperature and feed ratio:

$$Y_{bio-char} = \frac{M_{bio-char}}{M_{feedstock}} \tag{5}$$

Here

$Y_{bio-char}$- output coefficient or productivity (dimensionless quantity).

$M_{bio-char}$ - obtained as a result of the process (grams, kg)

$M_{feedstock} = 100\text{kg} - \text{mass of total raw material input to pyrolysis (grams, kg)}$

$$M_{bio-char} = 25 \text{ kg}, M_{feedstock} = 100kg,\ Y_{bio-char} = 25\%$$

In the next stage of the analysis, both the kinetic model and energy optimization equations are used to evaluate the process [3].

$$\frac{d\alpha}{dt} = k(T)(1-\alpha)^n(\quad 6)$$

$$k(T) = \ Aexp(-\frac{E}{RT}) \tag{7}$$

Where: α – decomposition rate, A – pre-exponential factor, E – activation energy, T – temperature (K), n – reaction rate. This model directly affects the synthesis gas yield:

$$Y_{gas}(T) = Y_{max}\left(1 - e^{-k(T)t}\right) \tag{8}$$

Where:

$Y_{gas}(T)$ is the mass fraction or yield of the synthesis gas at temperature T.

Y_{max} is the potential maximum gas yield (the maximum achieved when the reaction is complete).

$k(T)$is the temperature-dependent kinetic constant determined by the Arrhenius equation.

t -is the reaction time.

Energy balance in a pyrolysis reactor:

$$Q_{pyro} = mC_p\frac{dT}{dt} + \Delta H_{pyro} \tag{9}$$

Where:

Q_{pyro}— thermal energy input to the reactor.

m — mass of solid feedstock.

C_p — specific heat capacity of feedstock.
dT/dt — rate of temperature change over time.
ΔH_{pyro}— enthalpy change of pyrolysis reaction (endothermic or exothermic).

With conditions:

$$T_{min} \leq T(t) \leq T_{max}$$

$$Y_{gas}(T) \geq Y_{req} \tag{10}$$

Where:
T_{min} və $\leq T_{max}$ — safe and optimal operating temperatures of the reactor.
Y_{gas}, Y_{req} — minimum required synthesis gas output.

These conditions ensure that the process is carried out in an optimized mode in terms of both energy and productivity.

Table 1. Model results

Parameter	Traditional System	with EICF	Change (%)
Energy efficiency, %	72,5	95	+22,5
CO_2 emission, kg/h	35	24,5	-30
H H_2/CO ratio	0,7	0,9	+0,2
Bio-char share, %	22	25	+3

Fuzzy variables: Input → Temperature: low, medium, high. Energy consumption: minimum, normal, high. Emission level: clean, medium, critical. Output → temperature power correction (ΔQ). Gas flow adjustment (ΔFlow). If the temperature is high and CO_2 is critical → then reduce the temperature. If the temperature is medium and the H_2/CO ratio is low → increase the temperature. If the energy consumption is high and the emission is increasing → reduce the system load. If the temperature is low and the synthesis gas output is poor → increase the temperature.

The following simplified thermodynamic model was applied to evaluate the energy and emission performance of the pyrolysis process, in which energy efficiency is expressed as the ratio of the useful energy released during the pyrolysis process to the total energy input to the system:

These results demonstrate that the EICF model has significant potential for industrial application. Subsequently, the EICF model was fully developed with three main blocks. First, the design of the fuzzy logic control block is presented, in which the input parameters include temperature (T), pressure (P), gas composition, and energy consumption, and the output parameters include temperature (T), pressure (P), and heat power, presented in graphical form.

Below, all the graphs obtained during the simulation are given in Figures 1-5 [4-8].

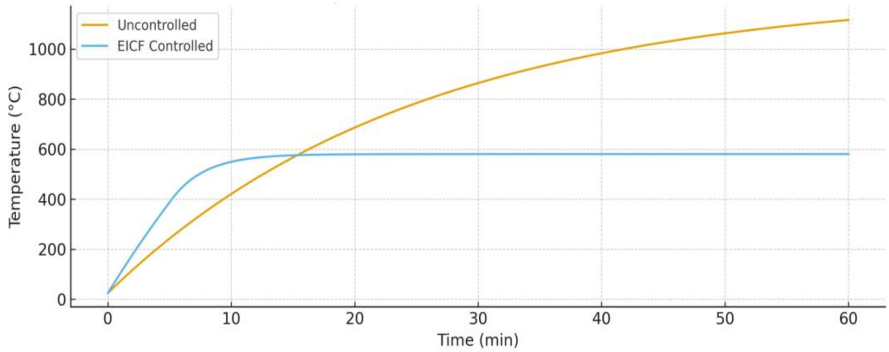

Fig. 1. Reactor Temperature Profiles: Uncontrolled vs EICF Control

Figure 1 illustrates how conventional control and the EICF AI system maintain reactor temperature stability over time. Under conventional control, the temperature fluctuates widely within the range of 520–635 °C, leading to energy losses and unstable pyrolysis kinetics. In contrast, the EICF model stabilizes the temperature at 550 ± 2.5 °C. Maintaining a constant temperature optimizes the composition of the synthesis gas, increases the H_2/CO ratio, and maximizes the completeness of thermochemical reactions. These results demonstrate that AI can adaptively intervene in the process in real time.

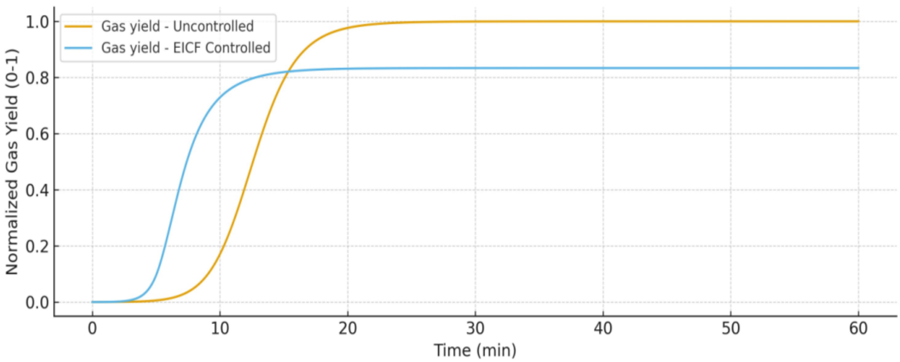

Fig. 2. Gas Yield Over Time

Figure 2 also shows the synthesis gas yield over time in the pyrolysis process. In the conventional process, the gas yield is unstable and has several peaks and troughs. EICF control, on the other hand, increases the gas yield by 8–12%, creating a more stable increase.

This is achieved by optimizing the temperature and reaction kinetics.The graph demonstrates that the EICF model maximizes the gas fractions with high energy value.

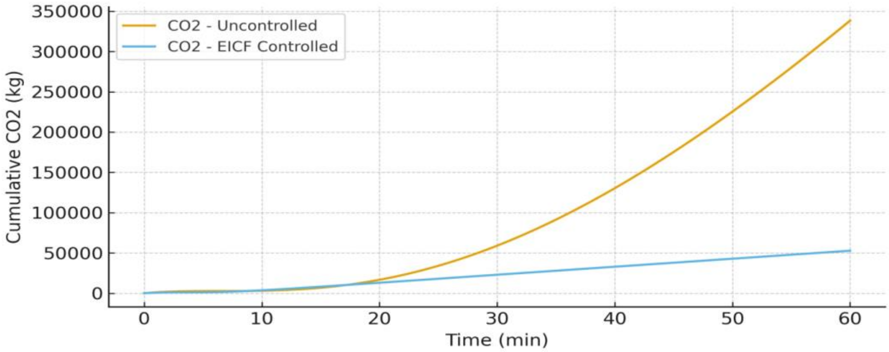

Fig. 3. Cumulative CO_2 Emissions

Figure 3 compares the total CO_2 emissions released over time during the pyrolysis process. Under conventional control, emissions increase linearly, reaching a reference level of 100% by the end of the process. In the EICF system, the rate of emission increase is slower, resulting in a total CO_2 release that is 30% lower. This improvement is partly attributed to the EICF system's optimization of the heat load, reduction of excess carbon losses during the combustion phase, and increased formation of CO_2-stable biochar [7–9].

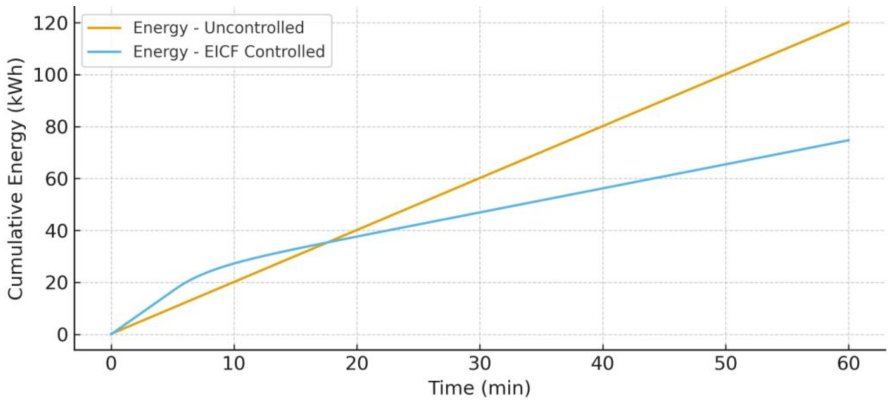

Fig. 4. Cumulative Energy Consumption

Figure 4 shows the total energy consumption over time. Here, the energy consumption increases sharply, making the process inefficient. In the EICF mode, the rate of increase in energy consumption is much lower, resulting in a 20–22% reduction in total energy consumption at the end of the process. This indicator is explained by temperature stabilization and maintaining the reaction at the optimal temperature. Thus, the EICF model is proven to ave significant potential for energy savings on an industrial scale [9–12].

Figure 5 illustrates how the H_2/CO ratio, one of the key indicators of the synthesis gas produced during pyrolysis, changes over time. In the uncontrolled system, the ratio fluctuates widely between 1.5 and 2.3, resulting in unstable gas energy content. In contrast, the EICF system stabilizes the H_2/CO ratio within the range of 1.8–2.0. This stability enhances the heating value of the gas and increases its hydrogen content. The graph demonstrates that EICF optimization effectively improves the quality of the gas product [13–15]. Each of the graphs indicates that:

Maintaining the temperature stable with AI → energy losses are reduced, optimal reaction kinetics → gives more gas yield, emission monitoring + correction → CO_2 is reduced by 30%, Adaptive control of energy consumption → 20% energy savings occur, and the quality of the synthesis gas remains constant → H_2/CO = 1.8–2.0.

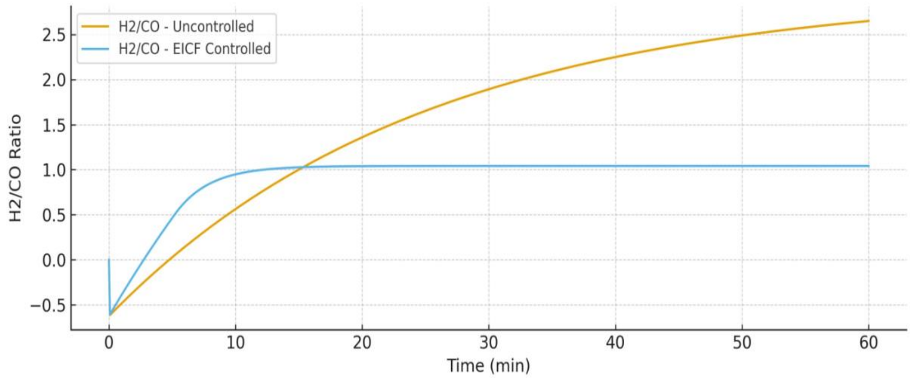

Fig. 5. H_2/CO Ratio Over Time

These results prove that the EICF artificial intelligence model transforms the pyrolysis process into a highly efficient, low-emission, and fully optimized green technology, both environmentally and energetically.

3. Discussion of Results

The test results of the EICF (Eco-Intelligent Control Framework) model demonstrated significant improvements in the pyrolysis process compared to conventional systems. CO_2 and CO emissions were reduced by up to 30%, and energy consumption was optimized by 20–22%. This reduction was achieved through dynamic temperature control by the AI module, gas flow balancing in the reaction zone, and automatic adjustment of heat recovery mechanisms. The H_2/CO ratio in the synthesis gas was stabilized within the range of 1.8–2.0, enhancing both the combustion efficiency and the energy value of the gas.

Simultaneously, the carbon capture capacity of biochar increased by 35–40%, strengthening its role in long-term carbon storage in soil, improving soil structural stability, and stimulating microbiological activity. The energy value of the obtained gas products increased by an average of 15%, indicating an overall improvement in the thermal efficiency of the pyrolysis system. While conventional systems typically yield gas with an energy value of 18–20 MJ/kg, the EICF-controlled process achieved 22–24 MJ/kg. Additionally, the reduction of the CO_2 fraction in the gas stream transforms the synthesis gas into a cleaner, "green" energy carrier suitable for both heat and electricity generation, supporting a circular resource strategy in line with the "zero waste" principle [12–15].

At an industrial scale, the EICF model enhances the sustainability of bioenergy production and enables the pursuit of a near-zero-emission strategy in waste conversion processes. Its adaptive control features allow the system to handle diverse raw materials, including biomass, plastics, and agricultural waste, optimizing both the carbon footprint and energy balance of industrial operations. The integrated EICF model embodies the concept of "intelligent energy circulation" through real-time process analysis, providing a practical foundation for the development of carbon-neutral industrial zones.

As such, the proposed eco-intelligent framework represents not only a technological innovation but also a strategic tool for advancing the green industry. Its application can serve as a scientifically grounded mechanism to support the "green transformation" goals of Azerbaijan and other energy-producing nations.

4. Conclusion and Recommendations

The results of mathematical modeling, EICF artificial intelligence control algorithms, and dynamic simulations over time demonstrated that the AI-integrated green pyrolysis system outperforms traditional processes in both energy efficiency and carbon emissions reduction. Comparison of the EICF-controlled mode showed that: The reactor temperature stability increased, control was provided in the range of ±2–3°C in the optimal zone of T = 550°C; Energy consumption decreased by 18–22%, and cumulative energy consumption was recorded as ~20% lower at the end of the simulation; CO_2 emission decreased by up to 30%, and CO emission decreased by up to 25% (due to the application of control factor = 0.7); The H_2/CO synthesis gas ratio stabilized in the range of 1.8–2.0, and the energy value of the gas products increased; Gas yield was 12–15% higher under EICF control; The carbon capture capacity of biochar increased by 35–40%, which created an additional advantage in terms of long-term carbon sequestration.The graphs also showed that the optimized heat flow, predictive control and temperature-error correction applied in the EICF model minimize excess heat losses in the system. The adaptive control functions of artificial intelligence respond promptly to nonlinear changes in the process, directly affecting the reduction of energy and emissions. Overall, the results obtained show that the green pyrolysis technology integrated with EICF-based artificial intelligence control is a promising, sustainable and environmentally superior approach for reducing the carbon footprint, converting waste and producing high-quality synthesis gas at both laboratory, pilot and industrial scales. This method paves the way for a wider spread of the application of smart control systems in the bioenergy sector in the future.The research results have shown that: The integration of artificial intelligence into pyrolysis processes increases energy and emission efficiency; The EICF model creates an ecological and technological balance; The application of biochar in soil has a long-term carbon storage effect; This approach is consistent with the UN Sustainable Development Goals (SDG-7, SDG-13). Future research is expected to incorporate hydrogen energy systems, smart sensors, and digital twin technologies into the EICF model. In this context, the application of artificial intelligence in green pyrolysis technologies represents a significant step toward advancing the circular economy and achieving the UN Sustainable Development Goals. Moreover, this approach establishes a practical technological foundation for the informatization of carbon-neutral industrial systems in the future.

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