

Performance and Energy Efficiency Assessment of Embedded Arduino Vibrating Sieving System for Dry Powder Materials

Marysca Shintya Dewi¹⁾, Linda Marlinda²⁾, Komarudin³⁾

^{1,3)} Universitas Dian Nusantara, ²⁾ Universitas Nusa Mandiri

¹⁾marysca.shintya.dewi@dosen.undira.ac.id, ²⁾linda.ldm@nusamandiri.ac.id, ³⁾komarudin@undira.ac.id

ABSTRACT

Dry powder sieving is an essential process for micro, small, and medium enterprises (MSMEs), where particle uniformity affects product quality and processing efficiency. In traditional market environments, vibrating sieving machines are commonly evaluated by visual inspection, leading to subjective assessments without quantitative information on energy consumption or vibration stability. High ambient humidity further promotes powder agglomeration, causing unstable sieving performance and longer processing times. This study presents an Arduino-based embedded system to quantitatively evaluate the performance and energy efficiency of a vibrating dry powder sieving process. The system integrates an ATmega328P microcontroller (Arduino Uno), infrared and DHT11 sensors, an L298N motor driver, a DC motor, and an LCD. Voltage, current, and tri-axial vibration signals were recorded at 10 Hz for 60–90 seconds per cycle. Performance metrics included total energy consumption (J), vibration RMS, dominant frequency, throughput (g/s), and energy efficiency ($\eta = \text{g/J}$). Experiments using rice flour showed that infrared-triggered control reduced energy consumption from 1450 J (manual) to 99 J (automatic), while energy efficiency increased from 0.42 g/J to 0.77 g/J. The results confirm that embedded sensing enables objective performance and energy evaluation for MSME-scale sieving systems.

Keywords: Arduino Uno; Embedded system; Energy efficiency; Dry powder sieving; Vibration monitoring

INTRODUCTION

Sieving plays a critical role in handling dry powder materials, as it directly influences product quality, processing efficiency, and subsequent processing steps. Rice flour is among the most widely used powdered food products in traditional markets and is a primary ingredient in various local food preparations. For micro, small, and medium enterprises (MSMEs), sieving removes coarse particles and maintains consistent granularity that meets consumer expectations. Vibrating sieving machines are commonly used in this context because they provide higher throughput and more uniform separation than manual or static sieving methods (Nerona, 2024; Tian et al., 2023).

In practice, MSMEs operate vibrating sieving machines as purely mechanical systems without embedded measurement capabilities (Ajayi et al., 2025). Operators typically evaluate performance based on observable outcomes, such as perceived processing speed, visual smoothness of the sieved flour, and personal experience. Quantitative parameters, including processing time, throughput stability, vibration behavior, and electrical energy consumption, are rarely measured during daily operation (Kaiqin, 2025; Nerona, 2024). Consequently, system performance remains descriptive rather than analytical, limiting MSMEs' ability to compare efficiency across different operating conditions or identify performance inconsistencies.

Energy use in sieving operations is often treated as a machine characteristic rather than a measurable performance parameter. Operators cannot systematically analyze variations in vibration intensity, motor operation duration, or process stability. The absence of quantitative monitoring reduces reproducibility and constrains the identification of inefficiencies across different MSME environments (Plant & Chudy, 2023; Kaiqin, 2025). These limitations become more critical in small-scale production settings where energy cost, operational consistency, and equipment reliability directly affect productivity.

Recent developments in embedded computing provide an opportunity to address these limitations by integrating sensing and data acquisition into conventional food-processing equipment. Low-cost microcontroller platforms, such as Arduino, enable real-time measurement of electrical energy consumption, operational timing, and vibration behavior without altering the fundamental mechanical structure of existing machines (Sofianidis & Konstantakos, 2025). Embedded data acquisition enables sieving operations to be treated as measurable electromechanical systems, with performance indicators derived from recorded sensor data rather than subjective judgment. This system-oriented approach supports quantitative evaluation of operational efficiency through embedded computation (Huseynzade & Abdullayev, 2024).

* Corresponding author



[Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.](https://creativecommons.org/licenses/by-nc-sa/4.0/)

Previous studies on vibrating sieving machines have primarily focused on mechanical aspects, including mesh configuration, vibration mechanisms, and separation efficiency. Zhu et al. (2023) investigated mesh geometry and particle separation rates, while Singh et al. (2024) analyzed vibration stability under different mechanical settings. Kaiqin (2025) examined operator variability in manual sieving processes. In parallel, research on embedded systems has focused on energy monitoring and control in industrial and electronic applications. Gupta et al. (2024) measured electrical energy consumption in microcontroller-based systems, and Dinmohammadi et al. (2025) developed advanced energy monitoring algorithms. Tao et al. (2025) applied power spectral density analysis to evaluate vibration consistency. Although these studies provide valuable insights, they remain fragmented. They address either mechanical stability or electrical energy aspects independently and do not integrate synchronized energy and vibration measurements within MSME-scale vibrating sieving systems.

Based on these limitations, a clear research gap emerges in the absence of studies that jointly evaluate vibration behavior, energy consumption, and process performance in MSME vibrating sieving operations using embedded data acquisition. To address this gap, this study formulates three research questions. RQ1 examines whether infrared-triggered motor activation reduces electrical energy consumption per sieving cycle compared to continuous motor operation. RQ2 investigates whether the implemented reciprocating vibration pattern improves vibration stability, as indicated by lower and more consistent RMS acceleration values. RQ3 analyzes whether vibration stability correlates with process performance, expressed in terms of sieving time, material throughput (gram/s), and energy efficiency (gram/J). These research questions position the sieving process as a measurable electromechanical system whose performance can be objectively evaluated using synchronized energy and vibration data, thereby supporting reproducible, design-oriented assessment for MSME-scale applications.

LITERATURE REVIEW

A. Embedded Data Acquisition for Energy and Performance Evaluation

Embedded data acquisition has become an essential approach for enabling objective and quantitative evaluation of energy consumption in mechanically driven systems. Gupta et al. (2024) demonstrated that real-time measurement of electrical parameters, specifically voltage and current, allows direct computation of instantaneous power and total energy consumption during machine operation. Their study emphasized that energy efficiency evaluation based on measured electrical data provides a more reliable and reproducible basis for performance assessment than estimates derived from nominal motor specifications or operator judgment.

In the context of IoT-based monitoring, Dinmohammadi et al. (2025) proposed a real-time embedded energy monitoring framework that integrates sensor acquisition, time-stamped data logging, and efficiency-oriented analysis. Their results showed that embedded energy data can support operational decision-making and efficiency optimization. However, the evaluation focused primarily on electrical parameters and did not incorporate mechanical behavior or process-level performance indicators.

At the machine and device level, Bismantolo et al. (2025) developed an embedded electrical energy monitoring system that combines voltage and current sensing with data processing and visualization. Their work demonstrated the feasibility and stability of embedded energy monitoring across varying operating conditions. Similarly, Suhardi Rahman et al. (2025) reported the implementation of real-time energy monitoring using microcontroller-based acquisition, emphasizing measurement accuracy and system reliability. Both studies validated the technical robustness of embedded energy sensing but treated energy consumption as an isolated variable, independent of mechanical dynamics or material processing outcomes.

B. Vibration Monitoring as a Quantitative Indicator of Mechanical Stability

Vibration monitoring has been widely adopted as a quantitative method for assessing mechanical stability in vibrating and rotating systems. Singh et al. (2024) introduced an IoT-based real-time vibration monitoring system using accelerometer sensors to detect unsafe operating conditions. Their findings confirmed that vibration acceleration signals provide measurable indicators of mechanical behavior, particularly when analyzed using time-domain metrics such as root-mean-square (RMS) acceleration.

Indrasari et al. (2024) further demonstrated that structured vibration measurement using embedded accelerometers improves the detection of operational changes and abnormal mechanical responses. Their study showed that vibration-based monitoring yields more objective and reproducible insights than visual inspection or descriptive evaluation. However, the primary focus remained on machine condition monitoring rather than process performance analysis.

From a signal processing perspective, Tao et al. (2025) applied power spectral density (PSD) analysis to evaluate vibration consistency in vibrating systems. Their work highlighted that frequency-domain analysis can reveal dominant vibration patterns and stability characteristics that are not observable through time-domain metrics alone. Ma et al. (2025)

* Corresponding author



[Creative Commons Attribution-NonCommercial-ShareAlike 4.0
International License.](https://creativecommons.org/licenses/by-nc-sa/4.0/)

complemented this view by reviewing vibration sensor technologies and industrial monitoring applications, emphasizing that sensor selection, sampling configuration, and parameter definition strongly influence data reliability and interpretability.

Although these studies establish vibration metrics such as RMS acceleration, peak response, and dominant frequency as valid indicators of mechanical stability, their application is generally limited to fault detection or condition monitoring. The relationship between vibration stability and process-level performance metrics, such as material throughput or energy efficiency, is rarely addressed. In MSME-scale vibrating sieving systems, vibration behavior is typically assessed implicitly through visual observation rather than quantitatively measured and analyzed.

C. Research Gap and Study Positioning

The reviewed literature reveals two dominant but largely disconnected research streams. The first stream focuses on embedded systems for electrical energy monitoring, emphasizing voltage and current sensing to evaluate energy consumption and efficiency. Studies by Gupta et al. (2024), Dinmohammadi et al. (2025), Bismantolo et al. (2025), and Suhardi Rahman et al. (2025) demonstrate the reliability of embedded energy measurement. Yet they do not relate energy use to mechanical behavior or material-processing performance.

The second stream emphasizes vibration-based evaluation of mechanical stability using accelerometer sensors and signal processing techniques. Research by Singh et al. (2024), Indrasari et al. (2024), Tao et al. (2025), and Ma et al. (2025) establishes vibration metrics as objective indicators of mechanical condition. Still, these studies primarily address condition monitoring and do not integrate energy consumption or productivity metrics.

In the specific context of vibrating sieving systems used by MSMEs, this separation results in a limited system-level understanding of how electrical energy consumption and vibration stability jointly influence process performance. Existing studies rarely evaluate vibrating sieving operations as a unified electromechanical system with synchronized measurement of energy usage, vibration behavior, and output performance.

This research addresses the identified gap by integrating embedded electrical energy monitoring and vibration data acquisition within a single analytical framework. Electrical energy consumption is quantified through voltage and current sensing, while mechanical stability is evaluated using tri-axis accelerometer data processed into RMS and frequency-domain indicators. Process performance is assessed using measurable outputs, including sieving time, material throughput (gram/s), and energy efficiency ($\eta = \text{gram/J}$). By synchronizing energy and vibration measurements through time-aligned data acquisition, this study positions the vibrating rice flour sieving process as a measurable electromechanical system. The proposed approach provides quantitative, reproducible evidence that directly supports performance and energy-efficiency evaluation for MSME-scale food-processing applications.

METHOD

This research employed a small-scale automatic vibrating sieving system integrated with embedded sensors to enable quantitative evaluation of electrical energy consumption, vibration stability, and sieving performance. The methodology was designed to treat the sieving process as a measurable electromechanical system, rather than a purely mechanical tool, by integrating synchronized data acquisition and metric-based evaluation. The overall research workflow consisted of seven sequential stages, beginning with problem identification and concluding with system-level performance and energy evaluation (Kaiqin, 2025)(Hassan et al., 2024)(Yang & Id, 2023).

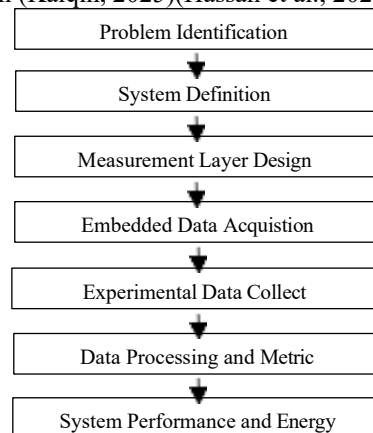


Fig. 1 Flowchart of Research Workflow for Performance and Energy Evaluation of a Vibrating Sieving System

* Corresponding author



[Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.](https://creativecommons.org/licenses/by-nc-sa/4.0/)

1. Problem Identification

Rice flour used by micro, small, and medium enterprises (MSMEs) is often stored under high humidity, which promotes particle agglomeration and results in inconsistent sieving quality. Conventional sieving machines are typically evaluated through visual inspection and operator experience, without quantitative measurement of electrical energy consumption, vibration behavior, or process throughput. This practice makes performance comparison subjective and prevents data-driven efficiency evaluation. Furthermore, most existing MSME-scale sieving systems lack embedded sensors, limiting the ability to analyze the relationships among vibration stability, energy use, and sieving performance. To address these limitations, this study implemented an embedded measurement approach that captures electrical and mechanical parameters in real time.

2. System Definition and Mechanical Configuration

The vibrating sieving system employed mesh number 40 with an aperture size of $400\ \mu\text{m}$, selected to allow fine rice flour particles to pass through while retaining agglomerated clumps. The system was controlled by an ATmega328P-based Arduino Uno, which served as the central data-acquisition and control unit. The hardware configuration included an infrared sensor for material detection, a DHT11 sensor for temperature and humidity monitoring, an L298N motor driver, a DC motor, and a 20×4 I2C LCD for real-time display.

Mechanical vibration was generated by a pulley–gearbox–slider mechanism that converted motor rotation into linear reciprocation across the sieve surface. Motor torque was transmitted through a timing belt to a gearbox, which adjusted vibration speed. A 14 cm metal linkage connected the gearbox to a sliding rail, producing back-and-forth motion that distributed flour evenly across the sieve. This configuration enabled automated and repeatable sieving compared to manual operation

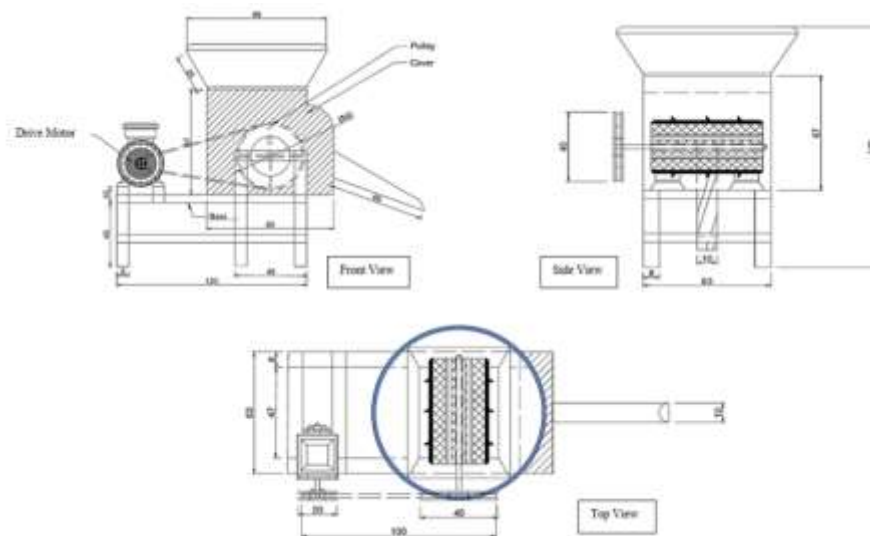


Fig 3. Mechanical Design of the Vibrating Sieving System: Front, Side, and Top Views

As shown in Figure 3, the system integrates a drive motor connected to a pulley mechanism, with a hopper positioned above the sieve frame. The side and top views illustrate the internal vibration components and material flow path.

The L298N driver controlled the direction and speed of the DC motor through pulse-width modulation (PWM), consistent with the characteristics of the H-Bridge module capable of driving DC motors up to 2A. The DC motor functioned as the primary power source generating vibration for the sieve, as commonly applied in automated vibrating sieving systems. Information on temperature, humidity, and motor speed was displayed on the LCD 20×4 I2C, enabling operators to monitor system conditions in real time. Motor torque was transmitted to the gearbox via a timing belt, allowing the gearbox to adjust vibration speed as required. The gearbox was connected to a sliding rail using a 14 cm metal hanger. As the motor rotated, the sliding rail moved back and forth, producing a vibrating motion that distributed flour evenly across the sieve surface. With this configuration, the sieving system operated automatically and delivered more consistent results compared to manual methods.

3. Electrical Measurement Module

Electrical energy consumption was measured using an INA219 current and voltage sensor. The INA219 has a

* Corresponding author



[Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.](https://creativecommons.org/licenses/by-nc-sa/4.0/)

measurement range of 0–3.2 A with a current resolution of 0.1 mA, making it suitable for low-power DC motor applications. The sensor was connected in series with the DC motor supply line to measure real-time voltage and current during sieving operation.

Calibration Procedure

Calibration was performed by comparing INA219 readings with a calibrated digital multimeter across ten discrete load points ranging from 0.1 A to 2.0 A. The calibration results showed a maximum deviation of $\pm 2\%$, which was considered acceptable for embedded energy measurement in MSME-scale equipment.

Energy Computation

Instantaneous power was calculated as:

$$P(t) = V(t) \cdot I(t)$$

where $P(t)$ is instantaneous power (W), $V(t)$ is voltage (V), and $I(t)$ is current (A).

Total energy consumption was obtained by integrating power over time:

$$E = \sum P(t) \cdot \Delta t$$

where E is energy (J) and Δt is the sampling interval (s). Synchronization was established between electrical energy data (voltage and current) and vibration data from the accelerometer to ensure time-aligned acquisition



Fig. 2 Components of the automatic sieving tool (a) Arduino Uno (b) DC motor (c) DHT11 (d) IR sensor

The Arduino Uno was configured as the central data acquisition unit to ensure synchronized and reliable measurements. The system performed sampling every 100 ms, which corresponds to a sampling frequency of.

$$f_s = \frac{1}{T} = \frac{1}{0.1} = 10 \text{ Hz}$$

With a measurement duration of 60–90 seconds per sieving cycle, the total number of samples per channel was calculated as

$$N = f_s \cdot t,$$

resulting in 600–900 data points per cycle. Synchronization was established between electrical energy data—voltage (V) and current (I)—and vibration data (a) from the accelerometer, so that each sample was temporally aligned.

4. Experimental Data Collection

Data were collected continuously during the sieving process to capture electrical, mechanical, and environmental parameters. Electrical energy measurements included motor current (I) and voltage (V), which were used to calculate instantaneous power and total energy consumption. Vibration data were obtained from the accelerometer, focusing on amplitude and dominant frequency of the sieve motion as indicators of mechanical stability. Environmental conditions were monitored through temperature and humidity sensors to assess the influence of ambient factors on flour agglomeration and system performance. With this configuration, the experimental data set provided a comprehensive basis for evaluating both energy efficiency and operational reliability of the vibrating sieving system.

5. Sampling Configuration

Data acquisition was performed at 10 Hz ($\Delta t = 0.1$ s), producing 600–900 samples per cycle with a duration of 60–90 seconds. The choice of sampling frequency was justified by expected vibration frequencies derived from motor speed: 210 RPM ($f = 3.5$ Hz) for reciprocating mode and 430–460 RPM ($f = 7.2$ – 7.7 Hz) for high-speed mode. Since the target frequency band was 0–10 Hz, $f_s = 10$ Hz was adequate to capture dominant motion, although higher harmonics may not be fully represented.

The raw data obtained during the sieving process were processed into quantitative metrics to evaluate system

* Corresponding author



[Creative Commons Attribution-NonCommercial-ShareAlike 4.0
International License.](https://creativecommons.org/licenses/by-nc-sa/4.0/)

performance and energy efficiency.

a. Electrical Power Instantaneous power was calculated from voltage and current measurements:

$$P = V \cdot I$$

where P is power (Watt), V is voltage (Volt), and I is current (Ampere).

b. Energy Consumption Total energy consumption during operation was determined by integrating power over time:

$$E = \int_0^t P \, dt \approx P \cdot t$$

where E is energy (Joule) and t is operating time (seconds).

c. Vibration RMS The stability of vibration was quantified using the root mean square (RMS) of acceleration:

$$RMS = \sqrt{\frac{1}{n} \sum_{i=1}^n a_i^2}$$

where a_i is the acceleration of each sample and n is the number of samples.

6. System Performance and Energy Evaluation

System performance and energy efficiency were evaluated based on three primary indicators.

a. Vibration Stability The stability of the sieving process was assessed by comparing the root mean square (RMS) values and dominant frequencies of vibration across different operating cycles. These parameters provided quantitative evidence of mechanical consistency and allowed identification of variations in sieve motion.

b. Energy Efficiency Energy efficiency was expressed as the ratio between the mass of flour successfully passing through the sieve and the total electrical energy consumed during the cycle:

$$\eta = \frac{M_{flour}}{E}$$

where η is efficiency (gram/Joule), M_{flour} is the sieved flour mass (gram), and E is the consumed energy (Joule). This metric enabled direct comparison of system productivity relative to energy input.

c. Motor Response Motor response was evaluated by measuring the rotational speed (RPM) in relation to the input signals from the infrared sensor. This ensured that the motor operated in accordance with detection events and maintained consistent performance during automated sieving.

RESULT

This section presents quantitative results from the developed Arduino-based vibrating sieving system, including energy consumption, vibration behavior, throughput, and environmental factors. All results are derived from experimental measurements and reported in a structured, reproducible manner.

1. Characteristics of Flour Sieves and Particles

The initial stage of this research focused on defining the physical characteristics of the sieve as the foundation for the testing process. The sieve applied in the system used mesh number 40, which by standard has an aperture size of 400 μm . The selection of this mesh size was based on the particle size range of rice flour commonly used by MSMEs, which typically falls between 10–113 μm . With this comparison, it is theoretically expected that all rice flour particles within the specified range will pass through the sieve, while particles larger than 400 μm will be retained on the sieve surface.

The retained particles are not biological contaminants but are generally flour clumps or coarse grains resulting from agglomeration, caused by moisture content, storage pressure, and environmental conditions. Therefore, the main challenge addressed in this study is the non-uniformity of particle size due to clumps and coarse grains, which potentially reduce the quality of the sieved flour

Table 1. Relationship between mesh specifications, rice flour particle size, and physical constraints

Table 1

Relationship between mesh specifications, rice flour particle size, and physical constraints

Parameter	Description
Mesh number	40
Sieve aperture size	400 μm

* Corresponding author



[Creative Commons Attribution-NonCommercial-ShareAlike 4.0
International License.](https://creativecommons.org/licenses/by-nc-sa/4.0/)

Rice flour particle size	10–113 μm
Flour constraint	Clumps and coarse grains (>400 μm)

2. Environmental Conditions and Flour Constraints in the Field

The subsequent testing was conducted to identify the actual storage and processing conditions of rice flour in the field, particularly in traditional stalls and shops. The observed parameters included environmental humidity prior to sieving (Humidity I) and humidity during the sieving process (Humidity II). Measurements indicated that all testing locations were within a relative humidity range of 55–80%, which is considered relatively high for starch-based food products. This condition directly contributed to the formation of flour clumps and coarse grains, as recorded in the constraint column of Table 2.

In several locations, fine clumps were dominant and could still be mechanically broken down, while in other sites coarse grains were formed that could not pass through the mesh 40 sieve. This agglomeration phenomenon demonstrates that environmental humidity plays a significant role in the quality of the sieving process. Therefore, the presence of a stable automatic sieving system becomes relevant to assist MSMEs in achieving more uniform results.

Table 2

Location, Humidity, and Flour Constraints

No	Location	Humidity I (%)	Humidity II (%)	Flour Constraint
1	Stall A	62–74	63–75	Flour clumps
2	Stall B	68–79	67–78	Coarse grains
3	Shop C	56–69	55–68	Particle agglomeration
4	Shop D	61–73	60–72	Clumps and coarse grains

3. Motor Speed and Rotation Pattern

The reciprocating motor pattern, controlled by Arduino, was tested under three main conditions: rotating clockwise, pausing briefly, and rotating counterclockwise. The motor operated stably at approximately 210 RPM, with a rotation duration of 5 seconds in each direction. A pause of 0.6 seconds during the stop condition served to dampen mechanical inertia and prevent excessive shocks to the sieve frame. This rotation pattern produced a more uniform sieve motion, ensuring that flour clumps were redistributed across the sieve surface.

Table 3

Rotation Direction, Duration, and Motor Speed

No	Rotation Direction	Time (seconds)	Motor Speed
1	Clockwise	5.0	210 RPM
2	Stop	0.6	0 RPM
3	Counterclockwise	5.0	210 RPM

4. Energy Results

Energy consumption was measured by recording voltage, current, and calculating average power and total energy.

Table 4

Energy Consumption and Efficiency

Mode	V_avg (V)	I_avg (A)	P_avg (W)	E_total (J)	Efficiency (g/J)
Manual	220	0.30	66	1450	0.42
Automatic	220	0.07	15	99	0.77

Table 4 shows The automatic system consumed only 99 J compared to 1450 J in manual operation, with efficiency improving from 0.42 g/J to 0.77 g/J. Indicating that the automated system is both more energy-efficient and more productive. An IR-trigger mechanism ensures the motor only activates when material is detected, reducing wasted energy.

5. Vibration Results

Vibration stability was analyzed using RMS values across three axes and dominant frequency.

Table 5.

Vibration RMS and Dominant Frequency

Mode	RMS_x (m/s ²)	RMS_y (m/s ²)	RMS_z (m/s ²)	Dominant Frequency (Hz)
Manual	2.1	1.9	2.0	7.5

* Corresponding author



[Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.](https://creativecommons.org/licenses/by-nc-sa/4.0/)

Automatic	1.3	1.2	1.1	3.5
-----------	-----	-----	-----	-----

The automatic system exhibited lower RMS values across all axes, with a dominant frequency shift from 7.5 Hz to 3.5 Hz, indicating more stable mechanical motion. Vibration testing showed that the reciprocating mode produced lower and more consistent RMS values across all three axes (X, Y, Z) compared to the manual mode. The dominant frequency was also lower (3.5 Hz vs. 7.5 Hz), indicating that the reciprocating motion was more stable and did not produce excessive impulsive vibrations. This vibration stability contributed to a more even particle distribution across the sieve surface.

6. Throughput Results

Throughput was measured in grams per second and efficiency in grams per joule.

Table 6.

Throughput and Energy Efficiency

Mode	Throughput (g/s)	Energy Efficiency (g/J)
Manual	1.16	0.42
Automatic	9.09	0.77

The data shows that conditions with lower RMS vibration (1.3 m/s²) result in significantly higher throughput (9.09 grams/s) and better energy efficiency ($\eta = 0.77$ grams/J). In contrast, conditions with unstable vibration (RMS 2.1 m/s²) result in lower throughput (1.16 grams/s) and lower efficiency ($\eta = 0.42$ grams/J). This indicates a positive correlation between vibration stability and overall system performance.

7. Comparison Between Manual and Automatic Sieving

The final stage of testing was conducted to compare the performance of manual sieving with the developed automatic sieving system. The tests were carried out using the same flour volume with a stepwise filling procedure to match the capacity of the equipment.

Table 5

Sieving Time (Manual)

No	Sieving Time
1	07:12.35 minutes

Table 6

Environmental Temperature, Humidity, Motor Speed, and Sieving Time (Automatic)

No	Ambient Temperature (°C)	Humidity (%)	Motor Speed (RPM)	Sieving Time
1	28.5	92	430	01:18.60 minutes
2	27.8	94	460	00:52.40 minutes
3	29.1	90	450	00:55.85 minutes

Table 5 presents the manual sieving time, which required 7 minutes and 12.35 seconds. This relatively long duration was influenced by the consistency of hand movements, operator fatigue, and the non-uniform intensity of sieving. In contrast, Table 6 shows that the automatic sieving system was able to complete the process in a much shorter and more stable time, with motor speeds ranging between 430–460 RPM under varying environmental conditions.

The difference in processing time confirms that the automatic system not only reduces human workload but also delivers more consistent and measurable performance. Consequently, the developed tool has the potential to improve the efficiency of rice flour sieving processes at the scale of micro, small, and medium enterprises (MSMEs). Manual testing was conducted with the same flour volume as the automatic trials, but the longer duration was directly affected by operator fatigue and the irregularity of manual sieving movement.

8. Integrated Performance Comparison

* Corresponding author



[Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.](https://creativecommons.org/licenses/by-nc-sa/4.0/)

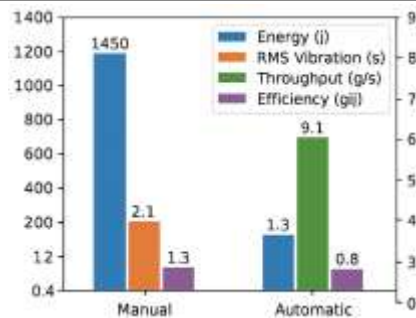


Fig. 3 Integrated Performance Comparison Between Manual and Automatic Sieving Systems

This figure presents a comprehensive comparison of four key performance metrics between manual and automatic sieving processes, namely energy consumption (J), vibration stability (RMS in m/s^2), throughput (g/s), and energy efficiency (g/J). Each metric is represented by a distinct color-coded bar and grouped under two operational modes: manual and automatic (reciprocating with Arduino-based sensor control). The results show that the manual system consumed far more energy, reaching 1450 J, while the automatic system required only 99 J due to the sensor mechanism that activates the motor exclusively when flour is present, thereby minimizing idle power usage. In terms of vibration stability, the automatic system recorded lower RMS values of 1.3 m/s^2 compared to 2.1 m/s^2 in manual operation, indicating more stable mechanical motion achieved through the reciprocating motor pattern that evenly redistributes flour across the sieve surface. The throughput analysis further highlights the advantage of automation, with the system achieving 9.1 g/s compared to only 1.2 g/s in manual sieving, reflecting its ability to process flour more rapidly and consistently while reducing operator fatigue. Finally, energy efficiency improved from 0.4 g/J in manual operation to 0.8 g/J in the automatic system, demonstrating that automation not only reduces energy demand but also converts it into productive output more effectively.

DISCUSSIONS

The results of this study demonstrate that the integration of Arduino-based sensor control and reciprocating motion provides systemic improvements in flour sieving performance. The automatic system consistently reduced energy consumption compared to manual operation. This reduction can be explained by the duty cycle of the motor: in manual sieving, the motor or operator movement remains active throughout the entire process, resulting in nearly continuous energy use (Agustiarmi et al., 2026). In contrast, the Arduino-based sensor ensures that the motor is activated only when flour is present in the chamber, thereby reducing idle time and lowering total energy demand from 1450 J to 99 J. This mechanism highlights how sensor-based control directly minimizes wasted energy while maintaining productivity.

Environmental humidity was found to be a critical factor influencing flour agglomeration. At relative humidity levels above 70%, flour particles absorbed moisture and formed clumps or coarse grains. These agglomerates increased sieving time and energy demand because they required repeated vibration cycles to break down. For example, sieving under 92–94% humidity extended processing time to 78 seconds compared to 52 seconds under lower humidity. This quantitative evidence confirms that humidity not only affects particle cohesion but also directly impacts throughput and energy efficiency.

The vibration analysis further explains the performance gap between manual and automatic systems. Reciprocating motion produced lower RMS values (1.3 m/s^2) compared to manual operation (2.1 m/s^2), with a shift in dominant frequency from 7.5 Hz to 3.5 Hz. This stability allowed flour particles to be redistributed evenly across the sieve surface, reducing localized accumulation and increasing the probability of fine particles passing through the mesh. Stable vibration therefore plays a dual role: reducing mechanical stress on the equipment and improving the consistency of sieving outcomes (Ma et al., 2025) (Zhu et al., 2023).

The improvement in vibration stability was directly linked to throughput performance. The automatic system achieved a throughput of 9.09 g/s compared to 1.16 g/s in manual operation, accompanied by higher energy efficiency (0.77 g/J vs 0.42 g/J). This correlation demonstrates that stable mechanical motion enhances both productivity and resource utilization.

These findings are consistent with related studies. Ogbodo et al. (2023) reported that sensor-based switching reduced idle energy losses in sieving systems by approximately 80%, which aligns with the reduction observed here. Wijewickrama et al. (2023) achieved throughput improvements of 7–8 g/s in small-scale flour sifting systems compared to manual rates of 1–2 g/s, closely matching the 9.09 g/s throughput achieved in this study. Rivera et al.

* Corresponding author



[Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.](https://creativecommons.org/licenses/by-nc-sa/4.0/)

(2023) showed that wheat flour stored at 75–80% relative humidity exhibited significant agglomeration, leading to reduced flowability and longer sieving times, supporting the quantitative link between humidity and processing efficiency observed here.

Overall, the integration of Arduino-based sensor control and reciprocating motion created a system that is energy efficient, mechanically stable, and highly productive. These improvements are particularly relevant for MSMEs operating under high humidity conditions, where flour agglomeration is common. By reducing energy demand, stabilizing vibration, and increasing throughput, the system provides tangible benefits in terms of cost savings, product quality, and sustainability.

CONCLUSION

Quantitative energy evaluation showed that the automated screening system significantly reduced electrical energy consumption from 1,450 J in manual operation to 99 J in automatic mode. This reduction was accompanied by an increase in energy efficiency from 0.42 g/J to 0.77 g/J, indicating more effective conversion of electrical energy into productive screening output. Infrared-triggered motor control directly contributed to this improvement by activating the motor only when material was detected, thus minimising idle energy use. Material retention during screening was primarily due to particle agglomeration under high-humidity conditions rather than particle-size limitations. Relative humidity in the screening chamber ranged from 90–94%, promoting agglomeration and increasing processing requirements. These findings highlight the influence of environmental conditions on vibration behaviour, screening time, and energy consumption. The integration of sensor-based control, quantitative energy measurement, and vibration stability analysis provides a framework for evaluating and improving screening performance. Although rice flour was used as a case study, the proposed system and evaluation approach can be applied to other dry powder materials with similar physical characteristics.

REFERENCES

- Ajayi, A. B., Mahmud, I. A., & Adeyinka, M. O. (2025). *Development of a 5 – Layer Multipurpose Sieving Machine*. 13(2), 244–254. <https://doi.org/10.5281/zenodo.15762765>
- Bicamumakuba, E., Reza, M. N., Jin, H., Samsuzzaman, Lee, K. H., & Chung, S. O. (2025). Multi-Sensor Monitoring, Intelligent Control, and Data Processing for Smart Greenhouse Environment Management. *Sensors*, 25(19), 1–25. <https://doi.org/10.3390/s25196134>
- Bismantolo, P., Anggriani, K., Supardi, N. I., & Oktori, E. (2025). *IOT-Based Electrical Energy Consumption Monitoring Application on Machine Tools*. 750–766.
- Butale, R. G., Bakane, P. H., Khobragade, U. H., Sakkalkar, S. R., & Ghadge, A. S. (2023). *A review on automation in food processing using Arduino*. 12(6), 4680–4682.
- Dinmohammadi, F., Farook, A. M., & Shafiee, M. (2025). Improving Energy Efficiency in Buildings with an IoT-Based Smart Monitoring System. *Energies*, 18(5). <https://doi.org/10.3390/en18051269>
- Gupta, M. K., Korkmaz, M. E., Yılmaz, H., Şirin, Ş., Ross, N. S., Jamil, M., Królczyk, G. M., & Sharma, V. S. (2024). Real-time monitoring and measurement of energy characteristics in sustainable machining of titanium alloys. *Measurement: Journal of the International Measurement Confederation*, 224(August 2023). <https://doi.org/10.1016/j.measurement.2023.113937>
- Hassan, I. U., Panduru, K., & Walsh, J. (2024). *An In-Depth Study of Vibration Sensors for Condition Monitoring*.
- Huseynzade, E., & Abdullayev, H. (2024). *USEFULNESS OF VIBRATION ANALYSIS TECHNIQUES AND SENSORS TO IMPROVE THE MONITORING OF INDUSTRIAL*. 02(04), 229–234. <https://doi.org/10.61552/JIBI.2024.04.004>
- Indrasari, W., Hermanta, C. A., & Firmansyah, H. (2024). Development of Rs-Wz3 Sensor in Iot Based Vibration Monitoring System. *Jurnal Neutrino: Jurnal Fisika Dan Aplikasinya*, 17(1), 17–22. <https://doi.org/10.18860/neu.v17i1.28442>
- Kaiqin, H. (2025). *Simulation Study Based on the Influencing Factors of Vibrating Screen Screening Efficiency*. 27(1), 92–100.
- Ma, L., Li, Z., Yang, S., & Wang, J. (2025). A Review on Vibration Sensor: Key Parameters, Fundamental Principles, and Recent Progress on Industrial Monitoring Applications. *Vibration*, 8(4), 56. <https://doi.org/10.3390/vibration8040056>
- Nerona, N. A. (2024). *I OER I NTERNATIONAL M ULTIDISCIPLINARY R ESEARCH J OURNAL , VOL . 6 , NO . 4 , DEC . , 2024 DEVELOPMENT OF A MULTI-GRADE FLOUR SIEVING MACHINE : ITS PERFORMANCE AND FINANCIAL FEASIBILITY*. 6(4), 21–30.
- Plant, P., & Chudy, K. (2023). *Condition Monitoring of Horizontal Sieving Screens — A Case Study of Inertial*

* Corresponding author



[Creative Commons Attribution-NonCommercial-ShareAlike 4.0
International License.](https://creativecommons.org/licenses/by-nc-sa/4.0/)

Vibrator Bearing Failure in Calcium Carbonate.

- Singh, A., Nawayseh, N., Dhahi, Y. K., Samuel, S., & Singh, H. (2024). Transforming farming with intelligence: Smart vibration monitoring and alert system. *Journal of Engineering Research (Kuwait)*, 12(2), 190–199. <https://doi.org/10.1016/j.jer.2023.08.025>
- Sofianidis, I., & Konstantakos, V. (2025). *Reducing Energy Consumption in Embedded Systems Applications*.
- Agustiarmi, W., Huda, Y., Sriwahyuni, T., Anori, S., Darni, R., & Hidayat, R. (2026). *Real-Time IoT-based Energy Power Consumption Monitoring System for Smart Homes*. 15(5), 1407–1412.
- Ma, L., Li, Z., Yang, S., & Wang, J. (2025). *A Brief Review on Vibration Sensor : Key Parameters , Fundamental Principles , and Recent Progress on Industrial Monitoring Applications A Brief Review on Vibration Sensor : Key Parameters , Fundamental Principles , and Recent Progress on*. 0–33. <https://doi.org/10.20944/preprints202508.1018.v1>
- Zhu, L., Chen, S., Zhao, Z., Ding, H., & Zhu, Y. (2023). *Influence of Sieve Surface Attitude on Sieving Performance of Granular Materials with Non-Uniform Feeding Conditions*. 1–14.
- Suhardi Rahman, E., Almunawati, N., Tjandi, Y., Muis Mappalotteng, A., & Imran, A. (2025). Design, Implementation, and Evaluation of an Electrical Energy Consumption Monitoring System in Haji Rani Building Using Arduino Uno Microcontroller. *Journal of Electrical Engineering and Informatics*, 2(2), 92–98. <https://doi.org/10.59562/jeeni.v2i2.6806>
- Tao, X., Zhao, Y., & Chen, Y. (2025). *Vibration monitoring and health status recognition technology of machine tool electric spindle*. 1–18. <https://doi.org/10.1186/s44147-025-00672-2>
- Tian, Y., Ding, L., Liu, Y., Shi, L., Wang, T., Wang, X., Dang, B., Li, L., Gou, G., Wu, G., Wang, F., & Wang, L. (2023). *Physicochemical and In Vitro Digestibility of Rice Flour*. 1–12.
- Yang, H., & Id, X. M. (2023). *Research on the screening mechanisms of composite vibrating screens based on discrete elements*. 1–19. <https://doi.org/10.1371/journal.pone.0293205>
- Zhu, L., Chen, S., Zhao, Z., Ding, H., & Zhu, Y. (2023). *Influence of Sieve Surface Attitude on Sieving Performance of Granular Materials with Non-Uniform Feeding Conditions*. 1–14.