Smart Separator: Optimizing Conveyor Belt, Vibration Feed, and Drum Speeds of Barrier Eddy Current Separator

Shohreh Kia[1][a], Benjamin Leiding[1][b]

[1]*Institute for Software and System Engineering , Technische Universität Clausthal , Arnold-Sommerfeld-Straße 1, Clausthal-Zellerfeld, Germany*

{*shohreh.kia, benjamin.leiding*}*@tu-clausthal.de*

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Abstract: Efficient separation of metals and plastics in recycling is crucial for improving material purity and reducing costs. This paper optimizes the performance of a Barrier Eddy Current Separator (BECS) for sorting aluminium, copper, plastic, and brass. The BECS consists of a conveyor belt, vibration feeder, and magnetic drum. Current methods rely on operator experience for speed and angle settings, often leading to suboptimal performance. This research applies a data-driven approach to determine optimal operational parameters. The study examines how varying conveyor belt speed (6.80 Hz to 87.70 Hz), vibration feeder amplitude (low, medium, high), and magnetic drum angle (20°, 30°, 40°) affect separation accuracy and energy consumption. Eighty-two experiments measured separation errors and energy use, with machine learning models identifying optimal settings. Experimental validation showed significant error reduction, achieving the lowest separation errors and energy consumption. Minimizing errors also eliminated rework, improving efficiency. Unlike conventional trial-and-error methods, this systematic approach enhances BECS calibration, demonstrating its effectiveness in improving recycling separation accuracy and energy efficiency.

1 INTRODUCTION

The increasing demand for sustainable recycling solutions has significantly emphasized improving the efficiency and accuracy of material separation processes in the recycling industry. Barrier eddy current separators (BECS) are widely used to separate non-ferrous metals like aluminium, copper, and brass from other materials like plastic. However, achieving optimal separation quality remains a challenge due to the dynamic interaction between the three primary components of the separator: the conveyor belt, vibration feeder, and magnetic drum. Each component operates at variable speeds, directly impacting the separation process (Rem et al., 1997). As they have been shown in Figure. 1

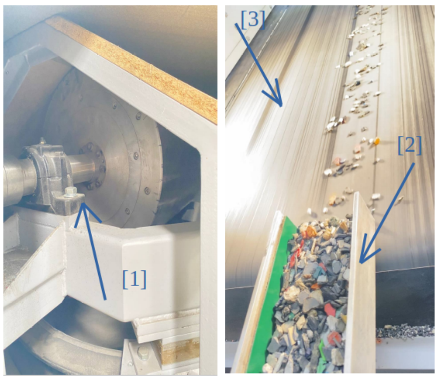

Figure 1: [1]Magnetic drum, [2]Vibration feed, [3]Conveyor belt.

The conveyor belt transports materials to the magnetic drum, while the vibration feeder regulates the flow and distribution of materials on the conveyor. The magnetic drum generates high-intensity magnetic fields to separate non-ferrous metals from non-magnetic materials. Finding the optimal speed configuration for these components is critical to minimizing separation errors and ensuring the purity of recovered materials. Furthermore, operational efficiency must balance energy consumption and machine durability. Excessive speeds may increase energy costs and wear on mechanical components, while insufficient speeds can lead to poor material separation and the need for reprocessing. Traditional manual adjustments to component speeds often lead to suboptimal performance,

[a] https://orcid.org/0009-0001-4046-5289
[b] https://orcid.org/0000-0002-9191-7548

making the process time-consuming and error-prone. This study optimizes the BECS system parameters to maximize material throughput while maintaining a sorting accuracy of 90%. The goal is to ensure efficient separation with minimal energy consumption. Experimental data, including separation error rates and energy consumption, were collected for various conveyor belts and vibration feeder speed combinations to achieve this. In contrast, the magnetic drum speed on the control panel was fixed at level 6, corresponding to 67.40 Hz as displayed on the PLC monitor, to ensure consistent operation and maintain safety across all experiments. A machine learning model analyses the data and identifies the optimal speed configuration that minimizes separation errors and energy consumption. By integrating advanced data analysis and optimization techniques, this study provides a framework for enhancing the quality of recycled materials while reducing operational costs and environmental impact (Wang et al., 2020; Nagel et al., 2020; Smith et al., 2019; Rem et al., 1997).

Note: All speed values are reported in Hertz (Hz), as used by the machine's frequency converters and PLC interface. The drives operate within a 0–50 Hz range (equivalent to 0–100% capacity). Conversion to meters per second (m/s) was not possible due to a lack of access to mechanical specifications. For the magnetic drum, Hz refers to revolutions per second. Each test separated fine particles (1–4 mm) of aluminium, copper, brass, and plastic. After separation, the misclassified materials were weighed to quantify the error for each category. Due to space constraints, only a selection of representative charts is shown below. These were chosen based on their closeness to machine-learning model predictions to support later evaluation. The full dataset, including all 81 scenarios and visual outputs, is publicly available on our GitHub repository.

1.1 Background

The BECS process is one of the most important industrial techniques for recycling non-ferrous metals from industrial and electronic waste. This method is based on the induction of eddy currents in non-ferrous metals, which generate Lorentz forces that separate them from other materials when exposed to the rotating magnetic drum (Roy et al., 2010). Aluminium, copper, and brass are among the most commonly recycled metals.

They are widely used in various industries, from electronics manufacturing to industrial packaging. With technological advancements and the increasing demand for high-quality recycling and energy-efficient processes, various research efforts have been made to improve BECS performance (Ahmed Nour El Islam and Youcef, 2016). Most of these studies have either focused on optimizing the physical design of the magnetic drum or using numerical modelling to analyze magnetic forces. However, simultaneous optimization of the operating speeds of different BECS components to enhance separation efficiency and reduce energy consumption has received less attention.

1.2 Problem

Achieving optimal and precise separation of non-ferrous metals has always been a significant challenge in the recycling industry. Improper speed adjustments of the conveyor belt, vibration feeder, and magnetic drum can lead to reduced separation efficiency, causing misclassification of materials and the need for reprocessing, which increases operational costs. Furthermore, a lack of precise control over component speeds can result in excessive energy consumption and higher electricity costs for recycling facilities. Figure. 2 shows separation challenges in a BECS system, where incorrect material sorting has occurred during the recycling process.

The major challenge is the absence of a data-driven model to determine the optimal speed configuration for BECS components. In many existing systems, speed adjustments are performed manually based on operator experience, which is time-consuming, prone to errors, and inefficient. Additionally, most previous studies have relied primarily on numerical simulations, with limited experimental validation under industrial conditions. Therefore, an approach to simultaneously optimizing the operating speeds of BECS components using real-world data and machine learning methods is essential. Such an approach can enhance material purity, reduce separation errors, lower energy consumption, and improve system safety, making BECS more reliable and efficient for industrial applications.

1.3 Existing Body of Knowledge and State of the Art

Various studies have been conducted on eddy current separators (ECS) to recover non-ferrous metals. Some studies (Yi et al., 2022; Bin et al., 2022) have focused on the effect of a single variable, such as temperature and particle size, on separation performance. Article (Yi et al., 2022) utilized liquid nitrogen to lower the material temperature, increasing its electrical conductivity and generating a more potent Lorentz force. In contrast, Article (Bin et al., 2022)

Figure 2: Errors collections.

investigated the effect of particle size on ECS performance, showing that reducing particle size increases particle rotation and alters the Lorentz force, making separation more challenging. Other studies (Smith et al., 2019; Shan et al., 2024b) have focused on optimizing the physical design of ECS devices, particularly the magnetic drum and magnetic pole arrangements. Article (Smith et al., 2019) demonstrated that increasing the drum speed or modifying the magnetic pole configuration can enhance the Lorentz force and improve separation efficiency. Article (Shan et al., 2024b)optimized the magnetic drum design, showing that a Halbach array configuration can increase magnetic field density by up to 75%. Several other studies (Bin et al., 2021; Huang et al., 2021) have utilized numerical simulations to predict ECS performance. They used numerical modelling to simulate particle trajectories in ECS separation, while Article (Li et al., 2018) li2018preliminary analyzed magnetic flux density and its impact on separation efficiency. Some studies (Shan et al., 2024a; Shan et al., 2025) have examined particle interactions and their influence on ECS performance. Article (Shan et al., 2024a) found that eddy current induction between particles can alter their movement trajectories, reducing separation efficiency. Article (Shan et al., 2025) explored the feasibility of vertical eddy current separation (VECS) and identified slight differences in electrical conductivity among metals, such as Ag/Cu and Pt/Pb, which make their separation challenging. Increasing the drum speed and magnet thickness was proposed to address this issue. Other studies (Ye et al., 2020; Huang et al., 2024) have focused on ECS applications for recycling specific waste materials, such as printed circuit boards (PCBs) and aluminum-contaminated plastics. Article (Ye et al., 2020) showed that optimizing magnetic drum design can enhance metal separation from PCBs, but challenges such as particle interactions and magnetic flux density effects remain. Article (Huang et al., 2024) used finite element analysis (FEA) to investigate magnetic field distribution and Lorentz forces to address aluminium contaminants in HDPE plastics. Finally, Articles (Ruan and Xu, 2012; Bai et al., 2023) focus on mathematical modelling and experimental testing to optimize BECS performance. Article (Ruan and Xu, 2012) developed a mathematical model to predict eddy current forces and showed that particle size and AC frequency significantly impact separation efficiency. Article (Bai et al., 2023), which focused on metal separation from lithium-ion batteries, proposed a novel combination of ball milling and BECS to achieve more energy-efficient metal recovery.

1.4 Gap Detection

A review of prior studies on ECS for non-ferrous metal recovery highlights several overlooked aspects. Most research has examined isolated variables, such as temperature, particle size, or magnetic drum speed, without considering their combined effects. However, in industrial settings, separation efficiency depends on multiple interrelated factors, including conveyor belt speed, vibration feeder speed, and magnetic drum speed. Optimizing a single parameter without accounting for system interactions often results in limited and unstable improvements.

Many studies (Ruan and Xu, 2012; Bai et al., 2023) rely heavily on numerical simulations without industrial experimental validation, reducing real-world applicability. While simulations provide valuable insights, industrial data is essential for practical optimization, as real-world conditions often differ from theoretical models. Additionally, most research (Ruan and Xu, 2012; Bai et al., 2023) prioritizes separation performance over energy efficiency, neglecting the impact of parameter adjustments on power consumption. Increasing component speeds without considering energy usage can lead to higher costs and reduced system performance.

Some studies (Smith et al., 2019; Shan et al., 2024b) propose physical modifications to the magnetic drum or field distribution but overlook safety concerns. Strong high-speed magnetic fields can generate excessive heat, shorten equipment lifespan, and pose fire hazards if ferrous particles become trapped. Despite its critical role, safety remains underexplored in prior research. Furthermore, solutions like new drum shell designs (Huang et al., 2024) enhance separation efficiency but lack adaptability, requiring costly modifications when material composition or size changes. This study introduces a data-driven approach to BECS optimization, evaluating key operational parameters—conveyor belt speed, vibration feeder speed, and magnetic drum speed—using machine learning to identify optimal configurations that minimize separation errors and maximize purity. Unlike previous studies that rely predominantly on simulations, this research incorporates real-world industrial data, ensuring practical applicability. Analyzing energy consumption at different speed settings optimizes separation efficiency and power usage, reducing operational costs. Magnetic drum speed is fixed at level 6 on the control panel, to enhance safety, prevent overheating, and mitigate fire hazards, ensuring stable and efficient separation while minimizing misclassification errors.

1.5 Research Questions

RQ: How can the optimal combination of component speeds in a BECS and the magnetic drum angle be determined using experimental data analysis and statistical modelling to minimize separation errors while optimizing energy consumption?

RQ1: What are the key factors to consider when developing a comprehensive and standardized dataset for optimizing the BECS process, considering component speeds, magnetic drum angle, and energy consumption?

RQ2: What technologies and approaches can be applied to analyze experimental data and optimize the operational settings of the BECS to enhance separation accuracy and reduce energy consumption?

2 SUPPLEMENTARY LITERATURE AND RELATED WORK

Many previous studies have focused on optimizing the performance of ECS. In some of these studies (Yi et al., 2022; Bin et al., 2022), the investigation was limited to the effect of a single variable, such as temperature or particle size, on the separation performance. However, in real-world industrial applications, multiple operational parameters, including conveyor belt speed, vibration feeder speed, and magnetic drum speed, play a crucial role in determining separation efficiency.

The present study addresses this limitation by analyzing the combined influence of multiple variables on separation efficiency and energy consumption rather than focusing on a single factor. Moreover, in Article (Yi et al., 2022), liquid nitrogen was used to lower the material temperature to improve separation efficiency. However, this method is impractical in large-scale industrial applications due to its high operational cost and process complexity. In contrast, the present study achieves separation optimization without needing expensive technologies, relying solely on the intelligent adjustment of component speeds to enhance system performance. Several studies (Smith et al., 2019; Shan et al., 2024b) primarily focused on the physical optimization of the magnetic drum design. These works demonstrated that increasing drum speed or altering magnetic pole configurations could enhance Lorentz's force and improve separation efficiency. However, such approaches have significant challenges, including high costs, increased maintenance requirements, and potential safety hazards. The present study proposes a software-based optimization approach rather than implementing expensive hardware modifications. This eliminates the need for costly physical redesigns of the magnetic drum or stronger magnets, which require continuous monitoring. Additionally, by keeping the drum speed within a safe range (60 - 70 Hz), the risks associated with overheating, which were overlooked in previous studies, have been effectively mitigated. Most previous research (Bin et al., 2021; Huang et al., 2021; Shan et al., 2024a; Shan et al., 2025) relied on numerical simulations to predict ECS performance. While

3D simulations can provide valuable insights, their accuracy in industrial settings is often compromised due to variations in real-world material properties and environmental factors. These studies used simulated numerical data instead of actual experimental results, which may lack the reliability for real-world implementation. The present study overcomes this limitation by conducting all experiments in a real industrial environment, where operational data were collected and analyzed. This approach enhances the reliability of the results compared to purely simulated models, ensuring the proposed optimization strategies can be directly applied in industrial settings. Another major limitation of previous studies (Bin et al., 2021; Huang et al., 2021) and (Ye et al., 2020) is their failure to account for energy consumption in ECS operations. These works focused on enhancing separation efficiency without considering that specific optimizations—such as increasing drum speed or magnetic field intensity—can significantly escalate energy consumption. The present study addresses this issue by accurately measuring energy consumption across various speed configurations. As a result, both separation efficiency and energy consumption have been optimized, leading to a reduction in operational costs. While Article (Bin et al., 2021) claimed that a redesigned magnetic drum could reduce energy consumption, no documented experimental data were provided to support this claim. In contrast, the present study leverages real-world data to quantify energy usage and integrates it as a key variable in the regression-based optimization model. Furthermore, none of the reviewed studies (Yi et al., 2022; Bin et al., 2022; Smith et al., 2019; Shan et al., 2024b; Bin et al., 2021; Huang et al., 2021; Shan et al., 2024a; Shan et al., 2025; Ye et al., 2020; Huang et al., 2024; Ruan and Xu, 2012; Bai et al., 2023) considered the safety implications of ECS operation. Hazards such as drum overheating, fire risks due to unintended iron particle presence, and the need for constant operator supervision at high speeds were ignored entirely. Additionally, all these studies focused on ECS technology, which does not apply to BECS due to differences in drum angles and their impact on the separation process. The present study meticulously addresses these critical aspects. Additionally, the impact of various operational parameters was systematically analyzed to ensure long-term machine stability and reduced operator intervention requirements. Some previous studies (Shan et al., 2024a) explored new casing designs for the magnetic drum, which were customized for a specific particle size range (e.g., 3–5 mm). However, this approach lacks adaptability since a completely new casing design would be required if the input material size varies, adding significant costs and complexity. Reviewing related works shows that most prior research either focused on isolated variables, relied solely on numerical simulations, or failed to consider energy efficiency and safety concerns. None of these studies addressed ECS adaptability for different material types and sizes in a practical industrial setting. In contrast, the present study provides a comprehensive optimization framework based on accurate experimental data. It simultaneously analyzes the impact of multiple operational parameters while ensuring energy efficiency and machine safety. By stabilizing drum speed, fire hazards and overheating risks are minimized, making the system more reliable for industrial applications.

Rather than introducing costly physical modifications, the present study utilizes a software-driven approach to adjust component speeds dynamically. This allows for greater adaptability across various material types without expensive hardware alterations. This methodology enhances flexibility, reduces operational costs to almost zero, and improves overall system efficiency, making it a practical and scalable solution.

3 CONSTRUCTING A RELIABLE DATASET FOR MACHINE LEARNING-BASED BECS OPTIMIZATION

The Barrier Eddy Current Separator (BECS) system is designed to recover non-ferrous metals such as aluminium, copper, and brass from mixed waste streams (Gomathi and Sridevi, 2015). Due to the system's complex physical dynamics and sensitivity to mechanical settings, achieving high separation quality requires precise tuning of operational parameters. This project optimizes separation efficiency and energy usage by experimentally analyzing the effects of conveyor belt speed, vibration feeder speed, and magnetic drum angle. A comprehensive dataset was developed through 81 experimental scenarios, systematically varying key operational parameters to support this. The magnetic drum speed was fixed at 67.40 Hz in all tests to maintain system stability and safety. The conveyor belt speed ranged from 6.80 Hz to 87.70 Hz, while the drum angle was set at 20°, 30°, and 40°. The vibration feeder was tested at low, medium, and high levels to assess its effect on material distribution and separation outcomes.

Figure. 3 to Figure. 11 illustrate these scenarios, showcasing representative vibration combinations, belt speed, and drum angle combinations. The complete dataset and the remaining experimental visualizations from all 81 test scenarios are available in the project's GitHub repository.

Each chart illustrates the separation errors (in grams) for the four target material classes. For visualization clarity, plastic errors are visualized using segmented stacked colors representing mixed material residues.

After each experiment, separation errors were quantified by measuring the weight of incorrectly classified materials within each category.

Figure. 12 shows the weight measurement of collected errors in wrong bins.

The errors recorded included:

- The amount of copper misclassified into the plastic fraction.
- The amount of plastic misclassified into the metal fraction.
- The amount of brass misclassified into the plastic fraction.
- The amount of aluminum misclassified into the plastic fraction.

Additionally, the device's electrical energy consumption was measured in each scenario using an Energy Logger (Sen, 2021; Nunn, 2013; Hirst et al., 2013) to assess the impact of different speed settings on power usage. Measurements were taken systematically across varying belt speeds, drum speeds, and vibration levels to capture the complete energy profile under different operational conditions. All collected data—including detailed records of separation errors, power consumption, and their corresponding speed settings—was carefully documented for each tested configuration. This ensured a structured dataset that allowed for precise analysis. The dataset underwent comprehensive analysis following the experimental phase to examine the interdependencies between operational parameters and energy efficiency. The goal was to identify optimal speed and drum angle combinations that minimize separation errors while optimizing power consumption, ultimately enhancing the system's overall efficiency.

4 MACHINE LEARNING-BASED OPTIMIZATION OF BARRIER EDDY CURRENT SEPARATION

Our approach focused on analyzing experimental data and optimizing the BECS operational settings using machine learning techniques to address the second research question. These settings include conveyor belt speed, drum speed, vibration speed, and drum angle, all of which directly impact the accuracy of material separation. To achieve this, a Multi-Output Regression machine learning model was implemented to predict the optimal operational settings, enhancing separation accuracy while minimizing operational costs. This chapter outlines the dataset and data Preparation, model implementation, and optimization process. It explains how the model processed and analyzed the collected data and how the results improved separation accuracy and reduced energy consumption.

4.1 Dataset and Data Preparation

The dataset used in this study was collected from a real-world industrial BECS system containing operational parameters and material separation error rates. The data is categorized into two main groups:

Input Features (X):

- Vibration Speed(low, medium, high)
- Magnetic Drum Speed (Hz)
- Conveyor Belt Speed (Hz)
- Separation Error for – aluminum, copper, brass, and plastic (grams)
- Drum Angle (degrees)

Output Variables (y):

- Optimized Vibration Speed
- Optimized Magnetic Drum Speed
- Optimized Conveyor Belt Speed
- Optimized Drum Angle

During preprocessing, missing values were identified and handled. To enhance the model's accuracy, MinMaxScaler normalized the input features, ensuring all variables were scaled within a standardized range. The dataset was split into 80% training data and 20% test data for model evaluation.

4.2 Model Development and Machine Learning Implementation

A Multi-Output Regression model (Peng et al., 2023) was implemented using the Scikit-learn library (Garreta and Moncecchi, 2013) to predict the optimal

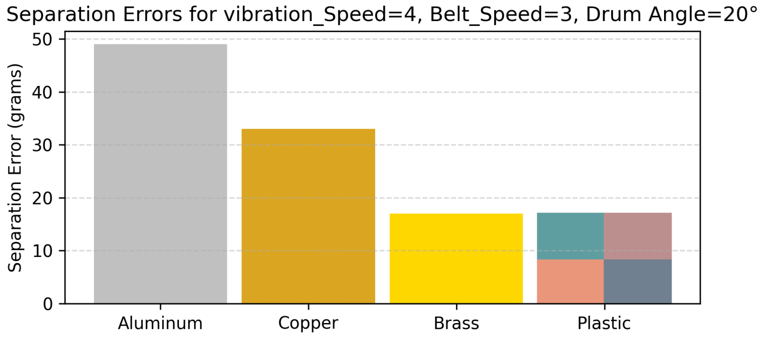

Figure 3: Vibration=4, Belt=3, Drum Angle=20°

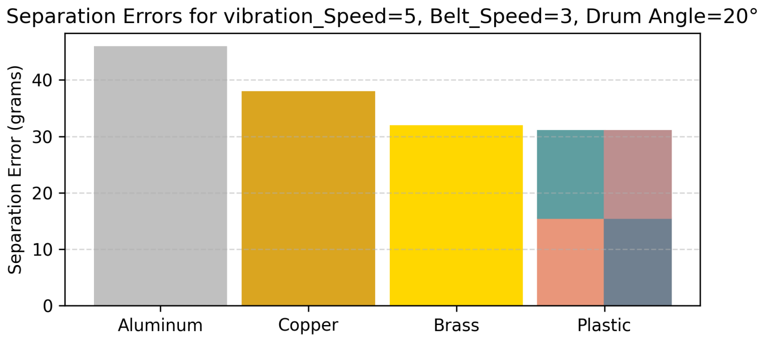

Figure 4: Vibration=5, Belt=3, Drum Angle=20°

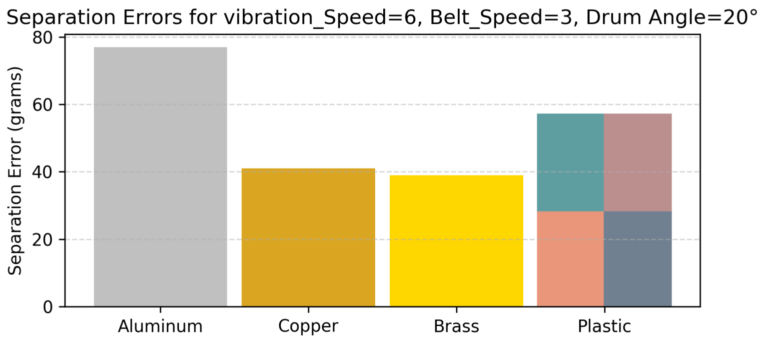

Figure 5: Vibration=6, Belt=3, Drum Angle=20°

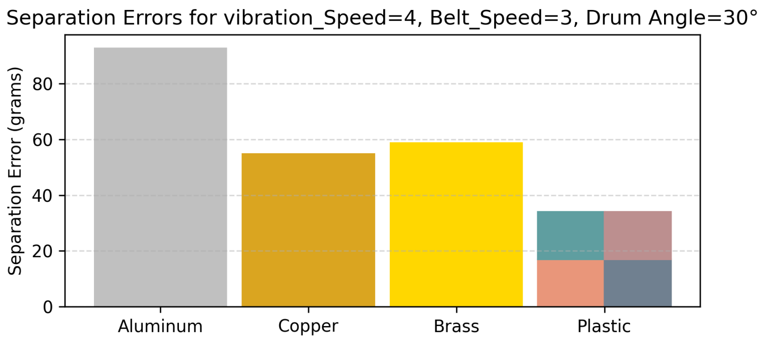

Figure 6: Vibration=4, Belt=3, Drum Angle=30°

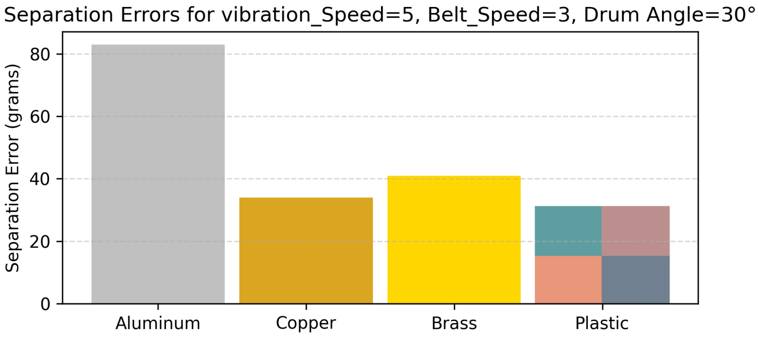

Figure 7: Vibration=5, Belt=3, Drum Angle=30°

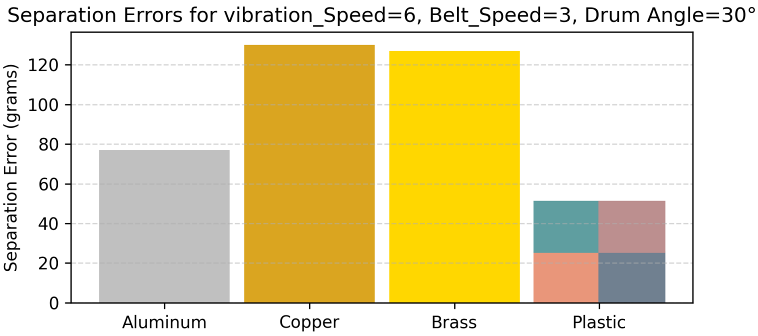

Figure 8: Vibration=6, Belt=3, Drum Angle=30°

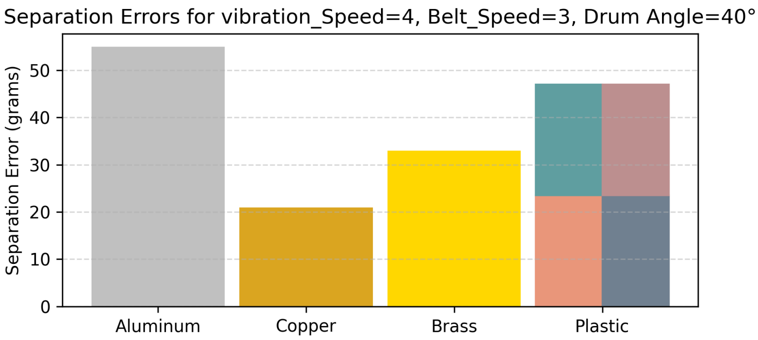

Figure 9: Vibration=4, Belt=3, Drum Angle=40°

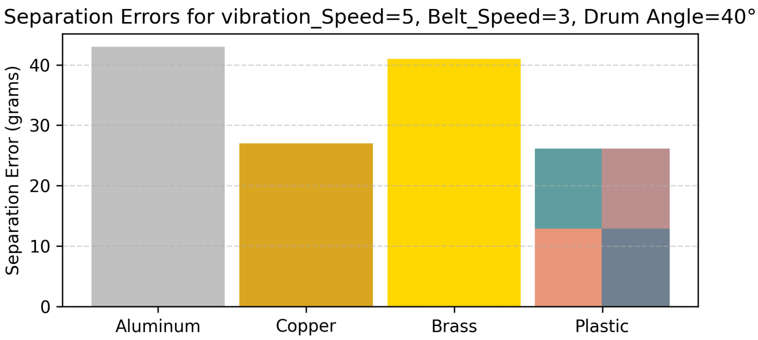

Figure 10: Vibration=5, Belt=3, Drum Angle=40°

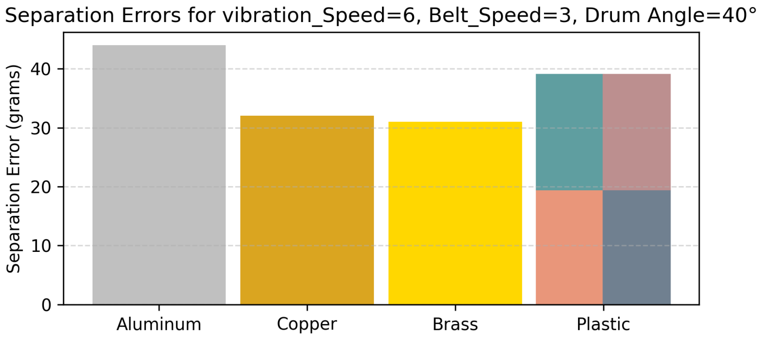

Figure 11: Vibration=6, Belt=3, Drum Angle=40°

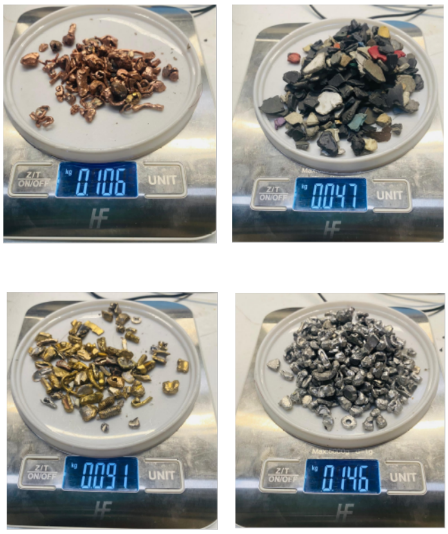

Figure 12: Errors weight measurement.

BECS settings. This approach allows for the simultaneous prediction of multiple target variables, making it well-suited for optimizing interdependent parameters. The Random Forest Regressor (Rodriguez-Galiano et al., 2015) was selected as the base model due to its ability to capture complex nonlinear relationships between input and output variables. This model leverages multiple decision trees to enhance predictive accuracy compared to simpler regression models. Multi-Output Regression with Random Forest Regressor:

$$y_j = f_j(X) + \varepsilon_j, \quad j = 1, 2, \ldots, m \tag{1}$$

where:

- $X = (x_1, x_2, \ldots, x_n)$ is the vector of input features, consisting of:
  - x_1: Vibration Speed (low, medium, high)
  - x_2: Magnetic Drum Speed (Hz)
  - x_3: Conveyor Belt Speed (Hz)
  - x_4: Separation Error for Aluminum in Plastics (grams)
  - x_5: Separation Error for Copper in Plastics (grams)
  - x_6: Separation Error for Brass in Plastics (grams)
  - x_7: Separation Error for Plastics in Metals (grams)
  - x_8: Drum Angle (degrees)
- y_j represents the predicted optimized operational settings, including:
  - y_1: Optimized Vibration Speed (low, medium, high)
  - y_2: Optimized Magnetic Drum Speed (Hz)
  - y_3: Optimized Conveyor Belt Speed (Hz)
  - y_4: Optimized Drum Angle (degrees)
- $f_j(X)$ is a nonlinear function approximated by the Random Forest model, trained to find the optimal settings for the BECS system.
- ε_j represents the model error, accounting for the discrepancy between the predicted and actual optimal operational settings.

After selecting the model, it was trained using the prepared dataset, learning the relationships between operational settings and separation accuracy. Once trained, the model was tested on unseen data to evaluate its predictive performance. The model's primary function is to take initial operational values and output the most effective configuration for maximizing separation efficiency.

5 Evaluation and Discussion

The MultiOutputRegressor was selected as the machine learning framework due to its capacity to simultaneously predict multiple output parameters critical to optimising the BECS system. These parameters—vibration speed, drum speed, conveyor belt speed, drum angle, and energy usage—are interdependent, and a change in one often affects the others. The chosen model architecture enables the training of dedicated regressors (Borchani et al., 2015) for each output while maintaining cross-dependencies. Random Forest Regressor (Rodriguez-Galiano et al., 2015), employed as the base estimator, is well-suited for detecting complex nonlinear patterns and provides accurate results even with relatively small datasets. It is also lightweight enough to run on standard CPUs or embedded systems with limited memory (e.g., 2–4GB RAM), making it an ideal solution for industrial settings with constrained computational resources. Deep learning models (e.g., neural networks) were deemed unsuitable due to limited data availability and overfitting risks. Classical models (Cook et al., 2022), like linear regression, also fail to capture complex nonlinear relationships between inputs and outputs.

Figure. 13 presents the separation error results obtained by applying the optimized parameter values predicted by the trained model. This model was trained on 81 real industrial test scenarios using actual material and equipment in an operational recycling facility. The recommended values for vibration speed, belt speed, and drum angle were tested in a real experiment. The results showed a noticeable reduction in misclassification errors—especially for aluminium, copper, and brass—compared to those observed in the original experimental dataset. This performance demonstrates the effectiveness of using machine learning for parameter optimization. Lower error rates mean materials need not be routed back into the separation process, saving significant energy and labour. In contrast, arbitrary or unbalanced parameter combinations can lead to severe issues. For example, if the drum speed is fixed at 6, but the vibration feeder is set too high (e.g., 7) and the conveyor belt too low (e.g., 3), excessive material accumulates on the belt. As shown in Figure. 14, this buildup creates a bulk that overwhelms the magnetic drum, which ends up ejecting the entire load instead of separating it. The resulting mess disrupts separation quality and spills material around the device, requiring human intervention for cleanup.

Figure 14: Material buildup caused by high vibration speed and low belt speed.

Similarly, very little material lands on the belt when the conveyor belt is too high relative to the vibration feeder (e.g., belt at 8 and vibration at 4). This situation, depicted in Figure. 15, leads to mostly empty belt operation. Even if a few particles reach the magnetic field zone, they pass too quickly to be separated correctly. This causes poor separation and unnecessary energy usage while accelerating mechanical wear due to underloaded operation.

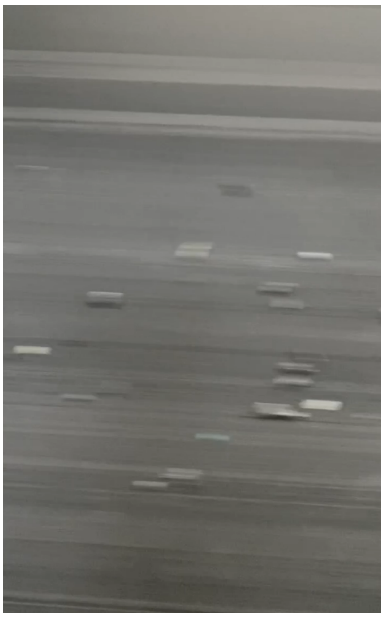

Figure 15: Sparse material flow due to high belt speed and low vibration feed.

By contrast, when the vibration feeder and belt speeds are well-balanced, the material spreads uniformly across the conveyor, enabling stable and efficient separation. An example of this can be seen in Figure. 16, where the material flow from the feeder onto the belt appears evenly distributed, a prerequisite for effective downstream separation. Hence, finding

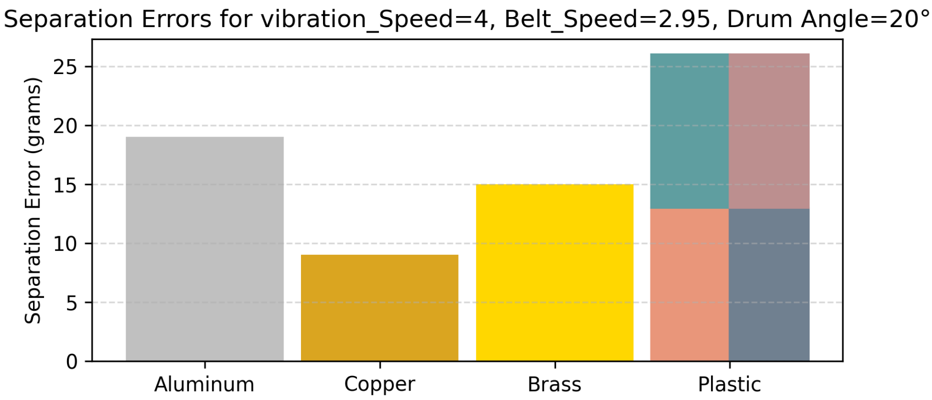

Figure 13: Separation errors using model-predicted parameters.

optimal and compatible speed combinations is essential for achieving high separation accuracy, improving energy efficiency and reducing the need for reruns. The model suggested in this work achieved this by learning directly from real industrial data. The chart in Figure. 13 reflects a scenario selected by the trained regressor as optimal, and the result confirms its superior performance. These findings underscore the potential of intelligent systems in enhancing the sustainability and reliability of industrial recycling processes.

Figure 16: Proper material flow with balanced vibration and belt speeds.

5.1 Post-Model Training Steps

Real-world industrial data from a BECS system was used for training. Initial material quantities included:

- 500 grams of aluminum
- 500 grams of copper
- 500 grams of brass
- 500 grams of plastics

uniformly mixed and processed. Separation errors under varying operational parameters were recorded. For example at:

- medium- vibration
- 47.30 Hz conveyor speed
- 30 degrees drum's angle

47 grams of aluminium were misplaced into the plastic bin. Similar copper, brass, and plastic errors were logged under different conditions. These error values and operational parameters served as input for model training. After training, the model proposed optimized parameters (e.g., vibration speed, conveyor speed, drum angle) to minimize separation errors. The Table 1 shows suggested optimized speeds.

To validate the model's results, we tested its recommendations under industrial conditions. During this phase, we reran the separation process, but this time, we used the machine learning model's suggested settings. The results showed a significant reduction in separation errors. Table 2 presents the recorded errors and the separation process's accuracy.

Additionally, energy consumption was measured throughout the process, revealing that the average energy consumption reached its lowest recorded level compared to all previous measurements. Power consumption data was measured before and after model implementation using an energy logger to evaluate the

Table 1: Optimized Table with Merged Cells

Final Model's Output		
Machine Components	Model Evaluation (Mean Absolute Error)	Predicted Output
Vibration Speed	0.0	medium
Drum Speed	0.0	67.40
Belt Speed	0.0547	36.60
Drum Angle	0.0	20.0

Table 2: Recorded Errors and Accuracy of the Separation

Material	Recorded Errors (gram)	Accuracy of Separation (%)
Aluminum	19	96.2
Copper	9	98.2
Brass	15	97.0
Plastic	26	94.8

impact of the machine learning model on energy consumption. The two images, Figures. 17 and 18, represent the system's power consumption under different conditions, which are analyzed and compared below.

- The total power consumption fluctuates between 1.2 kW and 1.4 kW.
- Power at Cursor 1 (09:58:38): 0.494 kW
- Power at Cursor 2 (10:05:26): 0.490 kW
- Delta (Power Difference): 0.041 kW
- The system's power consumption is relatively high and exhibits significant fluctuations.

- The total power consumption is now within 1.1 kW to 1.2 kW, which is lower than in the previous graph.
- Power at Cursor 1 (14:45:05): 0.430 kW
- Power at Cursor 2 (14:46:37): 0.418 kW
- Delta (Power Difference): 0.012 kW
- Energy consumption is lower, and fluctuations are significantly reduced.

Table 3 compares the machine's energy consumption in two scenarios: one during data collection while measuring all 82 cases and the other with the suggested optimized speeds applied to all three machine components.

The reduction in energy consumption is approximately 0.2 kW – 0.25 kW, representing a 15% – 18% decrease in total energy usage. This reduction in energy consumption directly impacts operational cost savings and enhances system sustainability, which can be highly valuable in industrial environments.

This model is not limited to a specific type of barrier eddy current separator but can also be applied to other recycling machines. For instance, it works for both a barrier eddy current separator and a simple eddy current separator. This flexibility allows different industries to customize the model based on their needs by adding new input variables or removing unnecessary ones. Recycling industries can modify the model according to their machine's conditions and obtain customized results.

One of the key factors contributing to the success of this project was the use of accurate industrial data. Unlike similar studies (Bin et al., 2021; Huang et al., 2021; Shan et al., 2024a; Shan et al., 2025) that rely on simulated data, our proposed model was trained on real-world industrial data. This makes its predictions far more reliable for practical applications. Previous studies often suffered from low accuracy because simulated data failed to capture unpredictable variables in real industrial environments.

Additionally, one major factor overlooked in previous studies (Yi et al., 2022; Bin et al., 2022; Smith et al., 2019; Shan et al., 2024b; Bin et al., 2021; Huang et al., 2021; Shan et al., 2024a; Shan et al., 2025; Ye et al., 2020; Huang et al., 2024; Ruan and Xu, 2012; Bai et al., 2023) was measuring energy consumption during the separation process. In our project, we recorded power consumption in all test scenarios. This is a key advantage for industries because lower energy consumption translates into lower operational costs on a large scale. This project was not financially expensive and was executed with almost zero financial cost. However, it was quite time-consuming.

The reason for this was the collection of accurate industrial data, which required running over 82 different test scenarios, meticulously recording errors, and processing experimental data. No similar research study has been conducted with such a large volume of real-world data because conducting industrial machine experiments, logging data, and accurately repeating each scenario is exceptionally tedious, time-consuming, and exhausting.

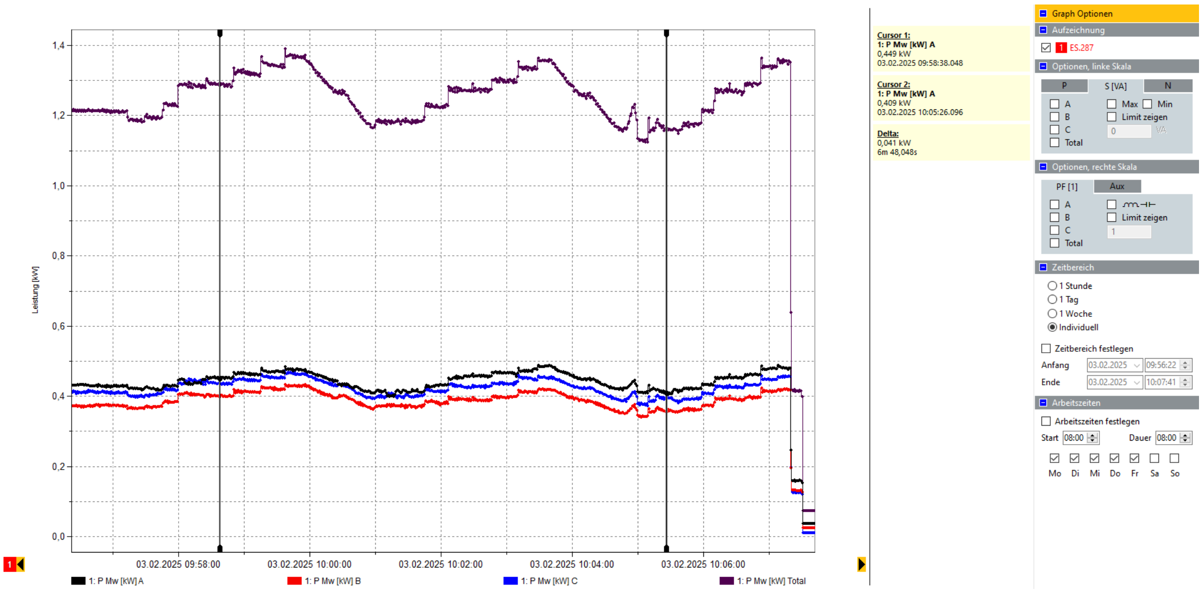

Figure 17: Energy Consumption Before Machine Learning Optimization.

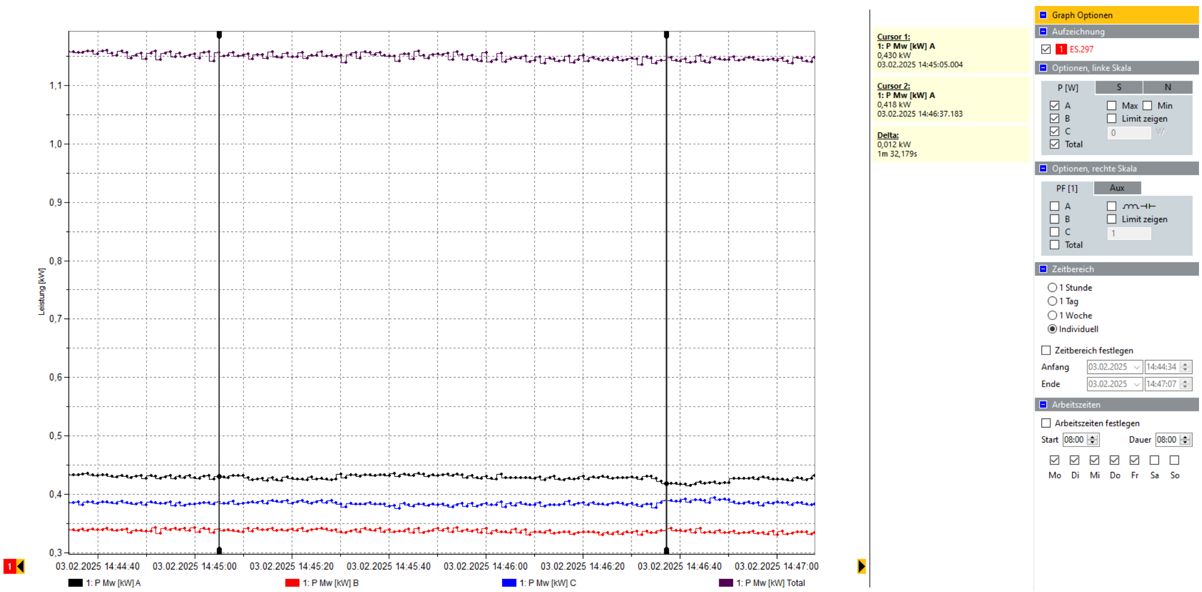

Figure 18: Energy Consumption After Machine Learning Optimization.

5.2 Limitations

The data collected in this study corresponds to materials that have undergone industrial pre-processing before entering the BECS. These materials passed through milling and screening stages before separation. As a result, all tested samples had particle sizes between 1 and 4 millimetres and were rounded without sharp edges. This characteristic facilitated magnetic drum calculations for detection and separation, improving separation quality compared to irregular or sharp-edged materials. Additionally, experiments demonstrated that the optimal drum angle decreases as particle size decreases. However, since this study focused solely on materials within the 1 to 4-millimeter range, its findings are limited to this size range. The model's performance for finer powders (less than 1mm) remains unexplored. Industries intending to adopt this approach should first analyze their materials' composition, shape, and size distribution. The model's effectiveness is highly dependent on the characteristics of the input materials, and its performance may vary when applied to materials outside the studied range. However, if the input materi-

Table 3: Comparison of Energy Consumption Before and After ML Optimization

Comparison	Before ML Optimization	After ML Optimization
System Condition	Higher power consumption with instability	Lower power consumption with increased stability
Average Total Power Consumption	1.2 kW – 1.4 kW	1.1 kW – 1.2 kW
Power Usage Variations	Significant fluctuations observed	Reduced variations, more stable operation

als align with the conditions examined in this study, the proposed optimization method can deliver highly accurate and reliable results. Moreover, experimental results indicated that particle size. Decreases, the optimal angle of the magnetic drum should also be reduced. This is because smaller particles are more sensitive to magnetic and gravitational forces, and at steeper angles, they may deviate from their intended separation trajectory. However, it is important to note that the scope of this study was limited to materials ranging from 1 to 4 millimetres in size. Therefore, the findings can only be generalized within this size range, and the model's performance on significantly finer materials—especially powders smaller than 1 millimetre—has not been evaluated. During this research, access to powder samples and particles smaller than 1 millimetre was extremely limited. Even if a more significant quantity had been available, conducting accurate experiments on such materials would have presented significant challenges. Unlike particles in the 1–4 mm range, where misclassified items could be visually identified and manually separated for weighing, powders made this process unfeasible. The naked eye could not easily distinguish ultra-fine particles, and manual separation was practically impossible. This limitation made it impossible to evaluate the model's accuracy on powdered inputs, as there was no practical method for reliably identifying or quantifying separation errors in those cases. Therefore, the proposed model's effectiveness has only been validated for materials within a specific particle size range. Extending its applicability to other material types—particularly powders—will require more precise detection and measurement tools to support future studies.

6 CONCLUSION AND FUTURE WORK

This study successfully optimized the operational parameters of the Barrier Eddy Current Separator (BECS) using machine learning techniques. Implementing the MultiOutputRegressor with a Random Forest base model identified optimal settings for key system components, significantly improving separation accuracy and reducing energy consumption. The optimized parameters determined by the model were:

- Vibration speed: medium
- Drum speed: 67.40 Hz
- Belt speed: 36.30 Hz
- Drum angle: 20.0°

Applying these optimized settings in actual industrial conditions resulted in a significant reduction in separation errors. The accuracy rates achieved for different materials were as follows:

- Aluminum: 96.2%
- Copper: 98.2%
- Brass: 97.0%
- Plastic: 94.8%

In addition to improving separation accuracy, the optimization also enhanced energy efficiency. The system's power consumption decreased from an initial range of 1.2 kW—1.4 kW to a more stable 1.1 kW—1.2 kW, leading to a 15%—18% reduction in total energy usage. This translates into lower operational costs and increased system sustainability, making the solution highly practical for industrial applications. Future research will enhance the system's adaptability by incorporating predictive mechanisms for detecting unwanted materials (e.g., sharp-edged or ferromagnetic contaminants) and expanding the dataset to cover a broader range of particle sizes. These improvements will further strengthen the optimized BECS system's applicability and robustness in diverse industrial settings. All the codes, recorded datasets, and other related needed information are available in GitHub (Kia, 2025).

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