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Noise Source Identification in Industrial Machinery Using Acoustic Analysis

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ABSTRACT

Industrial machinery can generate occupational noise that affects worker safety and machine reliability, yet general noise measurement does not show which component is responsible for the strongest sound. Objective: This study improves noise source identification in industrial machinery by combining acoustic signal analysis, frequency spectrum interpretation, and component level comparison for four representative machines. Methods: A lathe, a multi-spindle drilling machine, a cigarette manufacturing machine, and a pasta packaging machine were examined. Measurements were taken near motors, gearboxes, cutting zones, drilling heads, rollers, reels, and a packaging cutter using a calibrated sound level meter and a condenser microphone. Recorded signals were evaluated through waveform observation, dominant frequency estimation, and repeated component ranking. Results: The highest measured levels were produced by electric motor noise in the cigarette machine, lathe, and drilling machine, with values of 101.4, 101.6, and 103.5 decibels respectively. Gearboxes, rollers, reels, drilling heads, and the cutter also produced meaningful noise, but most were lower than the corresponding motors. The frequency spectrum showed distinctive tonal or cyclic components for each machine part. Conclusion: The method provides a practical route for locating dominant noise sources, prioritizing maintenance, and reducing occupational noise through targeted control of motors, transmissions, and cutting mechanisms.

INTRODUCTION

Industrial production depends on rotating, cutting, feeding, packaging, and power transmission systems that create complex acoustic fields during normal operation. A factory sound field is usually produced by several sources acting at the same time, including electric motors, cooling fans, gearboxes, belt drives, bearings, tool and workpiece contact, pneumatic actuators, and material handling mechanisms. Measuring only the total sound pressure level near a machine is useful for determining exposure risk, but it is not sufficient for engineering control. A high overall level does not explain which component should be repaired, enclosed, isolated, lubricated, or redesigned.

Noise control is therefore a source identification problem before it is a treatment problem. Occupational noise guidance emphasizes that continuous exposure to high levels can contribute to hearing damage and other workplace impacts, while machinery research shows that abnormal sound can also indicate faults, misalignment, bearing wear, poor lubrication, looseness, or unbalanced rotating parts (AlShorman et al., 2021). The same signal that is harmful to workers can therefore be useful to maintenance engineers when it is measured and interpreted carefully.

The present paper examines four industrial machines that represent common workshop and manufacturing conditions: a metalworking lathe, a multi-spindle drilling machine, a cigarette manufacturing machine, and a pasta packaging machine. These machines were selected because each contains several likely sound sources and because their acoustic signatures are not identical. The lathe combines spindle drive noise, gearbox meshing, and cutting interaction. The drilling machine combines a drive motor with repeated drilling head activity. The cigarette machine includes a high speed motor, rolling reels, a gearbox, and a rollers box. The pasta packaging machine adds a periodic cutting mechanism that is easily noticed by an operator even when its measured level is lower than other sources.

The research gap addressed in this paper is the need for a simple but systematic procedure that can be used in laboratories or workshops without relying only on advanced acoustic cameras or large microphone arrays. Recent studies have shown the value of array beamforming, sound source localization, and machine learning for source detection (Jekateryńczuk & Piotrowski, 2023). However, many industrial laboratories still begin with a sound level meter, a measurement microphone, and spectrum analysis software. This study therefore improves the original manuscript by organizing the measurement procedure, expanding the comparison with current literature, presenting clearer tables and figures, and translating the results into practical recommendations.

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The objective is to identify the dominant noise producing components in the selected machines by comparing measured sound pressure levels and dominant frequency characteristics. The contribution is practical rather than purely theoretical. The paper shows that component based measurement can rank noise sources, distinguish continuous motor related tones from mechanical process events, and guide maintenance actions. The study also demonstrates that the loudest perceived source is not always the most energetic source, especially when intermittent cutting or impact sounds attract human attention.

LITERATURE REVIEW

Modern noise source identification has moved from simple overall sound measurement toward spatial, spectral, and data driven interpretation. Microphone array methods are now widely discussed because they can transform simultaneous microphone recordings into acoustic maps that show where sound energy is radiated. Lan-Yue et al., (2017) reviewed microphone array based noise source identification and described how beamforming, near field acoustic holography, and hybrid methods are used to visualize sound fields. Liaquat et al., (2021) also showed that sound source localization research has become a broad field involving microphone arrays, acoustic vector sensors, and algorithmic estimation techniques. These studies are important because they show that industrial noise should be treated as a distribution of sources rather than as one undifferentiated level.

Beamforming is especially relevant when several components operate at the same time. Gannot et al., (2017) reviewed beamforming algorithms and explained that spatial filtering can help separate dominant radiating regions in complex environments. Long et al., (2022) demonstrated that microphone arrays can be combined with deep neural network methods to localize, separate, and reconstruct multiple sound sources. Roozbehi et al., (2024) extended this direction by reviewing artificial intelligence based acoustic source identification, where learning algorithms are used to classify or locate sources from measured acoustic data. These approaches are powerful, but they normally require synchronized sensors, array calibration, and appropriate processing expertise.

Sound intensity methods provide another route for source identification. Instead of only measuring pressure, an intensity probe estimates the direction and magnitude of acoustic energy flow. This can help distinguish true radiation from reflected sound. Miodragović et al., (2023) used sound intensity measurements to identify noise sources on a vertical computer numerical control milling machine and produced contour maps over different machine sides. Their work is directly relevant to the present study because it shows that component level noise diagnosis can be applied to machine tools rather than only to laboratory sources.

Acoustic measurement is also connected with condition monitoring. AlShorman et al., (2021) reviewed sounds and acoustic emission for early induction motor fault diagnosis, showing that motor sound can reveal electrical and mechanical problems. Gangsar and Tiwari, (2020) reviewed deep learning based condition monitoring for rotating machinery and emphasized that bearings, gearboxes, and shafts produce diagnostic signatures in vibration and sound. Bhuiyan and Uddin, (2023)reviewed transfer learning for industrial fault diagnosis using vibration and acoustic sensors, indicating that acoustic sensing is increasingly used when non-contact monitoring is preferred. Ye et al., (2025) linked sound based predictive maintenance with feature engineering and deep learning, reinforcing the idea that industrial sound has both safety and maintenance value.

Studies of rotating machinery are particularly useful for interpreting the present measurements. Electric motors can generate electromagnetic hum, bearing noise, rotor imbalance, structural vibration, and cooling fan noise. Gearboxes often generate tonal components related to gear meshing and broadband components related to wear or lubrication conditions. Cutting and drilling processes produce transient or semi-periodic signals caused by tool contact and material removal. Tama et al., (2023) show that signal features can be used to support fault diagnosis in rotating machinery and gearboxes. These findings support the expectation that every component type will have a different dominant frequency pattern and a different maintenance interpretation.

The reviewed literature shows three main gaps for this manuscript. First, many advanced source localization papers focus on algorithmic performance, while workshop level studies still need straightforward measurement procedures. Second, many machine diagnosis papers focus on detecting faults, while this paper first ranks the components responsible for excessive noise. Third, previous drafts of this work reported useful measurements but did not fully connect those measurements with recent acoustic source identification and predictive maintenance literature. The revised manuscript addresses these gaps by combining close range measurement, frequency spectrum interpretation, and component ranking in one practical framework.

METHOD

In this section, this study used a comparative acoustic measurement procedure to identify the main radiating components on four industrial machines. The method was designed to be repeatable with commonly available acoustic equipment. It began with a preliminary survey around each machine using a sound level meter. The survey was conducted during normal operation, and readings were taken near expected source locations such as motor housings, gearbox covers, cutting zones, drilling heads, roller assemblies, reels, and the packaging cutter. The purpose of this first stage was not to produce the final ranking, but to locate the areas where detailed recording should be performed.

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After the preliminary survey, a condenser microphone was placed close to each selected component. The working frequency range of the microphone was suitable for the dominant audible range of the machines. The close placement reduced the influence of unrelated sources and improved the connection between the measured signal and the component under study. This close range method does not replace standardized sound power measurement, but it is appropriate for diagnostic comparison when the research question is which component is locally dominant. Instrument selection and use were guided by general sound level meter requirements and sound intensity measurement principles described in international standards (International Electro technical Commission, 2013; International Organization for Standardization, 1993).

Each recording was taken while the machine operated under steady and representative conditions. The cigarette manufacturing machine was assessed at the motor, rolling reels, gearbox, and rollers box. The lathe was assessed at the spindle drive motor, gearbox, and cutting zone. The multi-spindle drilling machine was assessed at the motor and drill head area. The pasta packaging machine was assessed at the cutting mechanism because the cutter produced a distinct periodic sound during packaging operation. Measurements were repeated where possible so that a single abnormal transient would not dominate the interpretation.

The recorded acoustic signals were transferred to a computer for waveform and frequency spectrum analysis. The waveform was used to identify whether a signal was continuous, periodic, impulsive, or unstable. The frequency spectrum was used to identify the dominant frequency component associated with each measurement location. Component ranking was based mainly on measured sound pressure level, while the dominant frequency was used to explain the physical character of the source. For example, a motor related tone observed at different locations suggests that motor vibration is transmitted through the machine structure, while a low repeated frequency near a cutter suggests a process cycle rather than a continuous rotating source.

Calibration and plausibility checking were performed before interpreting the machine results. Reference tones were used to confirm that the measurement chain responded correctly to known frequencies. During analysis, the values were checked against the expected behavior of motors, gearboxes, and cutting mechanisms. The final evaluation used three criteria: the measured level in decibels, the dominant frequency in hertz, and the consistency of the source signature across locations. Figure 1 summarizes the measurement and analysis workflow used in the revised study.

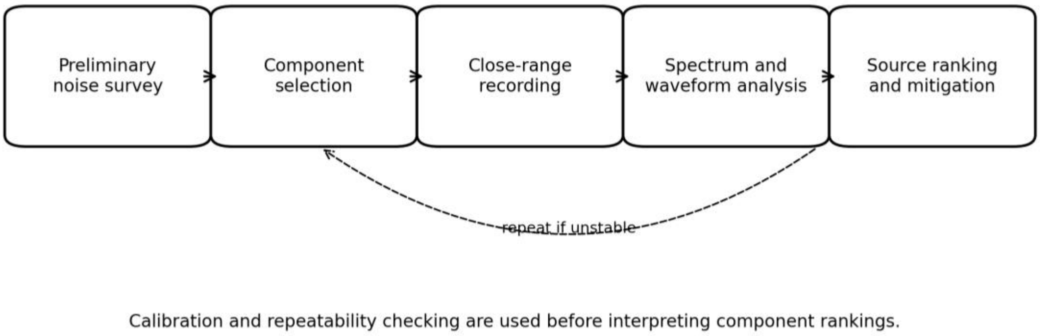

Figure 1. Measurement and analysis workflow for industrial noise source identification

RESULT

In this section, the acoustic evaluation of the industrial machinery revealed distinct variations in noise emission levels and frequency distribution across the different equipment types. Table 1 presents the measured sound pressure level and dominant frequency characteristics for the machine components examined in this study.

The values show that the electric motors were the dominant sources where motor measurements were available. The highest value was measured at the drilling machine motor with 103.5 dB at a dominant frequency of 183 Hz. The lathe motor and cigarette machine motor were also very high, at 101.6 dB and 101.4 dB respectively. The remaining components were lower, although some still exceeded common occupational reference levels and therefore remain important for noise control.

Table 1. Measured Noise Levels and Dominant Frequency Characteristics of the Investigated Machine Components

Machine	Component	Dominant frequency	Sound pressure level
Cigarette manufacturing machine	Drive motor	48.5 Hz	101.4 dB
Cigarette manufacturing machine	Rollers box	41.8 Hz	97.4 dB
Cigarette manufacturing machine	Rolling reels	83.8 Hz	93.8 dB
Cigarette manufacturing machine	Gearbox	147.7 Hz	93.5 dB
Lathe	Spindle drive motor	897 Hz	101.6 dB
Lathe	Gearbox	467.5 Hz and motor tone	99.5 dB

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Lathe	Cutting zone	341.7 Hz and motor tone	90.9 dB
Multi-spindle drilling machine	Drive motor	183 Hz	103.5 dB
Multi-spindle drilling machine	Drill head area	Approximately 2 Hz cyclic event	101.0 dB
Pasta packaging machine	Cutting mechanism	Approximately 0.6 Hz cycle	89.0 dB

In the cigarette manufacturing machine, the motor produced the highest level. Its value of 101.4 dB was 4.0 dB above the rollers box, 7.6 dB above the rolling reels, and 7.9 dB above the gearbox. Because decibels are logarithmic, these differences indicate a substantial change in acoustic energy rather than a small arithmetic difference. The rollers box remained an important secondary source, but the measured ranking indicates that controlling the motor would provide the largest first reduction in machine noise. The gearbox frequency of 147.7 Hz suggests a more mechanical tonal source, while the motor related frequency was lower and more persistent.

The lathe results showed a similar pattern. The spindle drive motor produced 101.6 dB and showed a dominant frequency around 897 Hz. The gearbox produced 99.5 dB, but the same motor tone appeared in the gearbox measurement, indicating that the motor sound or motor vibration was transmitted through the lathe structure. The cutting zone produced 90.9 dB, which was lower than the motor and gearbox, although it still represented a significant source during operation. The cutting zone spectrum included a characteristic component near 341.7 Hz, but the motor tone remained visible. This result shows why frequency interpretation is necessary in addition to level measurement.

The multi-spindle drilling machine had the highest motor reading in the dataset. The motor produced 103.5 dB at 183 Hz, while the drill head area produced approximately 101.0 dB with a low cyclic event near 2 Hz. The drill head sound was close to the motor level and would be clearly noticed by workers because periodic drilling activity creates a repeated acoustic pattern. Nevertheless, the motor was still the larger contributor by measured level. The small difference between the drill motor and drill head area suggests that any reduction strategy should address both the drive system and the process zone.

The pasta packaging machine differed from the other machines because only the cutting mechanism was measured in detail. The cutter produced 89.0 dB and had a low cyclic frequency linked to the packaging cycle. Although this value was lower than the motors on the other machines, the signal was intermittent and prominent to human perception because each cut formed a repeated event. The packaging result should therefore be interpreted as a process-specific source rather than as proof that the whole packaging machine is quiet. Further work should include the packaging motor, belt drives, pneumatic lines, and fan or blower sections.

Figure 2 visualizes the component level results. The chart makes the motor dominance clear for the cigarette machine, lathe, and drilling machine, while also showing that secondary sources are not negligible. The 85 dB reference line is included only as a practical occupational comparison and does not replace a full exposure assessment based on worker position, duration, weighting, and background noise.

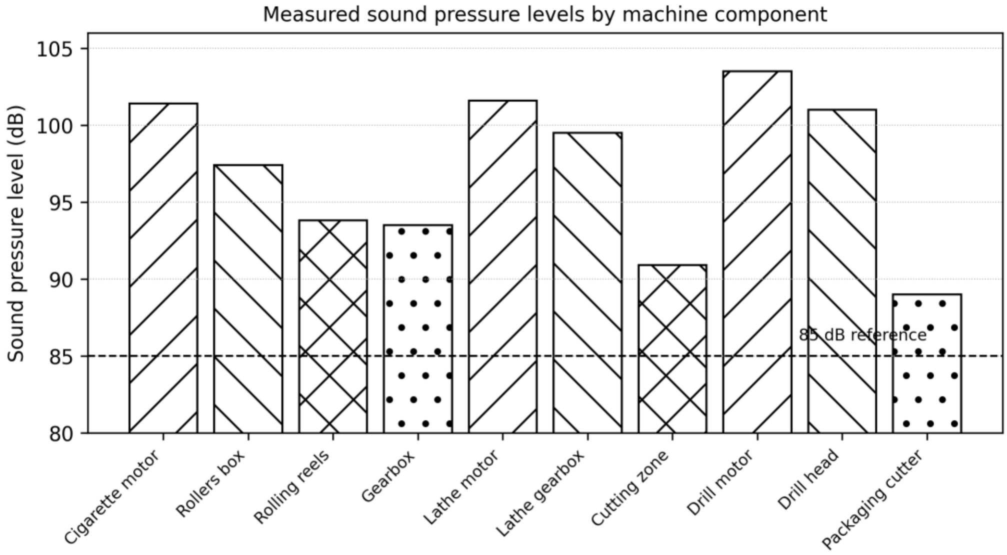

Figure 2. Sound pressure level comparison for measured machine components.

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DISCUSSION

The results support the general conclusion that electric motors are the primary sources of noise in the investigated machines. This finding is consistent with the literature on rotating machinery, where sound can be produced by electromagnetic forces, bearing motion, shaft imbalance, casing vibration, and cooling fan airflow (AlShorman et al., 2021; Ye et al., 2025). The motor was not only loud at the motor housing; its frequency signature also appeared in other measurement locations, especially on the lathe. This means that the motor can act as both an airborne source and a vibration source that excites other parts of the machine frame.

The gearbox and process components still require attention. In the lathe, the gearbox was only 2.1 dB lower than the motor. This small difference means that a motor enclosure alone may not provide enough improvement if gear mesh noise remains untreated. Gearbox noise may arise from tooth contact, backlash, worn bearings, poor lubrication, misalignment, or housing resonance. In the cigarette machine, the rollers box and rolling reels created lower but still substantial levels. These sources can affect perceived sound quality because tonal or cyclic components are easier to notice than steady broadband noise. Similar reasoning is used in acoustic diagnosis research, where spectral content helps distinguish gear, bearing, and drive related problems (Gangsar & Tiwari, 2020; Roy et al., 2023).

The drilling machine results show that process noise can approach motor noise when several tools operate together. The drill head area produced approximately 101.0 dB, which is only 2.5 dB below the motor. In practical terms, drilling noise reduction should not focus only on the motor. Tool condition, feed rate, spindle alignment, workpiece clamping, and structural damping should also be considered. A blunt tool or poorly supported workpiece may create additional chatter and impact noise. This supports the broader condition monitoring literature, where acoustic signals are treated as indicators of both source strength and mechanical condition (Bhuiyan & Uddin, 2023; Tama et al., 2023).

The packaging cutter illustrates the difference between measured intensity and human attention. A repeated cutting event at 89.0 dB may be perceived as disturbing even when it is lower than a continuous motor at more than 100 dB. Human operators often report intermittent impulsive sounds as more annoying than steady sounds because the onset and repetition attract attention. Therefore, noise control should consider both measured level and signal character. The cutter could be treated with localized damping, better mechanical alignment, adjustment of air pressure if pneumatic actuation is involved, or isolation of the cutting station. However, a complete assessment of the packaging machine would require additional measurement of the motor and drive subsystems.

The revised analysis also demonstrates the value of combining level ranking with frequency spectrum interpretation. A sound level reading tells which point is loudest, but a spectrum explains whether the measured source is likely a motor, gear mesh, cutting action, or periodic mechanism. This is why the lathe cutting zone did not simply represent cutting noise; the spectrum also contained the motor tone. Advanced microphone array and beamforming methods can improve this separation when sources overlap spatially, as shown by recent source localization studies (Licitra et al., 2023). The present method is simpler, but it follows the same logic by using measured level and spectral signature together.

The practical recommendations are straightforward. First, motors should be inspected for bearing wear, cooling fan condition, unbalance, mounting looseness, and alignment. Second, motor bases should be isolated where possible so that vibration is not transmitted through the frame. Third, gearboxes should be checked for lubrication, mesh condition, and casing resonance. Fourth, cutting and drilling zones should be assessed for tool sharpness, correct feed rate, clamping, and structural rigidity. Fifth, repeated process events such as packaging cuts should be treated with local damping or enclosure design. These actions are more efficient than applying general acoustic treatment to the whole workshop without knowing which component is dominant.

The main limitation is that the microphone was placed close to components. This approach is useful for source ranking but does not represent the exact exposure of a worker standing at a normal operating position. A full occupational assessment would need standardized measurements at worker locations with time weighting and background noise correction. Another limitation is that the machines were not tested under every possible load condition. Cutting depth, feed rate, tool wear, product flow, material type, and maintenance state may change the results. The pasta packaging machine also needs more complete measurement because only the cutter was analyzed in detail. Future studies should add sound intensity mapping, synchronized vibration measurement, or small microphone arrays to confirm source locations and to separate overlapping radiation paths more precisely.

CONCLUSION

This paper expanded and improved a manuscript on noise source identification in industrial machinery using close range acoustic measurement and frequency spectrum analysis. The study compared four machines and ranked the measured components by sound pressure level and dominant frequency. The main finding is that electric motors were the dominant sources in the cigarette manufacturing machine, lathe, and multi-spindle drilling machine, with measured levels of 101.4 dB, 101.6 dB, and 103.5 dB respectively. Secondary components such as gearboxes, rollers, reels, drilling heads, cutting zones, and packaging cutters also produced significant noise and should not be ignored in control planning.

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The contribution of the study is a practical diagnostic framework for workshops and laboratories. The framework begins with a preliminary survey, continues with close microphone recording, interprets spectra and waveforms, ranks the components, and converts the ranking into maintenance and mitigation priorities. The method is useful because it does not only state that a machine is noisy; it indicates which component should be treated first. The most important suggestion is that noise reduction should begin with motor maintenance, motor mounting, and motor enclosure design, followed by gearbox lubrication, tool condition control, and localized treatment of periodic cutting mechanisms. Future work should measure worker exposure positions, include more operating conditions, and compare the close range method with sound intensity mapping or microphone array localization.

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