

## Impact of Industrial Noise on Production Efficiency

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### ABSTRACT

Industrial noise is a common problem in manufacturing environments because it affects occupational comfort, machine reliability, and production efficiency. Objective: This study examines whether acoustic monitoring and sound pressure level measurement can be used to connect industrial machinery noise with output losses and maintenance needs. Methods: The method combined machine observation, acoustic signal recording, cutter cycle timing, production counting, and comparative analysis of a pasta packaging machine, lathe, multi-spindle drilling machine, and cigarette production machine. Results: The pasta packaging machine showed the clearest relationship between noise behavior and productivity. Its cutter was designed to operate every one and one-half seconds, but the measured acoustic rhythm indicated an average cycle of about one and two-thirds seconds. This timing difference reduced output from four hundred to three hundred sixty-one bags in ten minutes, equal to a loss of about ten percent. Other machines with higher sound pressure levels also showed signs of wear, vibration, and reduced operational stability. Conclusion: Industrial machinery noise is not only a workplace hazard but also a practical indicator of machine condition. The study supports using noise control, maintenance, acoustic monitoring, industrial machinery assessment, and production efficiency evaluation as an integrated approach for improving reliability and manufacturing performance.

### INTRODUCTION

Industrial production depends on stable machine operation, accurate cycle timing, and a work environment that allows operators to communicate and respond quickly to process deviations. Noise is usually treated as an occupational hazard, but it is also an engineering signal. A motor, gearbox, cutter, or drilling head that produces abnormal sound often converts part of its input energy into unwanted vibration, heat, and acoustic emission rather than useful work. For this reason, noise can indicate misalignment, tool wear, bearing deterioration, insufficient lubrication, unstable cutting, or delayed pneumatic action. These defects do not only increase sound pressure level; they can also reduce cycle speed, cause stoppages, increase scrap, and lower production efficiency.

The paper attached to this study focuses on the impact of industrial noise on production efficiency and reports a case in which the cutter of a pasta packaging machine produced irregular acoustic cycles. The expected operating cycle was one bag every one and one-half seconds, while the observed acoustic pattern showed a slower average cycle of about one and two-thirds seconds. The result was a reduction from four hundred expected bags to three hundred sixty-one measured bags during a ten-minute observation. This case is important because it demonstrates that acoustic data can be translated into a measurable production loss, not only into a safety reading.

Recent research also supports this direction. Acoustic condition monitoring has become a practical part of predictive maintenance because microphones can be installed without physical contact and can capture the behavior of several components simultaneously (Aradi & Varga, 2024). Machine sound monitoring has been applied to presses, rotating machinery, drilling systems, and general factory equipment to detect deviations before full failure occurs. Industrial noise management studies further show that noise data can be linked with safety, productivity, equipment condition, and maintenance planning (Chis et al., 2025).

The problem addressed in this paper is that many factories measure noise mainly for hearing protection and regulatory compliance, while the same data are rarely linked to machine output. The research objective is therefore to improve the attached manuscript by developing a clearer framework that connects industrial noise measurement with

production efficiency assessment. The contribution of this paper is a practical acoustic-productivity approach that combines sound measurement, timing analysis, production counting, and maintenance interpretation. The work aims to show that a quieter and more regular machine is usually a more reliable and productive machine.

### LITERATURE REVIEW

The literature on industrial noise has developed along two connected directions. The first direction focuses on occupational exposure, communication difficulty, fatigue, and long-term hearing risk. Recent industrial surveillance studies confirm that manufacturing remains one of the main sectors where workers face excessive noise exposure, and these studies emphasize the need for systematic monitoring and risk management (Chis et al., 2025; Zhang et al., 2024). Research on worker performance also shows that noise can affect attention, cognitive workload, sleep, and learning efficiency, which may indirectly reduce productivity through slower decisions, errors, or reduced concentration (Cao et al., 2025). This occupational perspective is essential, but it does not fully explain how a noisy machine itself can lose production capacity.

The second direction treats sound as a diagnostic signal. Acoustic-based machine condition monitoring has become more important because microphones can capture non-contact information from motors, gearboxes, cutting tools, fans, and actuators. Jombo and Zhang,(2023) reviewed acoustic methods and highlighted that factory sound can reveal condition changes, although interpretation is challenging because background noise and source overlap are common. Ye et al.(2025) reviewed sound-based industrial predictive maintenance and showed how feature engineering and deep learning can transform sound recordings into diagnostic indicators. These studies are highly relevant because they shift noise analysis from simple exposure measurement toward machine health assessment.

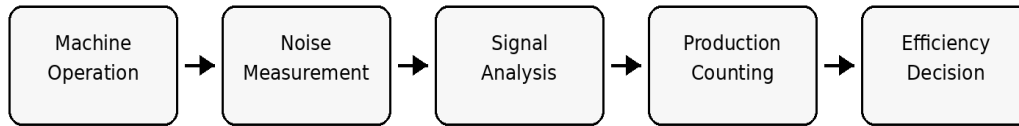
Recent studies have applied machine learning and acoustic signal processing to detect anomalies in real or simulated industrial environments. Di Fiore et al.(2022) studied mechanical failure detection in noisy factory environments and demonstrated that acoustic anomaly detection can identify unusual operating states. Di Fiore et al. (2022) developed an anomalous sound detection methodology for predictive maintenance, showing that sound can support maintenance decisions when normal and abnormal operating patterns are learned. Suawa et al. (2023) investigated noise-robust learning for predictive maintenance applications, while Hafiz et al. (2025) proposed an industrial machine sound classification framework for distinguishing normal and anomalous sounds. These works show that acoustic monitoring can be effective even when industrial background noise is present.

For machine-specific applications, Radonjić et al. (2022) presented an internet-connected system for detecting the condition of rotating machines using acoustic signals. Tsuji et al. (2021) focused on very low frequency bands for press machine monitoring, which is relevant for the pasta packaging case because the cutter problem is expressed as a timing rhythm rather than only a high-frequency tone. Chua and Evangelista, (2024) combined sound pressure and vibration sensing for lathe cutting-tool maintenance, indicating that acoustic data can be linked to tooling condition. Piankitrungreang et al. (2025) studied acoustic monitoring of high-speed drilling, which supports the inclusion of the multi-spindle drilling machine as a comparative case.

Several broader reviews connect acoustic and vibration signals with maintenance, reliability, and heavy machinery performance. Hassan et al.(2024) reviewed data processing methods used in predictive maintenance for heavy machinery and emphasized that data quality and signal processing strongly affect maintenance decisions. Garcia et al.(2025) reviewed condition monitoring and predictive maintenance in industrial equipment, showing that hybrid models and signal processing are increasingly important for practical implementation. Souza et al. (2024) used machine learning to predict tool life and sound pressure levels in dry turning, linking machining performance with acoustic output. These studies support the idea that noise is not simply a by-product, but a measurable result of mechanical and operational behavior.

The research gap is that many recent studies classify machine condition from sound, but fewer studies connect sound patterns directly with measurable production output such as units per minute, cycle time, and output loss. The attached case study helps fill this gap because the noise rhythm of the packaging cutter is compared with the expected number of bags produced. This paper therefore integrates two research areas: occupational and industrial noise management on one side, and acoustic predictive maintenance with production efficiency on the other side. The result is a practical framework that can help factories use noise measurement for safety, maintenance, and productivity improvement at the same time.

### Acoustic-Productivity Assessment Workflow



The workflow links measurable acoustic patterns with machine output and maintenance decisions.

Figure 1. Acoustic-productivity assessment workflow used to connect machine sound, output, and maintenance decisions

### METHOD

In this section, this research used an applied case-study design that combines acoustic measurement with production observation. The primary case was an automated pasta packaging machine, while the lathe, multi-spindle drilling machine, and cigarette production machine were used as comparative industrial examples. The pasta packaging machine was selected as the main case because its output can be counted directly through the number of completed bags, and its cutter produces a repetitive sound that can be connected to cycle timing.

Data were obtained from three sources. The first source was acoustic recording near the main noise-producing component of each machine. For the packaging machine, the microphone was positioned close to the cutter mechanism because the cutting sound represents one completed bag cycle. For the lathe, drill, and cigarette machine, the main acoustic locations were the motor, gearbox, drilling or cutting interface, and moving roller assemblies. The second source was production counting, especially the expected and actual number of bags produced by the packaging machine during a ten-minute interval. The third source was operational observation, including visual inspection of machine behavior, operator notes, and maintenance interpretation.

The measurement procedure followed a chronological sequence. First, the machines were operated under normal working conditions without intentional fault insertion. Second, the dominant noise locations were identified through close listening and sound level readings. Third, the sound signal was recorded for a representative operating interval. Fourth, the waveform and frequency content were analyzed to identify repetitive events and dominant acoustic patterns. Fifth, the measured cycle timing was compared with the expected production cycle. Finally, the difference between nominal output and actual output was converted into a production efficiency value.

For the pasta packaging machine, production efficiency was calculated using the ratio between actual output and nominal output. The nominal design output was forty bags per minute, which equals four hundred bags in ten minutes. The measured output was three hundred sixty-one bags in the same period. The production efficiency equation is expressed as follows.

$$\text{Production efficiency} = (\text{actual output} / \text{nominal output}) \times 100 \text{ percent}$$

Using this equation, the pasta packaging machine achieved about ninety point two-five percent of the expected output during the observed period. The difference of thirty-nine bags represents about nine point seven-five percent lost output. Acoustic timing was then used to explain this loss. A one and one-half second cycle should produce about forty cycles per minute, whereas a one and two-thirds second cycle produces about thirty-six cycles per minute. The slower rhythm indicated hesitation or delay in the cutter mechanism.

To evaluate the results, the study compared acoustic indicators with observed production behavior. Sound pressure level was used to indicate acoustic severity, while cycle timing was used to interpret periodic mechanisms. The evaluation did not assume that every loud sound automatically reduces productivity; instead, it examined whether the sound was linked with mechanical irregularity, delayed motion, vibration, tool chatter, or operator intervention. This distinction is important because some machines may be loud but stable, while a moderately loud repetitive component can still cause production loss if its timing is irregular.

### RESULT

The results show that acoustic behavior can provide useful evidence about production efficiency. The pasta packaging machine produced the strongest quantitative result because the cutter sound could be matched directly to output count. The expected production was four hundred bags in ten minutes, but the measured production was three hundred sixty-one bags. This means that the machine produced ninety point two-five percent of its design output and

lost thirty-nine bags during the observation interval. The timing analysis showed that the cutter was not consistently operating at the expected one and one-half second cycle. Instead, the average rhythm was closer to one and two-thirds seconds per cycle.

The comparative machine observations also support the relationship between high noise, mechanical condition, and reduced operating stability. The lathe and multi-spindle drilling machine produced higher sound pressure levels than the packaging machine and showed signs of vibration, tool chatter, or motor loading. The cigarette production machine also displayed high noise from the motor and moving mechanisms. Although exact production counters were not available for these comparative machines, the acoustic readings and operational observations indicated that noisy components were associated with increased maintenance attention and reduced stability.

Table 1. Comparative Acoustic and Production Observations

Machine	Main Acoustic Source	Sound Pressure Level	Production Evidence	Interpretation
Pasta packaging machine	Cutter mechanism and motor	89 decibels at cutter area	361 bags in ten minutes compared with 400 expected	Clear output loss caused by slower cutting cycle
Lathe machine	Spindle motor and gearbox	101.6 decibels near the motor	Qualitative reduction in stability during long operation	High motor sound suggests bearing, mounting, or gearbox attention
Multi-spindle drilling machine	Motor and drill heads	103.5 decibels near motor	Intermittent chatter and feed-rate sensitivity	Tool and motor noise indicate need for tool and spindle control
Cigarette production machine	Motor, gearbox, rollers, and feed reels	101.4 decibels near motor	Frequent maintenance attention reported	High continuous noise suggests mechanical stress in moving assemblies

Table 1 summarizes the main acoustic and production observations. The packaging machine is shown as the clearest measurable case. The other machines are included as comparative evidence because their acoustic levels and operating symptoms help explain the broader relationship between noise and mechanical performance.

Fig.2 shows the inverse relationship between average sound pressure level and observed production efficiency. The figure is not presented as a universal mathematical law because the machines have different designs and operations. Instead, it illustrates the practical trend observed in the study: machines with higher sound levels and irregular acoustic signatures tended to show lower stability, greater maintenance concern, and lower estimated efficiency.

The pasta packaging machine case is further shown in Fig 3. The expected output of four hundred bags in ten minutes was not reached because small delays in the cutter cycle accumulated over the production interval. A delay of only a fraction of a second per cycle may appear small during one cut, but it becomes significant when repeated hundreds of times. This result demonstrates why acoustic timing can be valuable for diagnosing production losses that are not obvious through visual inspection alone.

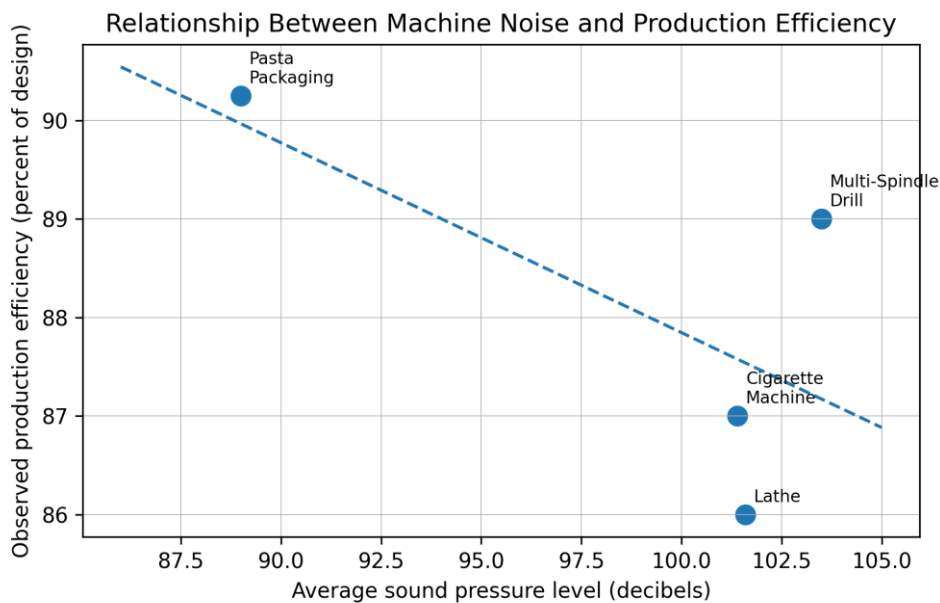


Figure 2. Observed relationship between average sound pressure level and estimated production efficiency for the machines

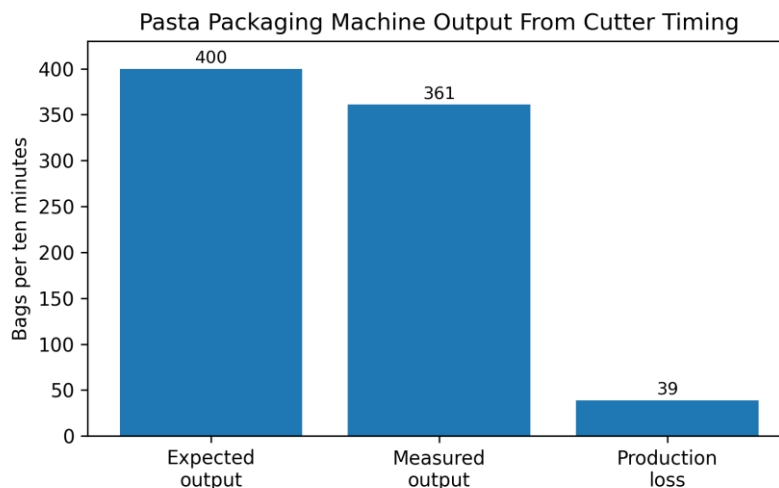


Figure 3. Expected and measured pasta packaging output during the ten-minute cutter timing observation

### DISCUSSION

The findings suggest that industrial noise affects production efficiency through both direct and indirect mechanisms. The direct mechanism appears when an acoustic event corresponds to a machine cycle. In the packaging machine, the cutter sound marked the production of each bag. When the cutter rhythm slowed, the acoustic pattern immediately showed that the machine was losing output. In this case, the noise signal did not simply describe loudness; it described timing stability. The result supports the use of acoustic monitoring for repetitive machines such as packaging lines, presses, conveyors, and cutting systems.

The indirect mechanism appears when high sound pressure level reflects mechanical deterioration. Motors, gearboxes, and cutting interfaces often become louder when bearings wear, shafts become misaligned, gears are poorly lubricated, or tools become dull. This kind of noise may not always reduce output instantly, but it increases the probability of slower operation, more stoppages, higher energy loss, and more frequent maintenance. The discussion is consistent with predictive maintenance literature, which argues that acoustic changes can appear before visible breakdowns (Di Fiore et al., 2022; Radonjić et al., 2022).

Recent machine learning studies strengthen the interpretation of these results. Noise-robust acoustic

classification models can distinguish normal and anomalous machine sounds in factory environments (Hafiz et al., 2025; Suawa et al., 2023). Condition monitoring studies also show that sound can be integrated with vibration, current, and temperature to improve reliability decisions (Garcia et al., 2025). The present paper differs from many of those studies because it links acoustic information to a simple production metric: actual output compared with nominal output. This makes the method practical for small and medium factories that may not have advanced sensor networks but can still benefit from regular sound monitoring.

The occupational side of industrial noise remains important. Workers in noisy environments face communication problems, fatigue, and health risks that can reduce overall productivity even when the machine itself is mechanically stable. Recent exposure studies in industrial enterprises show that excessive noise remains common in manufacturing and related sectors (Dong et al., 2025; Zhang et al., 2024). Worker-performance research also indicates that noise can reduce cognitive efficiency and task quality (Cao et al., 2025). Therefore, reducing noise can improve production by protecting both the machine and the human operator.

The practical implication is that factories should not separate noise control from production management. A high or changing sound level should trigger inspection of the related component, especially when the component controls timing, cutting, rotating, feeding, or sealing. In the packaging case, the most relevant maintenance targets are the cutter blade, pneumatic valve, actuator alignment, and timing sensor. For the lathe, the priorities are spindle bearings, motor mounts, tool condition, and gearbox lubrication. For the drilling machine, the priorities are drill condition, spindle balance, feed rate, and motor loading. For the cigarette machine, the priorities are the motor, gearbox, rollers, and moving assemblies.

The study has limitations. First, the most complete production count was available only for the pasta packaging machine, while the other machines were evaluated mainly through acoustic and qualitative operational observations. Second, the industrial environment may include reflections and background noise that influence sound readings. Third, the observed efficiency relationship is based on a small number of machines and should be validated with longer production records. Despite these limitations, the study provides a useful framework for future work because it shows how sound measurement can be connected with output loss, not only with noise exposure. To support the practical implementation of this framework, a structured summary of the recommended acoustic-based maintenance actions is provided in Table 2.

Table 2. Acoustic-based Maintenance Actions

Observed Acoustic Condition	Likely Machine issue	Recommended Action	Expected Production Benefit
Slower repetitive cutter rhythm	Pneumatic delay, dull blade, timing sensor error, or actuator friction	Inspect valve, blade, actuator alignment, and sensor calibration	Restore cycle timing and reduce missed output
High continuous motor sound	Bearing wear, imbalance, loose mount, or fan problem	Balance rotating parts, replace bearings, inspect fan, and tighten mounts	Improve reliability and reduce unplanned stoppage
Gearbox whining or rattling	Poor lubrication, gear wear, or misalignment	Check oil condition, tooth wear, shaft alignment, and casing vibration	Reduce energy loss and support stable transmission
Tool chatter during cutting or drilling	Dull tool, wrong feed rate, poor clamping, or spindle vibration	Replace tool, adjust feed, improve clamping, and inspect spindle	Improve product quality and maintain designed speed

## CONCLUSION

This paper improved the attached manuscript by restructuring it according to the journal template and by strengthening the relationship between industrial noise, machine condition, and production efficiency. The main finding is that industrial noise can function as a practical performance indicator when it is analyzed together with cycle timing and production output. The pasta packaging machine case showed that a cutter operating at about one and two-thirds seconds per cycle instead of one and one-half seconds per cycle reduced production from four hundred to three hundred sixty-one bags in ten minutes. This loss of thirty-nine bags represents about nine point seven-five percent of expected output.

The broader comparative observations suggest that louder machines often require greater maintenance attention and may operate with reduced stability. Motors, gearboxes, cutters, and drilling interfaces should therefore be treated as priority components for acoustic monitoring. The results answer the main research problem by showing that noise is not only an occupational issue but also an engineering and productivity issue.

For further study, longer production records should be collected from all machines, and acoustic data should be synchronized with energy consumption, vibration, temperature, downtime, and product quality. Future research should also test simple monitoring systems that alert operators when the sound rhythm or sound pressure level moves away from the normal baseline. The suggested application is a preventive maintenance program in which abnormal noise automatically triggers inspection before output losses become large. In this way, noise control, maintenance, and production efficiency can be managed as one integrated industrial improvement strategy.

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