Data Acquisition for Condition-Based Maintenance

Oleksandr Romanenko[1,*,†], Andrey Kupin[1,†] , Dmytro Zubov[2,†] and Vladyslav Holiver[1,†]

[1] Kryvyi Rih National University, Vitaly Matusevich 11, Kryvyi Rih, 50027, Ukraine
[2] University of Central Asia, 125/1 Toktogul Street, Bishkek, 720001, Kyrgyzstan

Abstract

Data acquisition (DAQ) systems are fundamental to condition-based maintenance (CBM), serving as the critical interface between physical machinery and digital analysis platforms. As industrial systems grow increasingly complex, effective maintenance strategies have evolved from reactive and time-based approaches to predictive methods that rely on real-time asset health monitoring. This shift has been enabled by advances in sensor technology and computational capabilities, making continuous equipment monitoring both technically feasible and economically viable. However, the success of CBM implementations depends heavily on the quality and reliability of their underlying data acquisition infrastructure. Poor data quality, inadequate sampling rates, or incomplete sensor coverage can result in missed failure indicators, false alarms, and suboptimal maintenance decisions, potentially leading to equipment failures, supply chain disruptions, and significant economic losses. This research examines foundational principles of data acquisition systems, addressing their structure, components, and functions. We have decomposed the DAS into three fundamental subsystems: measurement, conditioning and transferring, providing essential knowledge about data acquisition.

Keywords

Data, Data acquisition, Maintenance, Condition-based maintenance

1. Introduction

Maintenance is a critical aspect of any industrial process. It influences machinery availability, product quality, personnel safety, economic viability of manufacturing. As industrial systems become increasingly more sophisticated, the consequences of equipment failure extend far beyond simple repair costs, potentially causing supply chain disruptions, environmental incidents, and reputational damage. The evolution of maintenance strategies — from reactive approach to preventive time-based schedules and now to predictive methods reflects the growing recognition that maintenance is not merely a cost center but a strategic function.

Condition-based maintenance, or CBM for short, represents a paradigmatic shift in industrial maintenance philosophy. It has significantly transformed how organizations approach asset maintenance management. At its core, CBM is a maintenance approach built around the knowledge of the actual health conditions of equipment and systems through continuous or periodic monitoring of performance indicators, allowing maintenance crew to make decisions based on real-time data about asset health rather than intervening only on predetermined schedules or executing reactive responses to random failures.

CBM became possible for a couple reasons. The first being technological advancement in sensors technology, which has dramatically improved in terms of accuracy, reliability, and cost-effectiveness over the past two decades. Modern sensors can now detect changes in vibration patterns, temperature fluctuations, acoustic signatures, and chemical compositions with unprecedented

ICST-2025: Information Control Systems & Technologies, September 24-26, 2025, Odesa, Ukraine

* Corresponding author.
† These authors contributed equally.
romanenko74@knu.edu.ua (O. Romanenko); kupin@knu.edu.ua (A. Kupin); dzubov@ieee.org (D. Zubov); holivervlad@gmail.com (V. Holiver)
0009-0008-9316-1941 (O. Romanenko); 0000-0001-7569-1721 (A. Kupin); 0000-0002-5601-7827 (D. Zubov); 0000-0002-8276-5992 (V. Holiver)

precision. The second enabler is the evolution of data processing methods and communication technologies. The exponential growth in computational power has enabled real-time processing of complex multi-dimensional data, while advances in communication technologies have facilitated data transmission from remote or hard-to-access equipment locations.

Since CBM heavily relies on data, reflecting assets' physical conditions, it is essential to understand the data gathering process. While extensive literature exists on advanced analytics, machine learning algorithms, and decision-making frameworks for CBM, there is a notable gap in comprehensive examination of the data acquisition systems that serve as the foundation for all subsequent analysis. Data acquisition systems function as the critical interface between the physical world of machinery and the digital realm of analysis and decision-making, yet they are often treated as a given rather than a subject requiring careful study.

This paper focuses specifically on the data acquisition phase of condition-based maintenance, examining fundamental principles, system architectures, and design considerations that influence data quality and system reliability. While we acknowledge the importance of subsequent data processing, analysis, and decision-making phases, these topics are addressed only insofar as they inform data acquisition requirements.

The paper is organized as follows: Section 2 examines CBM fundamentals, including historical development, standard definitions, and system architectures that establish the context for data acquisition in CBM. Section 3 provides an analysis of data acquisition systems, including brief historical evolution from purely mechanical instruments to modern digital platforms, fundamental principles of operation, and systematic decomposition into three core subsystems: measurement, conditioning, and transferring.

2. Fundamentals of condition-based maintenance

2.1. CBM: History overview and definition

The condition-based maintenance approach has been around for decades. It originated in the late 40's as a method for detecting engine's liquids leaks. The application of CBM resulted in reduced engine failure rate, which in turn delivered significant economic benefits [1].

The US Department of Defense recognized the benefits of such maintenance approach and adopted it in the 1950s. After that, the CBM gradually started gaining popularity among industrial manufacturers and facility operators [2]. With current advances in technologies, CBM has become easier to implement, and now we see it being used in various domains: from military to healthcare.

Over the years there has been devised many definitions of CBM. Here we'll take a look at some of the definitions and will try to gain a comprehensive understanding of the concept which is required for further research.

The British implementation of EN 13306:2017 Standard defines condition-based maintenance as preventive maintenance which include assessment of physical conditions, analysis and the possible ensuing maintenance actions [3].

CBM is a maintenance approach that emphasizes the use of data-driven reliability models along with data collected from monitored systems [4].

In work [5] authors claim that CBM is a subtype of preventive maintenance and it purpose is to support decision-making process utilizing information obtained through condition monitoring.

It is evident from the provided definitions that condition assessment is a common element and the concept of CBM is constructed around it. Thus, retrieval of information describing these conditions is key part of CBM and has to be researched.

In the following sections we will explore the structure of CBM and examine how condition assessment data is collected, analyzed, and integrated into maintenance decision-making processes.

2.2. CBM Architecture

Condition-based maintenance is an elaborate multi-process activity that can be functionally represented as shown in Figure 1.

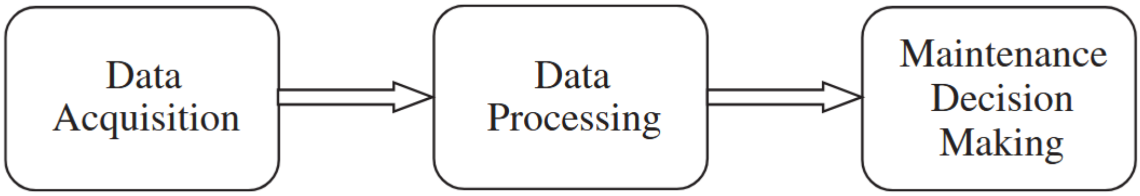

Figure 1: CBM constituent processes [6]

Figure 1 represents three sequential processes comprising CBM. Data acquisition involves collecting relevant data representing the operational health status of a system or piece of equipment. Data processing step encompasses data conditioning and analysis like statistical analysis, simulations using different modeling approaches etc [7]. Data processing results are next used for decision-making support. The diagram in Figure 2 shows CBM in more detail.

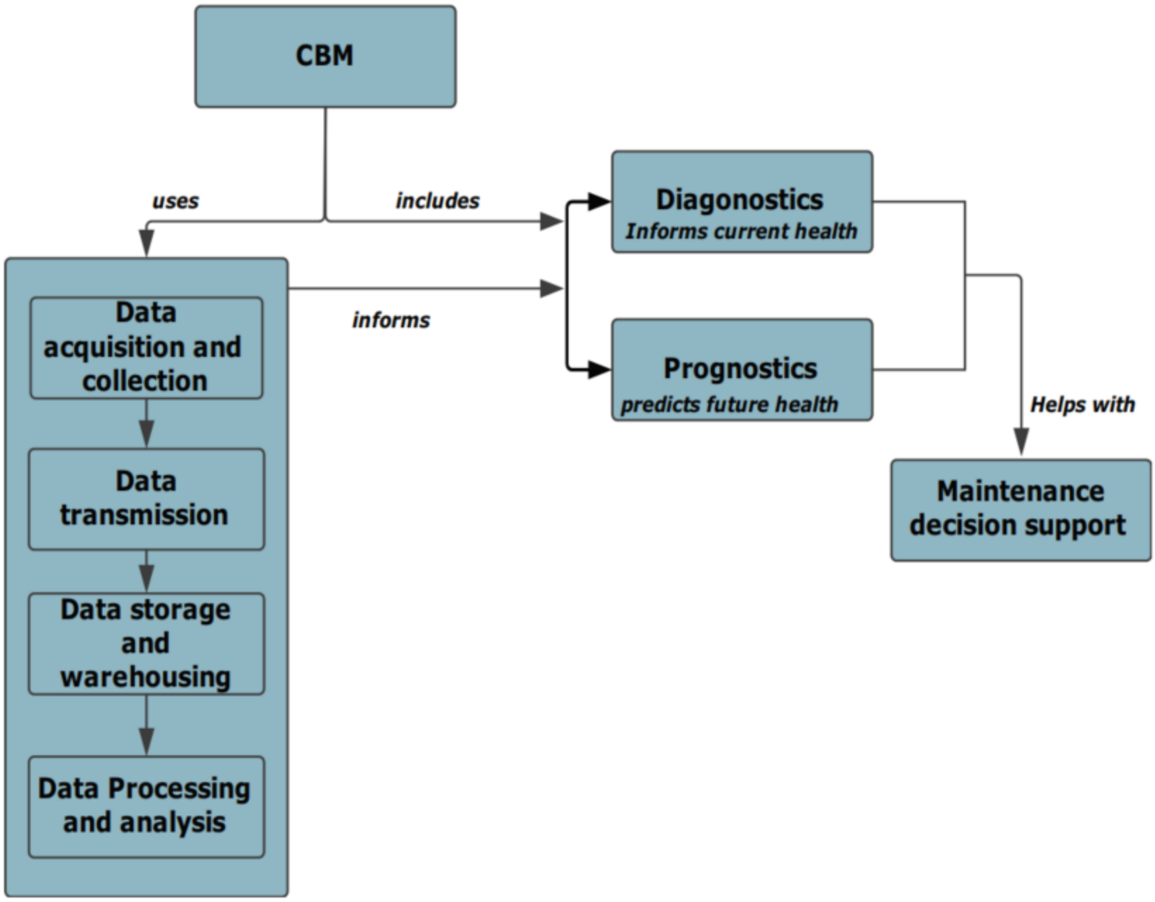

Figure 2: Detailed CBM representation [2].

The International Organization for Standardization defines the communication architecture for condition monitoring and diagnostics as shown in Figure 3. This architecture specifies data-processing functions of a condition monitoring and diagnostics system.

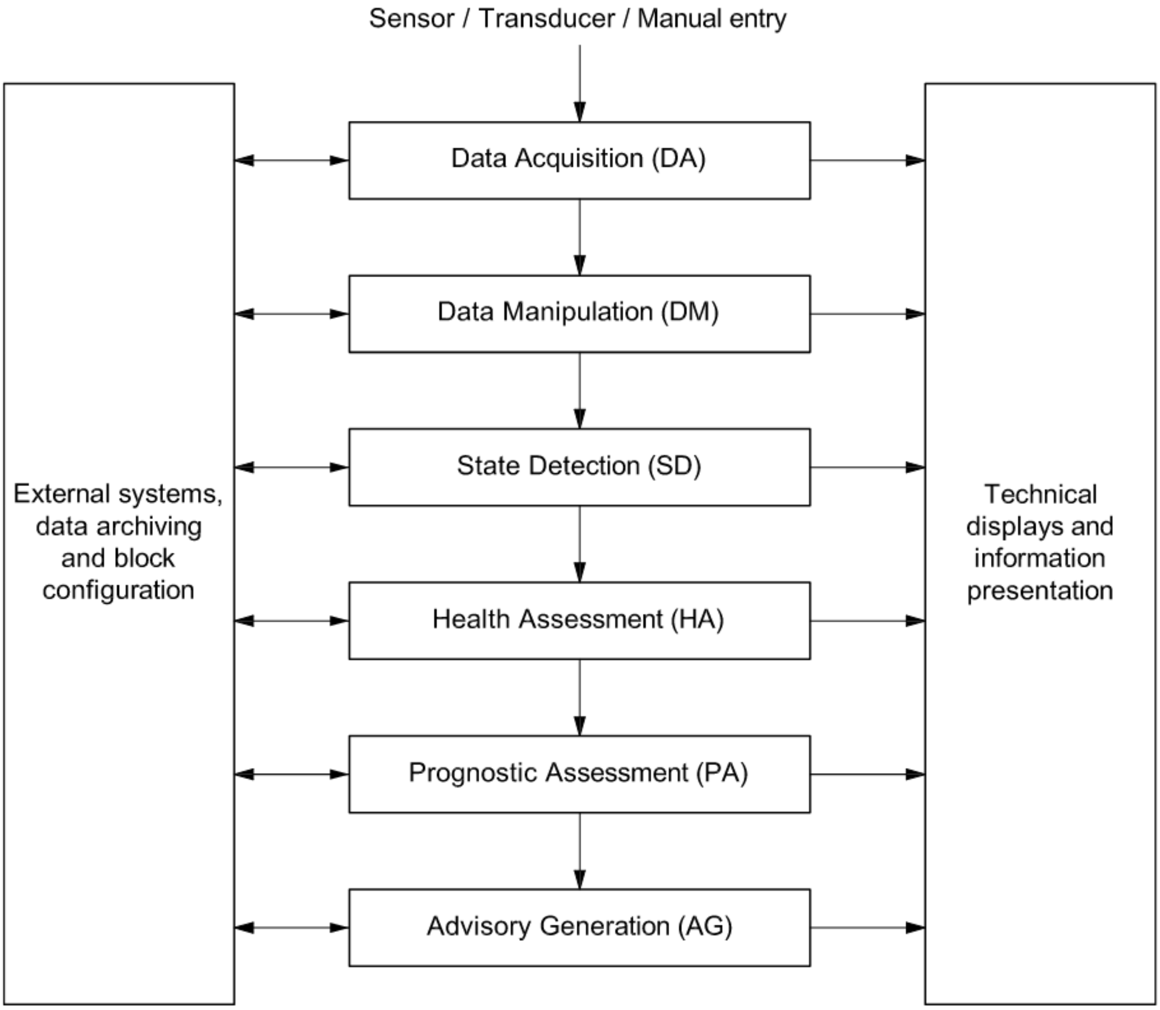

Figure 3: Data-processing block diagram [8].

The architecture developed by ISO defines functional blocks that are very similar to what we have seen in Figure 2. And all three diagrams that have been investigated shares the data acquisition function. So, data acquisition can be identified as the core component that underpins condition-based maintenance methodology, making it a critical area for further investigation.

The next part of this paper is devoted to the research of data acquisition systems, their structure, components and functions.

3. Data acquisition systems

3.1. Data acquisition - overall description

Apart from maintenance applications, Data Acquisition Systems (DAS) are utilized in various fields, including industrial control, scientific research, environmental monitoring and more. When we will introduce a definition of DAS it becomes clear that variations of such systems are widely used in almost all aspects of human activity.

As the name suggests, data acquisition system is used to acquire data from some type of source or in other words, it is a type of system that realizes the process of data acquisition.

According to [9] data acquisition is a process of acquiring raw data in the form of electrical or other physical phenomena from various sources and converting them into a measurable signal suitable for processing.

Another definition suggests that data acquisition is a process of gathering signals from real-world measurement sources and digitizing those signals for storage, analysis, and presentation [10].

Data acquisition is the process of capturing and measuring physical data and converting the results into a digital form that is further manipulated by a system [11].

All the provided definitions mention two functions of DAQ:

1. Data acquisition or data capturing
2. Data conversion (e.g. digitalization)

But all three definitions while capturing the essential aspects of DAQ, miss one critical process involved that is data transfer. This omission is significant because without effective data transfer, even the most accurate measurements and precise conversions become meaningless if they cannot reach the systems where analysis and decision-making occur.

In this work we define data acquisition as the process of measuring physical phenomena, conditioning the resulting signals, and transferring the acquired data to a destination system for further manipulations.

Under the term “manipulations” we imply storage, analysis or any other processing. We consider that DAQ encompasses the transformation from physical phenomenon to usable digital data, with storage being one of several possible endpoints rather than a mandatory component. If there are data processing capabilities integrated within the system that performs DAQ then such system might be termed as “data acquisition and analysis system”.

3.2. A short history of data acquisition

Before investigating the actual structure and constituents of data acquisition systems, we consider it necessary to examine such systems from a historical perspective.

The first means for gathering data were purely mechanical. In the late 1790s James Watt constructed a steam engine indicator - an instrument that would graphically record the cylinder pressure versus piston displacement through an engine stroke cycle (Figure 4). This device might be considered the first automated mean for data acquisition.

Figure 4: Watt’s Steam Engine Indicator [12]

The evolution from purely mechanical recording continued into the electromechanical devices like pressure indicator and recorder patented in 1888 by William Henry Bristol. This device was a chart recorder that used an electromechanical mechanism to drive a pen across paper at a steady rate, providing a permanent graphical record of pressure measurements over time [13].

Different variations of chart recorders, like the one shown in Figure 5 had been used for data logging until 1960s when data acquisition started shifting towards electronic means.

Figure 5: Chart recorder. [Public domain], via. dicksondata.com (https://dicksondata.com/product/8-pressure-chart-recorder).

The next major advancement in data acquisition came with the use of specialized computers. Systems like IBM 7700 or IBM 1800 (Figure 6) provided improved speed, accuracy, and automation in data collection.

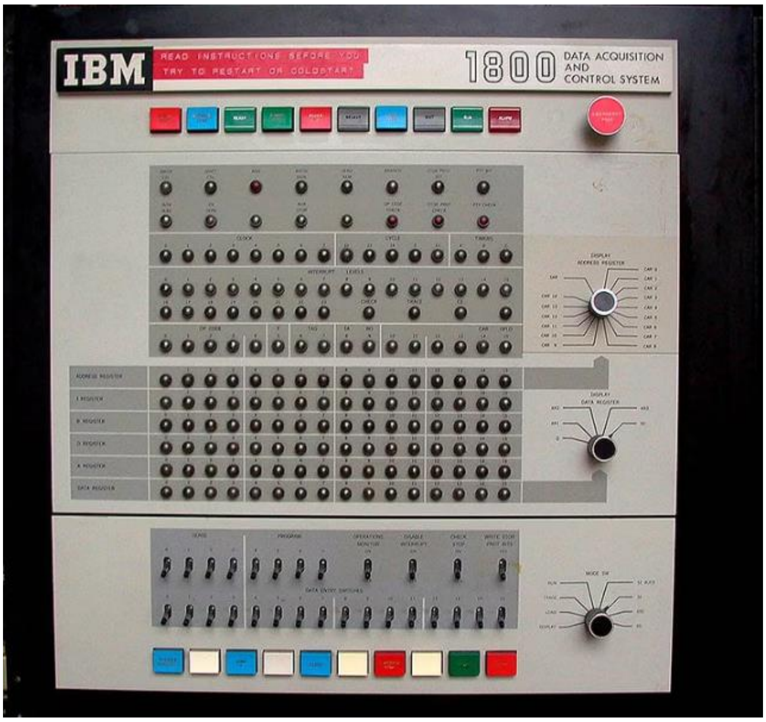

Figure 6: IBM 1800 Data Acquisition and Control System. [Public domain] via dewesost.com (https://dewesoft.com/blog/data-acquisition-history)

The introduction of personal computers in the 1980s transformed data acquisition. The PC-based approach provided enormous advantages: costs dropped from tens of thousands to hundreds of dollars, systems became easily customizable through software, and users could leverage rapidly improving computer performance.

Modern DAS implementations leverage modular design principles to achieve scalability and adaptability across diverse application scenarios. The modular nature of contemporary systems enables researchers and engineers to configure parameters like sampling rates or signal conditioning parameters according to specific use case scenarios. The integration of programmable hardware (like FPGAs) makes it possible to create reconfigurable hardware components performing real-time signal processing. Furthermore, the adoption of standardized communication protocols such as Ethernet-based interfaces ensures compatibility across different manufacturers and facilitates the creation of distributed measurement networks. This architectural flexibility, combined with comprehensive software frameworks that provide abstraction layers for system configuration, enables rapid deployment of customized acquisition solutions without requiring extensive hardware modifications or specialized programming expertise.

3.3. Data acquisition architecture

We have already defined three core actions required in order to implement data acquisition system:

1. Measurement
2. Conditioning
3. Transferring

Each of these three processes can be represented as discrete subsystems. The overall DAS architecture can therefore be visualized as shown in the Figure 7.

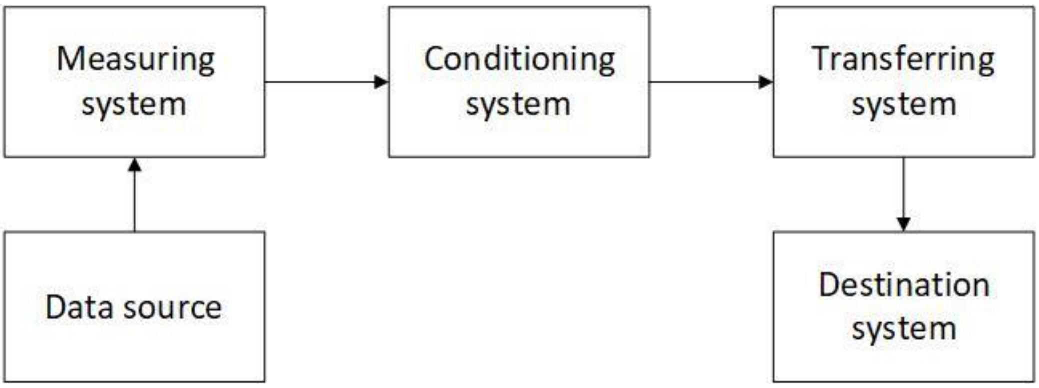

Figure 7: Structural diagram of a data acquisition system

As illustrated in the Figure 7 above, the data acquisition begins from data source which might be any object. In the context of maintenance data source is a piece of equipment to be maintained, for instance, it could be an electrical motor or CNC machine. This data source is characterized by some measurable physical phenomena that reflect its state. These phenomena might be mechanical vibrations, temperature, acoustic emissions, electrical parameters (current, voltage, power factor), fluid properties (in hydraulic systems), and other observable quantities that change as the equipment operates or degrades.

The measurement system serves as the interface between physical phenomena and other systems. Measurement is performed by sensors. The term “transducer” is often used alongside with “sensor”, however there are distinct differences between the two that we are determined to explain.

A transducer is a device that transforms one form of energy to another [14]. Most frequently transducers are used to convert non-electrical quantities into electrical signal.

A sensor is a type of transducer specifically designed in order to measure a physical quantity. It works by detecting (sensing) a desired physical quantity and transforming it into readable signals, typically electrical [15].

In summary, all sensors are transducers with the primary purpose of providing specific information about the physical environment, whereas not all transducers function as sensors, as they have a broader purpose encompassing any form of energy conversion.

Following the measurement stage, the acquired signals undergo conditioning – a process that involves signal processing to optimize the acquired signal and make it acceptable for next stages.

Conditioning includes, but is not limited to [16]:

- Amplification/attenuation (scaling)
- Isolation
- Sampling
- Filtering (noise elimination)
- Linearization
- Span and reference shifting
- Mathematical manipulation (e.g., differentiation, division, integration, multiplication or summation)
- Signal conversion (e.g., DC–AC, AC–DC, digital-analog, analog-digital, etc.)
- Buffering
- Digitizing
- Impedance matching

The specific conditioning operations required depend heavily on the characteristics of both the sensor output and the requirements of the subsequent processing stages. Next, we will briefly describe some of the most frequently performed conditioning tasks.

Amplification is a fundamental task in signal conditioning. Usually, the magnitude of a signal produced by a sensor is very weak (millivolt range) the amplification is required for further processing [17]. The amplification is done by special devices - amplifiers.

Filtering serves to eliminate unwanted frequency components and electrical noise that can mask the signals of interest. The basic filter selectively allows the desired signal to pass through it and blocks the undesired signal range based on the frequency [18]. In data acquisition systems, filters are used to preprocess signals before converting analog signal into digital, ensuring that only the relevant frequency components are captured.

Signal isolation is a technique used in electronic systems, and in DAS in particular, to separate different parts of a circuit to prevent unwanted interactions between them. This helps to protect sensitive components from high voltages, noise, and ground loops. Ground loops, which result from potential differences between the signal source ground and the measurement device reference ground, generate circulating currents that can distort measured signals. When these currents become excessive, they may cause equipment damage [16].

Analog-to-digital conversion (ADC) is another important process of the conditioning subsystem. ADC transforms continuous analog signals into discrete values that can be processed by digital computing systems.

Transferring system, as name suggests, transfers measured and conditioned values to a system where they will be processed. Transferring system may be realized as wired, wireless or combined communication system. Now, we will provide a concise overview of communication systems in general as the fundamental principles remain the same regardless of the specific implementation or application domain.

Any communication system consists of five essential components: source, transmitter, channel, receiver, and destination [19]. In the context of data acquisition for maintenance, the information source is a sensor, while the destination is typically a computer system running condition monitoring software or a centralized maintenance management system.

The transmitter prepares the data for transmission. It does so by modulating and encoding the signal according to specific protocols [20]. This includes adding headers, error detection codes, synchronization bits, and formatting the data into packets or frames. Common industrial protocols include Modbus, Profibus, EtherCAT, and OPC-UA, each offering different capabilities in terms of speed, reliability, and real-time performance.

The channel represents the physical medium through which data travels. For wired systems, this includes twisted-pair cables (RS-485, Ethernet), coaxial cables, or fiber optics. Wireless channels utilize electromagnetic waves across various frequency bands, from short-range Bluetooth and Zigbee to long-range cellular and satellite communications.

The receiver performs the inverse operations of the transmitter, extracting the original data from the received signal. This involves demodulation, error checking, packet reassembly, and protocol interpretation [19]. In maintenance applications, receivers must often handle multiple simultaneous data streams from numerous sensors while maintaining time synchronization and data integrity.

4. Data acquisition system model

4.1. Measuring subsystem model

The fundamental measurement process can be represented as a mapping function:

$$M : \Phi \rightarrow S, \tag{1}$$

where:

- Φ represents the space of physical phenomena
- S represents the space of sensor signals
- M is the measurement operator

For a specific measurement at time *t*:

$$s(t) = M[\Phi(t)] + n(t), \tag{2}$$

where:

- $\Phi(t)$ is the physical phenomenon at time t
- $s(t)$ is the measured signal
- $n(t)$ represents measurement noise

4.2. Conditioning subsystem model

The conditioning subsystem transforms raw sensor signals into signals suitable for further processing by digital systems. The conditioning process can be represented as:

$$Y_c = C_n \circ C_{n-1} \cdots \circ C_1(X), \tag{3}$$

where:

- X is input signal (raw sensor data)
- Y_c is output signal (conditioned signal)
- C_i is conditioning operator
- n is total number of conditioning operators

Alternatively, the conditioning process may be represented in a sequential notation:

$$X \xrightarrow{C_1} X_1 \xrightarrow{C_2} X_2 \xrightarrow{C_3} \cdots \xrightarrow{C_n} Y, \tag{4}$$

4.3. Transferring subsystem model

The transferring system can be formally represented as a tuple:

$$T = \langle S, T_x, C, R_x, D \rangle , \quad (5)$$

where:

- *S is source (in this case the source is a signal conditioner)*
- *T_x is transmitter function*
- *C is communication channel function*
- *R_x is receiver function*
- *D is destination system*

4.4. DAS model

Based on the provided scheme in Figure 7 and the models of the defined subsystems, the generalized model of the data acquisition system can be represented as a composite function:

$$DAS = M \circ Y_c \circ T , \quad (6)$$

where:

- M represents the measurement subsystem that transforms physical phenomena Φ into sensor signals S
- Y_c represents the conditioning subsystem that processes raw sensor signals through sequential conditioning operations (amplification, filtering, digitization, etc.)
- T represents the transferring subsystem that transmits conditioned data from source to destination

This composite model demonstrates that the overall data acquisition process is the sequential application of measurement, conditioning, and transferring functions. The output of each subsystem serves as the input to the next, creating a complete pipeline from physical phenomenon to usable digital data at the destination system.

Each of the defined subsystems is a complex research subject deserving separate investigation. The systematic decomposition we have presented establishes the foundation for more detailed analysis of individual components. We consider that recognition of the distinct functions and challenges within each subsystem is crucial for designing effective data acquisition systems for condition-based maintenance applications.

Conclusion

In this article we have tried to examine the place of data acquisition in the context of condition-based maintenance. It has been established that DAQ is an essential constituent of CBM as it provides data about equipment physical state.

Next, there has been conducted a research on DAS on its own. We explored what data acquisition is and provided a definition that, as we think, clearly captures the essence of this process. Based on the defined functions of DAQ we then decomposed the process into three fundamental subsystems: measurement, conditioning, and transferring - each serving a distinct purpose in the transformation of physical phenomena into usable digital information.

The measurement subsystem, through carefully selected sensors and transducers, provides the critical interface with the physical world. The conditioning subsystem ensures signal quality and compatibility through actions like amplification, filtering, isolation etc. Finally, the transferring subsystem delivers this processed information to analysis and decision-making systems.

Building upon presented decomposition, we have developed a formal mathematical model of the data acquisition system. The model represents DAS as a composite function of three sequential operations: measurement (M), conditioning (Y_c), and transferring (T). Understanding the defined subsystems and their mathematical relationships enables maintenance engineers to design, specify, and troubleshoot data acquisition systems that meet the demanding requirements of modern condition-based maintenance programs.

While this work provides foundational knowledge for DAS design, several important research directions merit further investigation. In the context of maintenance, we consider that further research should focus on data acquisition systems' design, particularly in the areas of optimal sensor placement strategies, adaptive sampling rate determination, and multi-sensor data fusion techniques that can enhance fault detection reliability and reduce false alarms. These research directions would provide the practical, actionable guidance needed to advance DAS implementation in industrial maintenance applications, bridging the gap between theoretical frameworks and real-world deployment challenges.

Declaration on Generative AI

During the preparation of this work, the author(s) used Claude Opus 4 in order to: Grammar and spelling check, Improve writing style, Abstract drafting, Content enhancement. Further, the authors used Scopus AI in order to: Content enhancement. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

References

[1] A. Prajapati, J. Bechtel, S. Ganesan: Condition based maintenance: a survey. Journal of Quality in Maintenance Engineering 18(4) (2012) 384–400. doi:10.1108/13552511211281552

[2] S. Rajesh, B. Francis: A Study of Condition Based Maintenance for Land Force Vehicles. Technical Report DSTO-GD-0664, February 2012.

[3] BS EN 13306:2017 - Maintenance. Maintenance terminology, Confirmed (2018).

[4] R. Wang, J. Gao, S. Li, J. Xu, Z. Liu: Condition-Based Dynamic Supportability Mechanism for the Performance Quality of Large-Scale Electromechanical Systems. IEEE Access 8 (2020) 117036–117050. doi:10.1109/ACCESS.2020.300473

[5] H.N. Teixeira, I. Lopes, A.C. Braga: Condition-based maintenance implementation: a literature review. Procedia Manufacturing 51 (2020) 228–235. doi:10.1016/j.promfg.2020.10.033

[6] D. Goyal, B.S. Pabla, S.S. Dhami, K. Lachhwani: Optimization of condition-based maintenance using soft computing. Neural Computing and Applications 28(S1) (2017) 829–844. doi:10.1007/s00521-016-2377-6

[7] R. Ivchenko, A. Kupin: Methodology for the Construction of Predictive Analysis Systems as Exemplified by the Mining Equipment in the Condition of Big Data and Simulation Methods. In: Proceedings of the 15th International Conference on ICT in Education, Research and Industrial Applications: Integration, Harmonization and Knowledge Transfer (ICTERI-2019), Kherson (2019) 448–453.

[8] ISO 13374-3:2012: Condition monitoring and diagnostics of machines. Data processing, communication and presentation Communication (2012).

[9] B. Malatest: Solving data acquisition problems with software-defined radio. EE Evaluation Engineering 58(9) (2019) 22–24.

[10] R.H. Bishop (ed.): Mechatronic System Control, Logic, and Data Acquisition. CRC Press (2017). doi:10.1201/9781420009026

[11] T. Kos, T. Kosar, M. Mernik: Development of data acquisition systems by using a domain-specific modeling language. Computers in Industry 63(3) (2012) 181–192. doi:10.1016/j.compind.2011.09.004

[12] Watt Steam Engine Indicator (Replica, 1927). National Museum of American History. URL: https://americanhistory.si.edu/collections/object/nmah_846148.
[13] Pressure indicator and recorder. US Patent 389635A, September 18, 1888. URL: https://patents.google.com/patent/US389635/en.
[14] M. Suar, N. Misra, N.S. Bhavesh (eds.): Biomedical imaging instrumentation: applications in tissue, cellular and molecular diagnostics. Primers in biomedical imaging devices and systems, Academic Press, London (2022).
[15] G. Selvolini, G. Marrazza: Sensor principles and basic designs. In: Fundamentals of Sensor Technology, Elsevier (2023) 17–43. doi:10.1016/B978-0-323-88431-0.00018-1
[16] J. Park, S. Mackay: Practical data acquisition for instrumentation and control systems. Practical professional books, Newnes Elsevier, Oxford (2003).
[17] J. Ding, G. Yin, H. Hu: Research on the low-frequency weak signal detection method based on MFB topology filters. In: 2023 IEEE 6th International Conference on Automation, Electronics and Electrical Engineering (AUTEEE), Shenyang, China (2023) 758–764. doi:10.1109/AUTEEE60196.2023.10407157
[18] A. Pant, A. Kumar: EEG Signal Filtering Using Rectangular FIR Window Method. In: 2024 International Conference on Computer, Electronics, Electrical Engineering & their Applications (IC2E3), Srinagar Garhwal, Uttarakhand, India (2024) 1–7. doi:10.1109/IC2E362166.2024.10827368
[19] Introduction to Communication Systems. Fosco Connect. URL: https://www.fiberoptics4sale.com/blogs/wave-optics/introduction-to-communication-systems.
[20] Principles of Communication Systems | Basic Block Diagram. EEEGUIDE.COM. URL: https://www.eeeguide.com/principles-of-communication-systems/.