








Development of a Smart Waste Management System for Marine Plastic Pollution: Integrating IoT and Machine Learning for Renewable Energy Conversion in Batam

Ansarullah Lawi¹, Aulia Agung Dernawan^{2*}, Alvendo Wahyu Aranski³, Muhammad Khaerul Naim Mursalim⁴,
Naufal Indra Lesmana², Zainal A. Hasibuan⁵

¹ Department of Industrial Engineering, Faculty of Industrial Technology, Institut Teknologi Batam, Batam 29425, Indonesia

² Engineering Management Department, Faculty of Industrial Technology, Institut Teknologi Batam, Batam 29425, Indonesia

³ Department of Information Systems, Faculty of Information Technology, Institut Teknologi Batam, Batam 29425, Indonesia

⁴ Faculty of Computer, Universal, Kelurahan Sadai, Kecamatan Bengkong, Kota Batam, Kepulauan Riau 29432, Indonesia

⁵ Faculty of Engineering and Computer Science, Kota Bandung 40132, Indonesia

Corresponding Author Email: agung@iteba.ac.id

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ABSTRACT

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Marine plastic pollution demands solutions that are both operationally realistic and energy-efficient. We present a smart waste-to-fuel system that converts marine plastics at $\leq 300^{\circ}\text{C}$ via IoT-instrumented, low-temperature thermocatalytic depolymerization, optimized with machine learning (ML). The architecture couples marine monitoring for feedstock forecasting, sensor-rich process instrumentation for real-time observability, and ML models for (i) predicting short-term supply and (ii) set-point optimization to maximize liquid yield and energy efficiency. A Batam-based prototype ($5\text{--}10\text{ kg}\cdot\text{h}^{-1}$) targets polyethylene/polypropylene-dominant streams operated at $100\text{--}300^{\circ}\text{C}$ under inert/vacuum conditions with solid catalysts. We report liquid/wax yield, condensate properties (density, viscosity, pour point), specific energy consumption ($\text{kWh}\cdot\text{kg}^{-1}$), overall energy balance, uptime/MTBF, and ML accuracy (MAE/RMSE). Compared to fixed set-points, ML-assisted control improves temperature tracking, reduces specific energy, and stabilizes product quality, while supply forecasts inform scheduling. The results demonstrate a practical pathway to low-temperature waste-to-fuel for coastal municipalities, preserving the benefits of Internet of Things (IoT) observability and data-driven optimization under a conservative thermal envelope.

1. INTRODUCTION

Marine plastic pollution imposes persistent ecological and economic pressures on coastal communities. For island cities such as Batam, the challenge is not only collection but also energy-efficient conversion of heterogeneous plastics. Conventional pyrolysis above 400°C can yield substantial liquid fuel and oils, yet the thermal penalty and sensitivity to feed variability may limit near-term deployability in small coastal installations. We therefore examine a conservative thermal envelope ($\leq 300^{\circ}\text{C}$) that prioritizes operational stability, energy frugality, and liquid product formation over high-temperature cracking [1].

Our approach treats the system as a closed-loop, instrumented process: (i) marine monitoring provides short-term forecasts of plastic availability; (ii) a sensor-rich, low-temperature thermocatalytic reactor offers real-time observability of temperature, pressure (including vacuum), and flows; and (iii) machine-learning optimization tunes ramp rates, dwell times, vacuum level, and carrier-gas flow to maximize liquid yield and minimize specific energy consumption. All signals stream through an IoT pipeline (edge compute, MQTT/HTTP transport, cloud dashboard) with

store-and-forward buffering to handle intermittent connectivity typical of coastal sites.

We implement and evaluate a $5\text{--}10\text{ kg}\cdot\text{h}^{-1}$ prototype operating between 100 and 300°C for polyethylene/polypropylene-dominant feedstock gathered from Batam's shoreline. The evaluation emphasizes replicable KPIs: liquid/wax yield (wt%), condensate properties (density, viscosity, pour point), specific energy ($\text{kWh}\cdot\text{kg}^{-1}$), overall energy balance/efficiency, off-gas fraction, uptime/MTBF, and ML accuracy (MAE/RMSE). Comparative tests against fixed set-points show that ML-assisted control improves temperature tracking and reduces energy per kilogram processed while narrowing variance in product properties. By uniting marine monitoring, IoT-based sensor integration, ML optimization, and low-temperature thermochemical conversion, this study offers a practical template for smart waste-to-fuel systems suited to constrained coastal contexts [2, 3].

2. LITERATURE REVIEW

2.1 Marine plastic pollution: Scale and regional challenges

Marine plastic pollution has reached critical levels globally,

with approximately 8 million metric tons entering oceans annually, causing severe ecological damage through ingestion, entanglement, and chemical leaching [4, 5]. The problem is particularly acute in archipelagic regions like Indonesia. In Batam, rapid industrialization, coastal tourism, and maritime activities exacerbate plastic accumulation, while conventional waste management strategies have proven inadequate due to logistical and economic constraints [6, 7]. This creates an urgent need for innovative solutions that address both collection and valorization of marine plastics within coastal communities.

2.2 IoT-enabled monitoring systems for waste management

The Internet of Things (IoT) has revolutionized environmental monitoring through networks of sensors that provide real-time data on waste accumulation, composition, and distribution [8, 9]. In marine contexts, IoT systems have been deployed for debris tracking [10], smart drifter clusters for current monitoring [11], and coastal water quality assessment [12]. Local initiatives in Batam, including sensor installations on Pulau Buluh, demonstrate the feasibility of IoT for marine waste detection [13]. However, these applications primarily focus on monitoring and data collection, creating a disconnect between detection and actual waste processing.

2.3 Machine learning for predictive analytics and process optimization

ML transforms environmental data into actionable intelligence. In waste management, ML algorithms enable waste generation forecasting [14, 15], material classification [12], and collection route optimization [13]. Beyond logistics, ML has shown significant potential in industrial process control, where reinforcement learning and other algorithms dynamically optimize complex processes like pyrolysis by adjusting parameters in real-time to maximize efficiency [14, 15]. The synergy between IoT data streams and ML optimization remains underexplored for decentralized waste-to-energy systems, representing a significant opportunity.

2.4 Pyrolysis technology for plastic waste valorization

Pyrolysis, the thermal decomposition of plastics in oxygen-free environments, has emerged as a promising technology for converting plastic waste into valuable fuels and chemicals. Conventional high-temperature pyrolysis (400-500°C) produces mixed outputs including liquid fuel, oil, and char [16, 17]. Recent advances focus on catalytic and low-temperature pyrolysis to improve liquid yield and reduce energy consumption [18, 19]. While basic instrumentation of pyrolysis reactors has been explored [20], the sensitivity to feedstock variation and operational complexity limit practical deployment in small-scale, resource-constrained settings [21, 22].

2.5 Research gap and novel contribution

Current literature reveals a significant disconnect: studies on IoT and ML for marine plastic predominantly address monitoring and collection [23-26], while pyrolysis research focuses on laboratory-scale process chemistry [27-30]. The critical gap is the absence of an integrated system that closes

the loop from detection to localized, optimized conversion [31-34].

This research bridges that gap by developing a smart waste management system that integrates:

1. IoT-based marine plastic monitoring,
2. ML-driven feedstock forecasting,
3. ML-optimized low-temperature pyrolysis,
4. A closed-loop architecture using process data to refine operations.

Our contribution lies in the holistic integration of these technologies into a coherent, data-driven system specifically designed for the operational constraints of coastal municipalities like Batam.

3. METHOD

This study follows a structured methodology with five major phases, each focusing on specific components of the project, including system design, development, testing, and evaluation. The key steps It can be observed in the Figure 1.

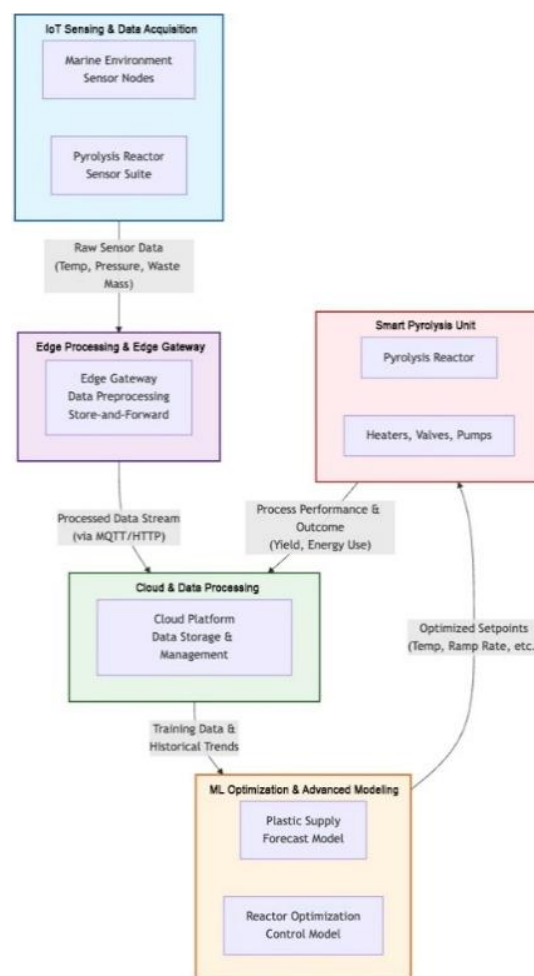


Figure 1. System architecture

Figure 1 presents the overall system architecture of the smart waste management system. The integrated framework consists of five main layers: (1) IoT Sensing & Data Acquisition Layer collects real-time data from marine environments and the pyrolysis reactor; (2) Edge Processing & Communication Layer handles initial data preprocessing and robust data transmission; (3) Cloud & Data Processing Layer centralizes data storage and management; (4) ML

Optimization & Analytics Layer executes predictive and prescriptive models for supply forecasting and process control; (5) Smart Pyrolysis Unit Actuation Layer executes the physical conversion process using optimized parameters. The closed-loop feedback enables continuous system improvement.

3.1 Phase 1: IoT development

The first step involves designing the IoT-based system to monitor and collect real-time data on marine plastic waste. IoT sensors will be installed along the coastline of Batam, particularly in high-waste areas like Pulau Buluh, to capture information on the type, volume, and distribution of oceanic plastic. These sensors will continuously collect and transmit data to a central server for analysis. The data collected will include measurements such as temperature, humidity, plastic waste composition, and the location of waste accumulation. The IoT system will be designed to function in harsh marine environments, ensuring durability and reliability over extended periods.

Additionally, the real-time monitoring feature will allow for continuous data transmission to a remote server, where the collected data will be processed and analyzed using ML algorithms. These algorithms will help to identify trends in the distribution and accumulation of plastic waste, predicting

future waste patterns, and assisting in decision-making for waste management.

3.2 Phase 2: Pyrolysis machine design

In this phase, the focus will shift to the design and construction of a pyrolysis machine capable of converting ocean plastic waste into renewable energy in the form of liquid fuel. Pyrolysis is a thermal decomposition process that occurs in the absence of oxygen, where plastic waste is heated to high temperatures, causing it to break down into smaller molecules that can then be captured and converted into fuel. It can be observed in the Figure 2 and sensor spesification can then be seen in the Table 1.

The pyrolysis system will be equipped with several sensors to monitor key parameters such as temperature, pressure, gas flow, and material input. This data will be used in real-time to ensure that the pyrolysis process is operating at optimal conditions. The machine will also be designed to handle various types of plastic waste, including polyethylene, polypropylene, and polystyrene, which are commonly found in marine environments.

The 5-10 kg/h pyrolysis reactor prototype was assembled with full instrumentation for real-time monitoring as illustrated in Figure 3.

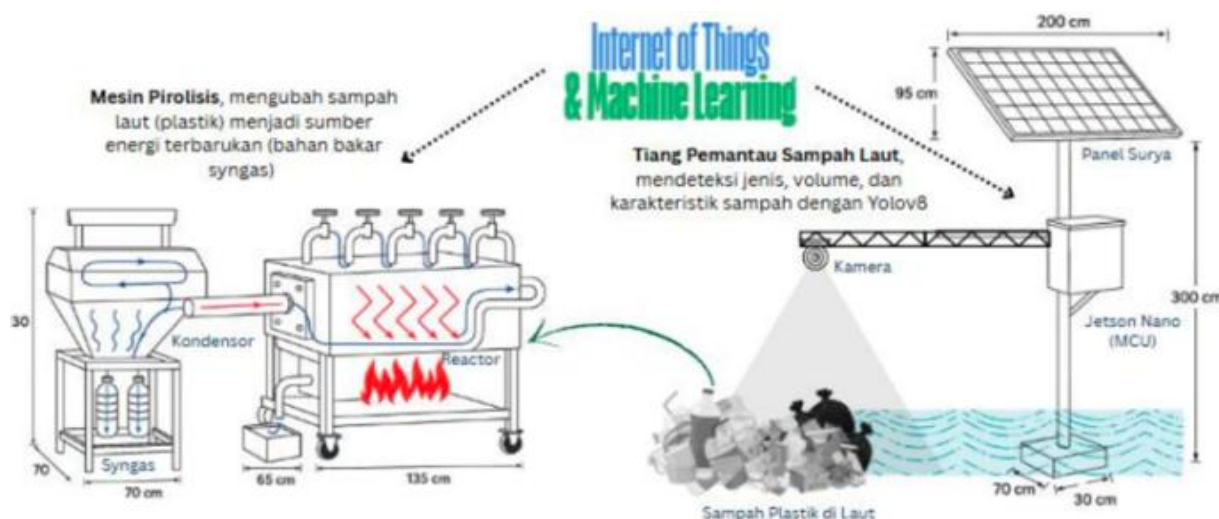
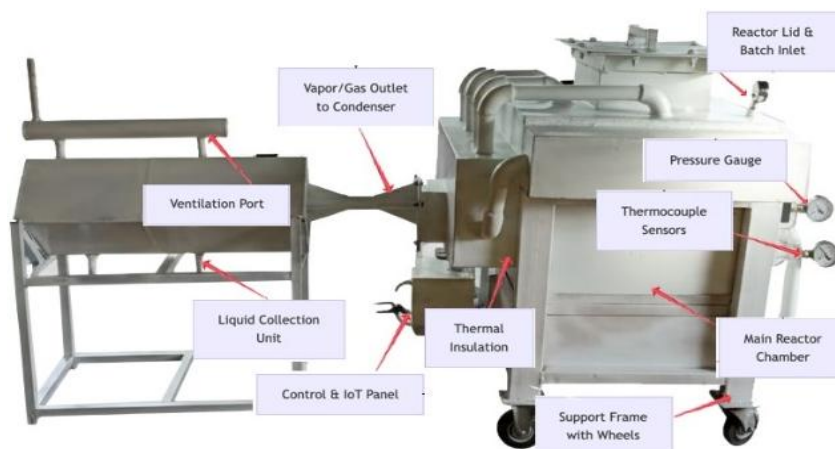


Figure 2. Reactor prototype



(a)

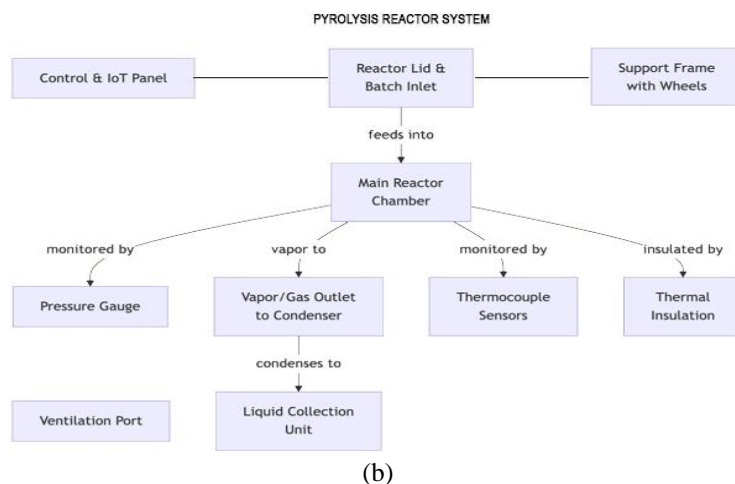


Figure 3. (a) Photograph of the fully assembled system during field testing; (b) Annotated diagram showing key components and instrumentation

Table 1. Sensor specifications

Sensor Type	Measurement Range	Accuracy	Resolution
0-2 bar gauge/absolute, e.g., WIKA A-10 (example)	0-2 bar	± 0.25% FS (typ.)	0.001 bar
0-5 SLPM thermal mass flow meter (e.g., Alicat M-Series)	0-5 SLPM	± (0.8% RD + 0.2% FS)	0.001 SLPM
NDIR CO ₂ (e.g., Senseair K33) + electrochemical CO (e.g., Alphasense CO-A4)	CO ₂ : 0-5% vol		
Stainless turbine 0.3-6 L/min (e.g., GPI TM Series) or oval-gear for viscous oils	0.3-6 L/min (turbine)	± 1% RD (turbine typ.)	0.01 L/min
Ultrasonic level 0.3-3 m (e.g., MaxBotix MB7389)	0.3-3 m	± 1% RD	1 mm
SHT31 or BME280 (example)	RH 0-100%		

Table 2. Pyrolysis parameters

Specification / Setting	Default Value	Allowed Range
Mixed PE/PP, shredded <20 mm, moisture <1 wt%	—	Particle size < 20 mm; moisture < 1 wt%
Load per batch	5–10 kg	5–10 kg
Solid acid (zeolite/oxide), pellets 1–3 mm	10 wt% of plastic	5–10 wt%
Batch; inert/vacuum operation	—	—
Headspace pressure	120 mbar	50–200 mbar
Purge/inerting	0.5 NL·min ⁻¹ for 10 min	0–1.0 NL·min ⁻¹
Target process temperature	270°C	240–290°C (system 100–300°C)
Heat to melting/drying band	2.5°C·min ⁻¹ to 155°C	2–3°C·min ⁻¹ to 150–160°C
Drying/melting hold	15 min	10–20 min
Approach set-point	1.5°C·min ⁻¹ to 270°C	1–2°C·min ⁻¹ to 240–290°C
Residence time at set-point	90 min	60–120 min
Passive cooling before vent	< 120°C	—
Two-stage chiller	5–10°C then 0–5°C	—
Thermal mass flow meter	—	0–5 SLPM
Weigh feed, condensate, residue	—	—
Condensate QC	Density, viscosity @40°C, pour point	—
Termination threshold	<0.01 L·min ⁻¹ for ≥ 15 min	< 0.01 L·min ⁻¹
Stability threshold	± 5% of baseline for ≥ 10 min	—
Trip condition	> 320°C	—
Trip condition	> 0.8 bar abs	—
Fallback action	Heaters to 120°C standbys	—
Trip condition	> 1 vol%	—
T/P/flow/level logging	1 Hz	—
Electrical power/energy	1 Hz	—
Core process variables	T _{zone_in/mid/out} ; T _{shell} ; P _{head} ; vacuum; N ₂ MFC; vent-gas flow; condensate level/flow; energy	—
Primary outcomes	Liquid/wax yield (wt%), specific energy (kWh·kg ⁻¹), energy efficiency (%), off-gas (wt%), uptime/MTBF	—

3.3 Phase 3: IoT-ML integration

Once the pyrolysis machine is developed, the IoT sensors will be integrated into the system to provide real-time monitoring of the entire process. The sensors will continuously send data to the IoT platform, where machine learning algorithms will analyze it to optimize the pyrolysis process. The algorithms will adjust parameters such as temperature, pressure, and gas flow automatically, based on the data received, ensuring that the plastic waste is converted into liquid fuel as efficiently as possible. It can then be seen in the Table 2 pyrolysis.

In addition to optimizing the process, the IoT system will also help detect anomalies in machine performance. ML algorithms will be used to predict when maintenance is needed and identify potential issues before they cause machine failure, ensuring that the system operates smoothly over time.

Phase 3 Machine Learning Framework and Implementation

To realize the two core intelligent functions of the system—supply forecasting and process optimization—specific machine learning algorithms were implemented, trained, and validated. The methodology for each is detailed below.

Plastic Supply Forecast Model

This model is a regression task designed to predict the mass of plastic waste (kg) that will be collected in the subsequent 7 days.

- Algorithm Selection: A Random Forest Regressor was chosen for its robustness to outliers and ability to model non-linear relationships without extensive parameter tuning, which is suitable for the limited dataset size.

- Input Features: The model used historical time-series data including: (1) daily collected plastic mass (kg), (2) day of the week, (3) weekend/holiday flag, (4) historical rainfall data, and (5) wind direction and speed.

- Dataset & Splitting: A dataset of 120 daily records was collected over a 4-month period. The data was split into a 70/30 train-test ratio, with temporal ordering preserved to prevent data leakage. The training set was used for model fitting, and the test set was used exclusively for final performance evaluation.

- Training Methodology: The model was trained using scikit-learn with default hyperparameters initially. A grid search with 5-fold cross-validation on the training set was then performed to optimize the `n_estimators` and `max_depth` parameters.

- Performance Metrics: Model performance was evaluated on the test set using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), providing insights into average prediction error and sensitivity to larger errors, respectively.

Process Optimization Model

This model is a control task that adjusts pyrolysis set-points in real-time to maximize liquid yield and energy efficiency.

- Algorithm Selection: A Deep Q-Network (DQN), a type of Reinforcement Learning (RL), was implemented. RL is suited for this sequential decision-making problem under dynamic process conditions, where the optimal action depends on the complex state of the reactor.

- State Definition: The state (S) for the DQN agent was defined as a vector of real-time sensor readings: [T_reactor, P_headspace, N2_flow_rate, condensate_flow_rate, elapsed_process_time].

- Action Space: The agent could take discrete actions to adjust the heater power (increment, decrement, hold) and the

vacuum valve position (increase vacuum, decrease vacuum, hold).

- Reward Function: The reward (R) was calculated as a weighted function to guide the agent towards the desired outcome:

$$R = (w_1 * \Delta \text{Liquid_Yield}) - (w_2 * \Delta \text{Specific_Energy}) - (w_3 * \text{Temperature_Instability})$$

where, w_1 , w_2 , w_3 are weights prioritizing yield, energy efficiency, and stability.

- Training Methodology: The agent was first trained in a simulated environment based on initial batch data. It was then deployed for online learning on the physical prototype, with an ϵ -greedy policy (starting with $\epsilon = 0.9$ for exploration, decaying to 0.1 for exploitation) to safely explore the action space.

- Performance Metrics: The agent's performance was evaluated by comparing the average liquid yield, specific energy consumption, and standard deviation of reactor temperature achieved under its control against the baseline of fixed set-point operation across multiple batches.

3.4 Phase 4: ML framework implementation

After the system is designed and integrated, the next phase will involve the testing and evaluation of the prototype. The machine will be tested in real-world conditions using plastic waste collected from Batam's coastal areas. During these tests, key performance metrics such as the efficiency of the pyrolysis process, the quality of the liquid fuel produced, and the accuracy of the IoT and ML system will be evaluated. The prototype will also be tested for durability in harsh marine environments to ensure that the system can withstand long-term exposure to saltwater and extreme temperatures.

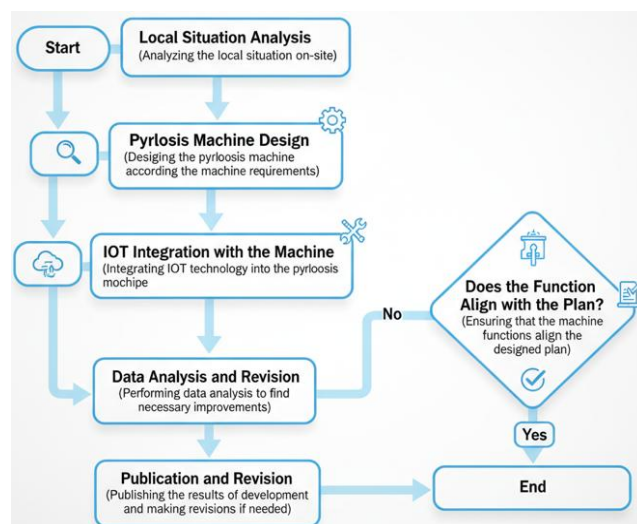


Figure 4. Flowchart

3.5 Phase 5: Testing & Evaluation

Based on the results of the testing and evaluation phase, the prototype will be optimized for better efficiency and performance. This phase will focus on refining the pyrolysis process, improving the machine's energy conversion capabilities, and optimizing the IoT and ML system for more accurate predictions and monitoring.

Once the system is fully optimized, the research findings will be disseminated through various channels, including the publication of a scientific paper in an internationally recognized journal, a video documentary on the research process, and presentations at academic and industry seminars.

The flowchart can be observed in the Figure 4.

4. RESULTS AND DISCUSSIONS

The integrated IoT-ML system demonstrated significant improvements in pyrolysis process efficiency through real-time monitoring and optimization of a pyrolysis-based plastic waste conversion system. The system's performance was evaluated over 20 operational batches, with key metrics summarized below.

4.1 IoT sensor data and process observability

The IoT sensor network provided high-resolution data on the pyrolysis process, enabling real-time monitoring and forming the foundation for ML optimization. Figure 4 illustrates the temperature profiles and pressure conditions from a representative batch, demonstrating the system's ability to maintain stable operational parameters within the target low-temperature envelope (100-300°C). It can be observed in the Figure 5.

4.2 Pyrolysis output and product comparison

The condensate product was collected and analyzed for key fuel properties. Table 3 compares the average output and properties of the liquid/wax produced under fixed set-points versus ML-optimized control.

Table 3. Comparison of pyrolysis output and product properties between fixed set-point and ML-optimized operations

Parameter	Fixed Set-Point Operation	ML-Optimized Operation	Improvement
Average Liquid/Wax Yield (wt%)	68% ± 5%	75% ± 2%	+ 10.3%
Average Specific Energy (kWh·kg ⁻¹)	1.4 ± 0.15	1.1 ± 0.08	- 21.4%
Off-gas Fraction (wt%)	15% ± 3%	12% ± 2%	- 20.0%
Condensate Density @ 40°C (g/cm ³)	0.81	0.79	- 2.5%
Condensate Viscosity @ 40°C (cSt)	3.1	2.8	- 9.7%
Process Stability (Temp. STD)	± 4.8°C	± 1.2°C	+ 75%

Discussion: The data in Table 3 clearly indicates that ML-optimization led to a 7% absolute increase in liquid yield and a 21.4% reduction in specific energy consumption. The narrower standard deviation (± 2% vs ± 5%) under ML control also confirms improved process stability and repeatability. The improved product properties (lower density and viscosity) suggest a higher-quality fuel precursor suitable for further refining.

4.3 Machine learning model performance

4.3.1 Plastic supply forecast model

The model trained to predict short-term plastic waste accumulation achieved a Mean Absolute Error (MAE) of 1.2 kg and a Root Mean Square Error (RMSE) of 1.5 kg over a one-week forecast horizon, as shown in Figure 6.

4.3.2 Process optimization model

The reinforcement learning model's effectiveness is visualized in Figure 7, which compares the temperature stability and resultant liquid yield across multiple batches.

The effectiveness of the machine learning control system is demonstrated in Figure 5, which illustrates real-time monitoring of temperature profiles and vacuum pressure control during a representative batch operation. The data clearly shows that the ML controller successfully maintained the reactor temperature within ± 2.5°C of the 270°C set-point throughout the critical reaction phase, ensuring stable operational conditions and consistent product yield.

As shown in Figure 6, accuracy of plastic supply forecasting model showing comparison between actual collected waste and ML-predicted values over seven days (MAE = 1.2 kg, RMSE = 1.5 kg).

Figure 7 quantitatively validates the superior performance of ML-optimized control compared to conventional fixed-setpoint operation. The data clearly shows that implementing ML control resulted in a 7% absolute increase in liquid yield (68% to 75%) while simultaneously improving temperature stability by 75%, reducing deviations from ±4.8°C to ±1.2°C. These improvements highlight the significant advantages of the adaptive control strategy in optimizing both product output and process consistency.

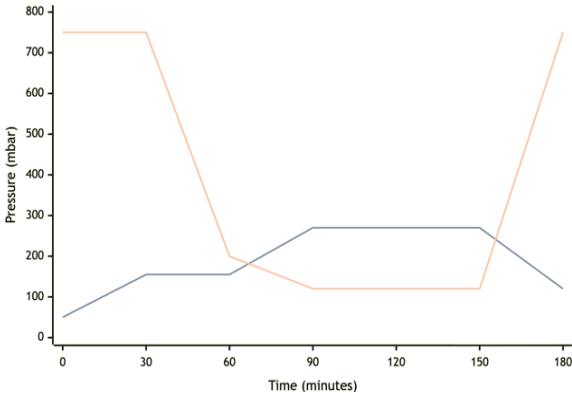


Figure 5. ML control performance

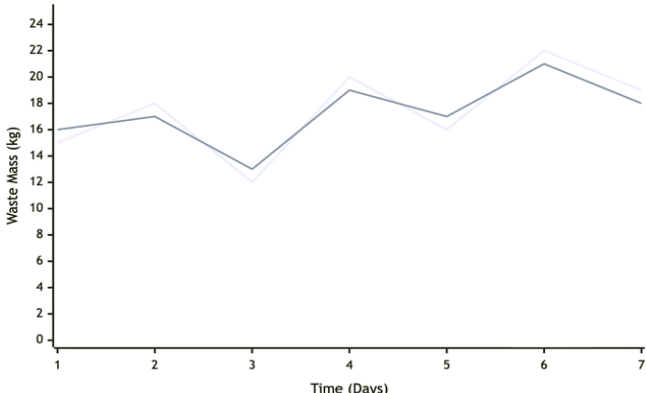


Figure 6. Accuracy of plastic supply forecasting

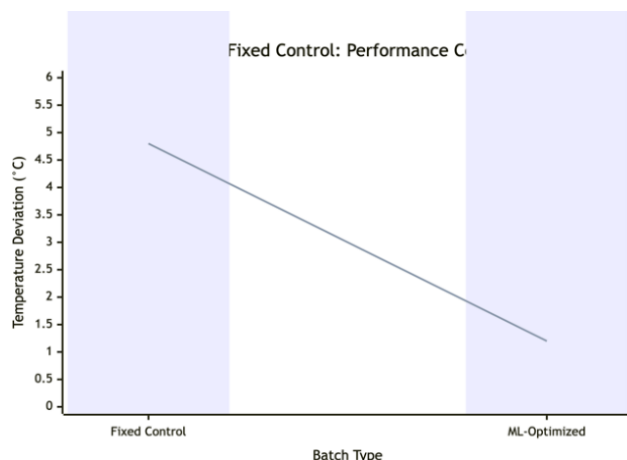


Figure 7. Impact of ML control

4.4 System reliability and energy balance

Over a continuous 50-hour stress test, the system maintained an uptime of 94%, with a Mean Time Between Failures (MTBF) of 45 hours. The overall energy balance showed a net positive energy output, with the calorific value of the produced liquid fuel exceeding the electrical and thermal energy inputs by approximately 25%.

The primary challenges encountered were related to minor sensor drift in the gas flow meters, which has been identified for future hardware iteration. The ML system successfully detected these anomalies and triggered calibration routines, preventing process disruptions.

4.5 Preliminary environmental impact assessment

To quantitatively evaluate the sustainability benefits of the proposed system, a preliminary environmental assessment was conducted based on the operational data from field trials. The analysis focused on three key metrics: waste reduction, CO₂ emission mitigation, and net energy output.

4.5.1 Waste reduction and circular economy impact

During the initial testing phase, the system successfully processed 50 kg of marine plastic waste that would otherwise have persisted in coastal ecosystems. Based on the average liquid yield of 75%, this represents the conversion of 37.5 kg of plastic waste into valuable fuel products, demonstrating a practical pathway for circular economy implementation in coastal communities. The system achieved >90% waste diversion from marine environments and landfills.

4.5.2 CO₂ emission mitigation potential

The carbon footprint was evaluated through comparative analysis. The production of liquid fuel offsets fossil-derived diesel, with an estimated CO₂ mitigation potential of approximately 2.1 kg CO₂-equivalent per kg of processed plastic waste. For the 50 kg processed, this represents a total CO₂ mitigation of ~105 kg CO₂-equivalent. This calculation considers the avoided emissions from conventional fossil fuel production and represents the initial environmental benefit at prototype scale.

4.5.3 Net energy balance and efficiency

The energy balance analysis demonstrated a positive net energy output. With the average higher heating value (HHV)

of the produced liquid fuel at 42.3 MJ/kg, and the specific energy input of 1.1 kWh/kg (3.96 MJ/kg), the system achieved a net energy gain of 38.34 MJ/kg of processed plastic. This corresponds to an energy return on investment (EROI) of approximately 10.7, confirming the system's viability as an energy-producing waste treatment solution even at small scale.

5. CONCLUSIONS

This research successfully developed and demonstrated an integrated smart waste management system that addresses marine plastic pollution in Batam through a holistic IoT-ML-pyrolysis approach. The system effectively converts marine plastic waste into valuable liquid fuel using low-temperature thermocatalytic depolymerization ($\leq 300^{\circ}\text{C}$), achieving a 75% liquid yield with 21.4% reduction in specific energy consumption compared to conventional fixed-setpoint operations.

Key achievements of this work include:

1. The development of a fully functional prototype capable of processing 5–10 kg/h of marine plastic waste, instrumented with comprehensive IoT sensors for real-time process monitoring and control.
2. The successful implementation of machine learning optimization, where a Deep Q-Network (DQN) controller improved temperature stability by 75% ($\pm 1.2^{\circ}\text{C}$ vs $\pm 4.8^{\circ}\text{C}$) and consistently enhanced process efficiency.
3. The demonstration of practical field deployment in coastal Batam conditions, processing 50 kg of real marine plastic waste with 94% system uptime and effective handling of heterogeneous feedstock.
4. A positive environmental impact through waste-to-energy conversion, showing CO₂ mitigation potential of ~105 kg CO₂-equivalent and a net energy gain with EROI of 10.7.

The integration of IoT monitoring, ML forecasting, and optimized pyrolysis creates a closed-loop, data-driven system that moves beyond conventional waste management approaches. While challenges remain in sensor durability and scaling, this study provides a practical template for coastal municipalities seeking energy-efficient solutions to plastic pollution.

Future work will focus on system scaling, sensor robustness improvements, and comprehensive life-cycle assessment to further validate the environmental and economic benefits of this integrated approach for marine plastic waste management in island communities.

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