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A CONCEPTUAL ARCHITECTURE FOR AI-ENABLED PREDICTIVE MAINTENANCE OF PNEUMATIC SYSTEMS IN AUTOMOTIVE MANUFACTURING: TOWARD MAINTENANCE 4.0

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Abstract

Industry 4.0 and the Emergence of Maintenance 4.0 Manufacturing companies commonly compressed air for their operations to produce productivity. Compressed air drives the pneumatic parts of the machinery in the factory. The machineries hand tools, material handling system, component manufacturing machines in almost manufacturing companies. Compressed air is one of the most important but waste making utilities in industries. The waste is difficult measure and control as it is invisible. Most of the maintenance professionals follow the periodic preventive maintenance or breakdown maintennace. So, this type of energy and failure take surprising. And difficult to detect. This conceptual paper suggests a layered architecture that includes sensing devices, computation, Cloud analysis and decision-making support for AI- enabled predictive maintenance. Covering losses and controlling the sustainability goal. This pneumatic system detection helps to support for AI enabled predictive detection maintenance aligning Industry 4.0 principle. The architecture of the methodology is illustrated in such a way that air leak detection management becomes autonomous for real time monitoring of the machines in manufacturing scenario grounded in predictive maintenance practices. The paper analyses the literature on predictive maintenance and prescriptive maintenance, on ultrasonic and infrared detection supporting industry 4.0 adoption. The paper contributes to the structured, practitioner relevant framework for maintenance 4.0 research and proposes a methodology for the future empirical validation in automobile manufacturing companies. The future implications and suggestions are discussed with the framework limitations.

Keywords: Predictive Maintenance, Maintenance 4.0, Pneumatic System, Industry 4.0, Compressed Air Leak Detection, Decision Support System, Conceptual Framework.

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1. Introduction

Machine maintenance is seen as part of waste management so they were giving attention only to the machines when they are failed to operate. This type of sign is still seen in some companies. This reactive maintenance is very costly as it is unplanned breakdown. This disturbs the scheduling, customer commitment. As manufacturing has grown more complex the maintenance has moved from the periphery of operations to the Centre of competitive strategy (Zonta et al., 2020). The Compressed air is most focused utility as it is more costly, and pneumatic components appear in almost all automotive industries. These industries are paint shop actuators, to assembly line clamping tools.

Compressed air is also more expensive to generate (Saidur et al., 2010). In manufacturing units compressed air is costliest utility. As per unit of delivered compressed air is costly. And becomes more waste due to air leakages in the compressed air network supplied to machinery.

A single minute unseen leak can run continuously for months and quietly add to the electricity bill which will be not easily recognized (Czopek et al., 2022).

Industry 4.0 has introduced sensors, connectivity, and machine learning that will help principle, detect such losses early. Further guiding suggesting timely action (Amruthnath & Gupta, 2018). However, predictive-maintenance research focuses on vibration analysis and temperature monitoring on rotating machinery online, that helps bearings and motors failures (Zonta et al., 2020). Compressed air recent reviews cover fault detection in compressed air systems (Borg et al., 2023; Mallia et al., 2023). But not an integrated decision architecture. Though there are major losses and their energy footprint. Therefore there is a gap between what Industry 4.0 technology can do and how that technology is managed for pneumatic maintenance in troubleshooting practice.

This paper helps to address that gap. This paper proposes a conceptual architecture that connects sensing, data analytics, and human decision-making into one single system for pneumatic real tie leak detection and support maintenance. The concept architecture is laid in maintenance methodology and inside the practical realities of automotive manufacturing in India. Here cost sensitivity and workforce readiness supports what any new system must achieve.

This paper has three objectives:

1) To propose a conceptual architecture for AI-enabled predictive maintenance for pneumatic circuits.
2) To show how the architecture works on compressed-air leak management scenario.
3) To suggest how frame work will help for testing the framework empirically in future research.

2. Theoretical Background

2.1 The Evolution of Maintenance Strategies

Maintenance Methodology has moved in four major stages. The first, run till failure, which is purely reactive maintenance practice. This method is easy to follow but can be costly because it leads to unexpected downtime. The extra damage caused by these unplanned stoppages usually ends up being more expensive than regular maintenance fixes. In the second stage, maintenance is done on a regular schedule, and parts are replaced even if they aren't broken yet. This helps avoid sudden equipment failures, but it often results in using spare parts and labor unnecessarily.In the third stage, maintenance uses data from sensors to track how well equipment is working and to plan repairs only when they are truly needed. (Do et al., 2015; Hector & Panjanathan, 2024, Jardine et al. (2006), Zonta et al., 2020; Achouch et al., (2022)). In the fourth and most recent stage that is prescriptive maintenance which goes further still (Ansari et al., 2019). It does not just predict

machine failure, it recommends the best action to be taken to correct, considering into account cost, urgency, and resource availability. Figure 1 summarizes this progression.

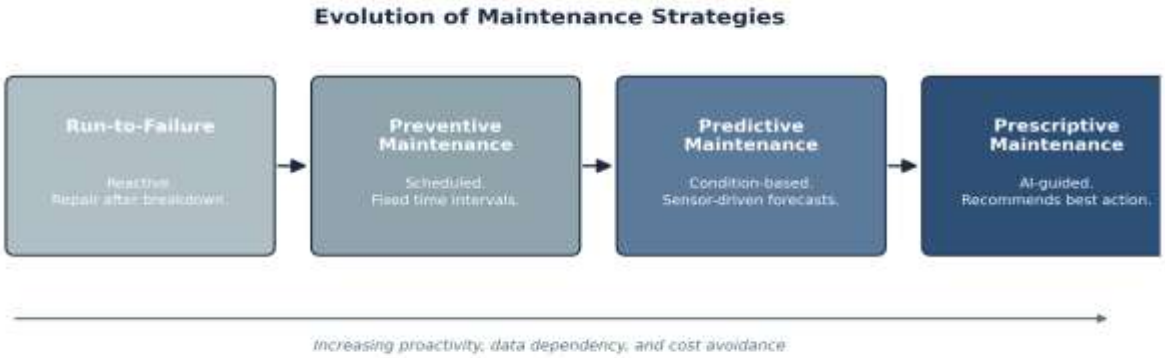


Figure 1. Evolution of maintenance strategies from reactive repair to prescriptive AI-guided decision-making

The way maintenance is handled has changed over time, starting with fixing things after they break and moving toward using AI to make smart decisions. Each step in this process is important and depends on the previous one. You can't jump straight to using predictions for maintenance without first having good data to work with. Similarly, you can't go straight to AI-based decisions without first having reliable predictive models. This step-by-step approach helps build the structure of the system that will be discussed later in this paper.

Industry 4.0 is structured on the integration of physical equipment with digital systems. Sensors capture data from machines in real time and monitor. That data passes through networks to computing systems, where machine learning models turn raw signals into early warning of failure (Amruthnath & Gupta, 2018). When it comes to maintenance, researchers are starting to use the term Maintenance 4.0 more often.This term describes a maintenance approach that uses data, is connected, and can offer suggestions and recommendations on its own to some extent.

2.2 Pneumatic Systems as a Maintenance-Critical, Energy-Critical Domain

Pneumatic systems depend on compressed air that move the actuators, operate machinery, and power automated processes. Compressed air is not free, generating electricity is needed. The industry surveys commonly report that compressed air is meaningful share of a manufacturing site's total energy bill (Saidur et al., 2010). A large amount of this energy is wasted due to leaks in the joints, connections, valves, and old seals of pneumatic systems. (Saidur et al., 2010; Borg et al., 2023). Remaining unaddressed minor leakages can indicate larger equipment failures with energy losses. Since similar wear that causes a leak often points to a component which are nearing to the end of its service life.

Two non-contact methods lead the leak detection in current practice. Ultrasonic detection listens to the high-frequency turbulence that is leaking from air produces network (Czopek et al., 2022). It gives a signal well above the range of normal factory noise. On other hand Infrared thermography instead looks for the temperature change that occurs surrounding a leakage point. Comparative studies suggest that ultrasonic detection is highly sensitive and helpful for small leaks. Whereas the thermography performs effectively for larger orifices and offers a visual record

that non-specialists can interpret easily to understand (Dudic et al., 2012; Hassan et al., 2020). Combining both methods, instead relying on either one alone, gives a more complete picture of leakage severity and location.

Despite the maturity level of these detection technologies, they are rarely integrated within broader digital maintenance architecture. Most compressed-air audits are performed periodically (Borg et al., 2023). Manual exercises are there rather than continuous, real-time-connected ones. This is precisely the gap identified which propose the architecture seeks to close with solution.

2.3 Industry 4.0 Adoption in Indian Automotive Manufacturing

Any new architecture plan intended for Indian automotive plants must fit the reality of technology adoption that how this work. B ig challenges is for Empirical studies consistently identify high implementation cost, limited technical skill, and acceptance about return on investment as leading barriers to Industry 4.0 adoption among Indian manufacturers (Kamble et al., 2018; Khanzode et al., 2021, Raj et al., 2020). Automotive industries specific research adds further details: fear of technological outdated too quickly and unclear who is managing these projects of digital initiatives. Also, slow adoption of technology even though the underlying technology is ready to use (Ojha et al., 2024).

These fact findings is important for maintenance architecture design. A system that assumes the requirement of unlimited budgets, specialist of data-science on staff, or immediate top-management support to the project is unlikely to survive contact with a typical Indian plant floor. Because of these challenges the system proposed in this paper is designed to be modular, so the plants can adopt it in the individual layers, such as simple sensing and connectivity, before spending money to advanced and full automated systems.

3. Research Gap and Objectives

The literature studies reviewed above reveal three gaps.

1. Most predictive-maintenance research focuses on rotating machinery (Zonta et al., 2020; Borg et al., 2023; Mallia et al., 2023). It leaves out pneumatic systems even though under their prevalence and energy cost.
2. Current leak detection studies only look on measurement accuracy rather than how the detection data should help full into a broader decision-making system (Czopek et al., 2022; Borg et al., 2023).
3. Industry 4.0 adoption studies shows barriers in the Indian manufacturing industries, but these are rarely translating into concrete design guidance for a maintenance architecture (Raj et al., 2020; Ojha et al., 2024).

- This paper aims to address these gaps through three main goals:
- To propose a multi-layer conceptual framework that connects sensing, data, analysis, and human decisions to support predictive maintenance for pneumatic systems.
- To illustrate the architecture through an example of compressed-air leak management scenario grounded in automotive manufacturing practice.
- To outline a step-by-step methodology for validating the framework in future research, using real data collection from automotive plant.

4. Proposed Conceptual Framework

4.1 A Layered Architecture for Pneumatic Predictive Maintenance

The proposed architecture organises seven layers design for predictive maintenance need of pneumatic system. Moving from the physical asset to the human decision-maker every layer must performs a distinct function, and they depend on the layer below it is functioning correctly.

Figure 2 Presents the full architecture. The physical asset layer includes the compressors, valves, actuators, and piping that all together make up the pneumatic system itself. The sensing layer like ultrasonic, pressure, flow, temperature, and vibration sensors attach to these assets. These generates the raw signals that is all required to the higher layers.

The edge acquirement layer conditions and pre-processes these signals near to their source. Thus, reducing the volume of data that must transmitted further and catch the obvious anomalies early. The connectivity layer transfers this data, using wired either wireless industrial network, to storage and computing resources that are in use. The analytics and digital twin layer is where raw data becomes give the correct insight. Machine learning models trained on historical failure and leak data estimate the likelihood and the severity of emerging problems. Whereas a digital twin allows managers to simulate the outcomes of different maintenance methods (Tao et al., 2019; Errandonea et al., 2020).



Figure 2. Proposed conceptual architecture for AI-enabled predictive maintenance of pneumatic systems.

The analytics and digital twin layer is where raw data becomes give the correct insight. Machine learning models trained on historical failure and leak data estimate the likelihood and the severity of emerging problems. Whereas a digital twin allows managers to simulate the outcomes of different maintenance methods. The decision support layer interprets these evaluations into concrete recommendations for decision making (Ansari et al., 2019). This is also integrating with existing computerised maintenance management systems and enterprise resource planning systems to check and verify spares availability and generate work orders into system automatically. Finally, the human interface layer involves maintenance managers and technicians at the centre of

the system. They review the abnormalities, question, and where necessary take priority over the recommendations that the system produces (Lee & See, 2004). And further their decisions and actions feed back into analytics layer, so the system improves further with use.
This feedback loop is measured. A prescriptive solution system that never learns from human correction will flow away from the specific conditions of the plant it serves. Additional feedback keeps the system architecture responsive to local human expertise instead replacing it.

4.2 Illustrative Application: Compressed-Air Leak Management

To make the architecture rigid consider how it would function for compressed-air leak management, a common issue to almost every automotive plant. Figure 3 below shows the decision loop this example would follow within the architecture system. Continuous ultrasonic monitoring, potentially supplemented real time thermographic scans. Which would detect leaks as they occur rather than waiting for a preventive scheduled audit. Each detected leak would be divided according to severity. Obtaining on established thresholds from leak-detection research, and its likely electrical cost would be estimated. Table 1 represents figures for this estimation step, based on standard compressed-air engineering relationships (the US DOE *Compressed Air System Sourcebook* for the orifice table).

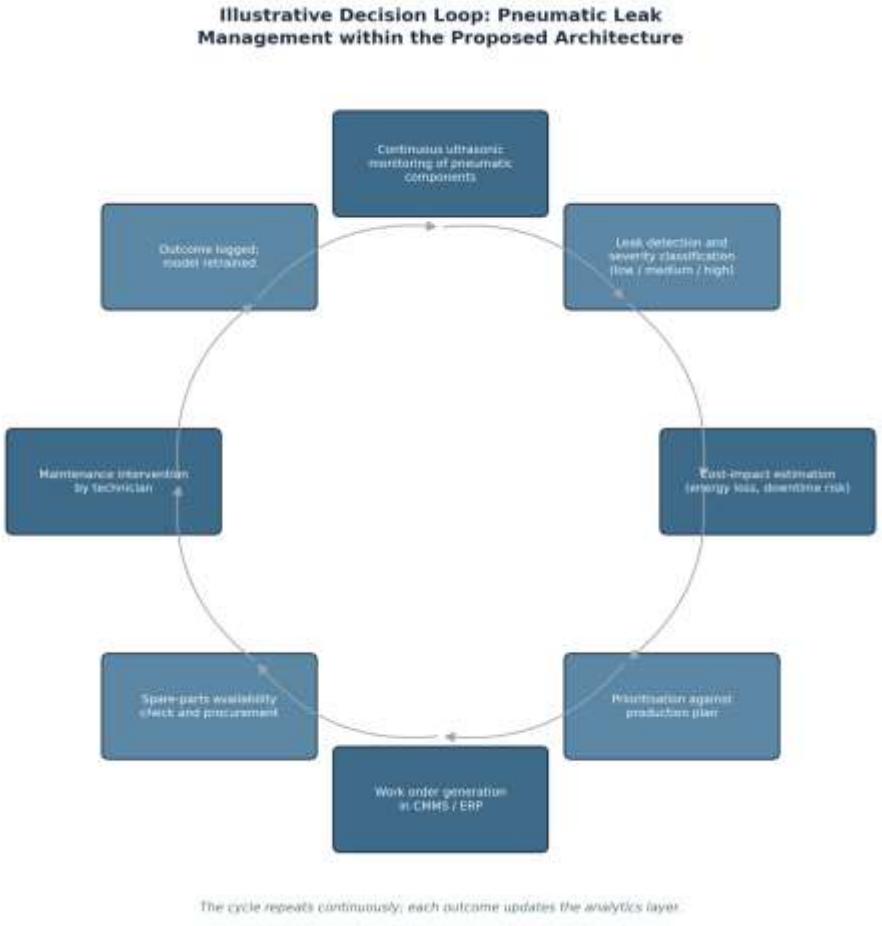


Figure 3. Illustrative decision loop for pneumatic leak management within the proposed architecture.

This is done to avoid dependency on the primary data collected for this paper. The underlying assumptions are for continuous operation, the electricity tariff typical of Indian industrial users, and a specific power ratio normally cited in compressed air energy audits (Radgen & Blaustein, 2001).

Orifice Diameter (mm)	Estimated Air Leakage (cfm)	Estimated power Wasted (Kw)	Illustrative Annual Energy Cost (INR)
1.6	6.5	1.08	~ 51,300
3.2	26	4.33	~2,05,700
6.4	104	17.33	~8,23,600

These figures show the order of magnitude involved whereas not a specific plant's measured performance. The system evaluation of leaks application of the framework should replace them with data collected on site. Once severity and cost are evaluated the system will priorities the leak according to the production plan. Later generate a work order in the plant's maintenance system with check spares availability and support the maintenance technician who carries out this repair. The outcome of this repair would then be logged and used to further refine the underlying models and that closing the loop shown in Figure 2.

This scenario shows how the seven layers work together in a familiar maintenance issue. It also depicts that the architecture system does not require an entirely new set of tools. It requires existing connecting tools that already exist, such as ultrasonic detectors, spares databases, and maintenance software, into a single, continuously learning system.

5. Research Methodology

As this is a conceptual paper, this study does not report any primary empirical data. Its contribution is the architecture itself that developed through a structured conceptual research process (Jaakkola, 2020; Gilson & Goldberg, 2015). Figure 4 below outlines this process and the steps intended to extend it into empirical state.

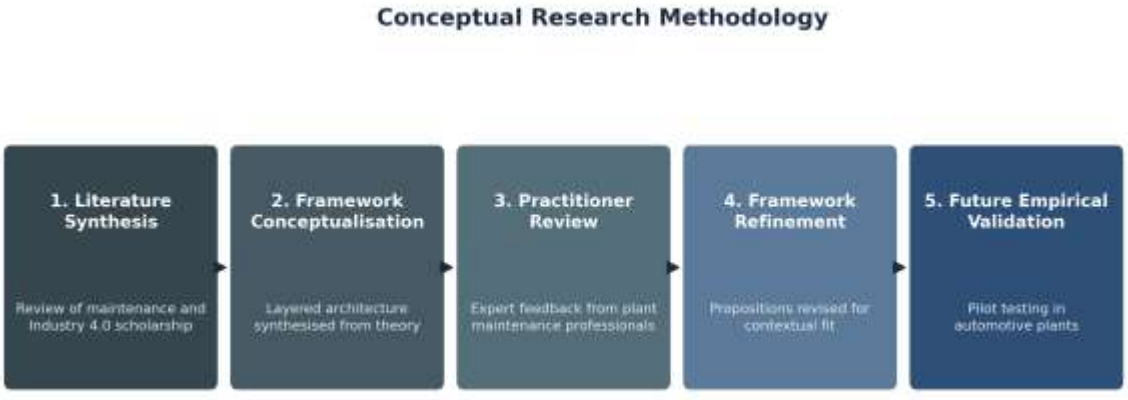


Figure 4. Conceptual research methodology, from literature synthesis to proposed empirical validation.

The architecture was built in two stages. First literature on maintenance theory, Industry 4.0 architecture, compressed-air leak detection, and Industry 4.0 adoption in Indian manufacturing was reviewed. This was done to identify the functional layers a pneumatic predictive-maintenance system requires. Second further these layers were organised into the framework displayed in Figure 2, checking at each step that the resulting structure stayed reliable with existing maintenance theory. And also with the practical constraints documented in the Indian manufacturing adoption literature.

This conceptual framework is a initial starting point rather than a ready finished tool. Three further steps are proposed for future research. 1.The framework should be reviewed by practising maintenance managers and engineers in automotive plants. This is to check whether its layers and terminology match how professionals actually think about pneumatic maintenance. 2. The framework should be enhanced based on this feedback of the decision support layer. Whereas the integration with existing plant software will vary from one company to another. 3.A pilot implementation should be carried out in one or more automotive plants. This is for measuring outcomes of the implementation, such as leak-detection lead time, energy savings, and technician acceptance of system recommendations. This pilot stage will connect naturally to the survey-based and statistical validation methods already utilised in related Maintenance 4.0 research in this setting.

6. Discussion

6.1 Theoretical Implications

This paper contributes to maintenance theory by covering the established evolution from reactive to prescriptive maintenance into the domain of pneumatic systems (Ansari et al., 2019; Zonta et al., 2020). This will align with the existing Industry 4.0 architecture research has largely skipped. It also merges two bodies of literature that rarely meet the technical literature on leak detection methods and the organisational literature on Industry 4.0 adoption obstacles. This paper has designed a system with real world contraints . Many companies faces different challenges such as budgets and short of technical skill manpower.

This offeres a pratical version for maintenance 4.0 theory. This approach also understands not all manufacturing plant are ready for advance technology.

6.2 Managerial Implications

For maintenance managers this architecture gives a way to step by step method investment. Any plant does not need to adopt every layer at once it can develop gradually with other methodology (Giliyana et al., 2024; Raj et al., 2020). Basic sensing and connectivity can be implemented at first. That will relatively costs low before a plant commits to advanced analytics solutions or a full digital twin. This phased method matches the resource limitations documented in Indian manufacturing adoption research. This aligns to gives managers a clear reasoning for each stage of implementation investment. The architecture also highlights workforce willingness as a design requirement. This is not an second thought that the human interface layer works only if technicians are trained to interpret and act on system recommendations. Also if their feedback is genuinely used to improve the system.

6.3 Policy Implications

Compressed-air leakage wates energy and affects industrial efficiency targets and business goals (Saidur et al., 2010). The systematic approach supports national goals for improving energy effeciancy and sustainable manufacturing. The digitalisation programs by government can use this

framework to help the smaller companies. It provides a low risk and practical entry point for business taking initial steps in the industry 4.0 implementation.

7. Limitations and Future Research

This paper has three main limitations.

1) It is aconceptual paper, the architecture in this has not yet been tested empirically, and its practical performance need to be demonstrated.

2) The illustrative cost figures on Table 1 are general scale for estimates based on standard engineering relationships. This is not exact measurements from a specific plant. It should not be read as validated findings.

3) The paper focuses on automotive manufacturing Plants and the architecture's relevance to other industries or regions has not been established and would requires separate validation.

Future researchers need to test the steps described in section 5 to prioritise the empirical validation beginning with practitioner trail review and moving toward a pilot implementationof the concept. Next researchers should also look closely the human factors involved in prescriptive maintenance adoption tectnology. Since trust between technicians and automated result is likely to determine whether any such system succeeds in practice, regardless of its technical complexity (Lee & See, 2004).

8. Conclusion

Pneumatic systems are very common and are costly to run. But this is ussually ignored for the studies of predictive maintenance and relatively under-served by predictive-maintenance research. This paper has proposed a seven-layer conceptual architecture model. This model connects sensing, data, analytics, and human decision-making to address this gap. The illustrated architecture model is explained through a compressed-air leak management scenario relevant to automotive manufacturing. This framework is designed to be adopted in stages making it easy to implement.

The suggested model helps to overcome the reflecting resource and skill constraints documented in Indian manufacturing research. It proposes a clear path toward empirical validation in automotive plants. As manufacturing continues to develop in digitalise frameworks that connect established maintenance theory to practical results. The sector-specific implementation will be needed to ensure that Industry 4.0 investment is helping the real problems and energy savings on the shop floor.

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