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MASTER THESIS

CONDITION-BASED MAINTENANCE FOR THE OPTIMIZATION OF SMART MANUFACTURING PROCESSES USING INFRARED THERMOGRAPHY

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Résumé (Français)

L'Union Européenne, dans le cadre de son programme Capacity-Building projects in the field of Higher Education ERASMUS+ a lancé en mars 2018 le projet « Algerian National Laboratory for Maintenance Education Project No. 586035-EPP-1-2017-1-DZ-EPPKA2-CBHE-JP" (https://anlmed.com/). Un des volets de ce projet concerne la mobilité des étudiants de quatre universités algériennes dont l'UMBB. Cette mobilité d'une durée de cinq mois à l'UDJG consiste en la réalisation du projet de fin d'études de master avec pour thème : Condition-Based Maintenance for the Optimization of Smart Manufacturing Processes (SMP) using Infrared Thermography (Maintenance conditionnelle pour l'optimisation des procédés de fabrication intelligents par thermographie infrarouge).

Dans le mémoire nous avons développé dans la partie théorique les concepts fondamentaux de la maintenance en générale et de la maintenance préventive conditionnelle (MPC) en particulier. Nous avons ensuite décrit les techniques de surveillance largement utilisées dans ce domaine telles que : l'analyse des huiles, la thermographie, l'analyse vibratoire etc. Un chapitre entier est consacré à la thermographie infrarouge. Ce choix est dicté par la puissance et l'efficacité de cet outil de diagnostic qui permet de détecter des variations thermiques annonçant l'apparition d'éventuels défauts majeurs pouvant affecter la sûreté de fonctionnement de l'équipement de production.

Les expériences ont été menées dans le laboratoire de mécatronique de l'Université "Dunarea de Jos" de Galati - Faculté d'Ingénierie, Département d'Ingénierie de la fabrication. La partie expérimentale comprenait la surveillance conditionnelle de deux types d'imprimantes 3D : Creality CR-10S Pro et Ultimaker 2+. Bien que l'objet principal de la recherche concernait la thermographie infrarouge (par caméra thermique) nous avons aussi procédé à la surveillance de ces deux machines avec deux autres méthodes de la maintenance préventive conditionnelle à savoir : la mesure des vibrations (par vibromètre) et la mesure sonore (par sonomètre) Les résultats obtenus à partir de ces trois techniques nous ont permis déjà d'évaluer l'intérêt de les associer dans ce genre d'analyse et également d'en faire une interprétation exacte des phénomènes constatés sur les équipements étudiés.

Et enfin, nous avons introduit les réseaux bayésiens pour modéliser l'ensemble du système « surveillance et fonctionnement » afin de suivre et d'évaluer le comportement global des machines en temps réel et évidemment prendre les bonnes décisions de maintenance.

En conclusion, le projet de fin d'études de master aborde des recherches fondamentales et expérimentales complexes ayant une large application dans le domaine du génie industriel, et plus particulièrement dans la maintenance conditionnelle.

Abstract (English)

In the framework of European Union initiative, ERASMUS + program, Capacity Building in the field of Higher Education project entitled "Algerian National Laboratory for Maintenance Education" ANLMED, project no. 586035-EPP-1-2017-1-DZ EPPKA2-CBHE-JP (https://anlmed.com/) was funded and implemented starting March 2018. One of the objectives of this project is related to the mobilities of students from four Algerian universities, including the Université M'Hamed Bougara de Boumerdes (UMBB) to European universities. During the mobility in "Dunarea de Jos" University of Galati (UDJG) was elaborated and completed the Master thesis entitled "Conditional Based-Maintenance for the Optimization of Intelligent Manufacturing Processes by Infrared Thermography" (Maintenance conditionnelle pour l'optimisation des procédés de fabrication intelligents par thermographie infrarouge).

In the thesis are elaborated and developed, in the theoretical part, the basics of maintenance, in general, and the in particular the fundamental concepts Conditional Based-Maintenance (CBM). Later on, the concept related to condition monitoring (CM) techniques, in different industrial applications are presented, such as: oil analysis, infrared thermography (IRT), vibration analysis, ultrasonic analysis, acoustic analysis and electrical analysis. An entire chapter is dedicated to infrared thermography. This choice is appointed by the potential and efficiency of this diagnostic method, that allows to detect temperature variation, revealing the appearance of major defects that may affect the operational safety of the production equipment.

The experimental part was conducted in the Mechatronics Laboratory of "Dunarea de Jos" University of Galati - Faculty of Engineering, Department of Manufacturing Engineering and included the conditional monitoring of smart manufacturing process, in this case of Additive Manufacturing (AM) process using Fusion Deposit Modelling (FDM) technology, performed using two 3D printers: Creality CR-10S Pro and Ultimaker 2+. The main purpose of the research was to analyse and test three different methods of conditional-based maintenance using three types of conditional monitoring, namely: vibration (by vibrometers), sound (by sound level meters) and temperature (by thermal camera and infrared thermography). Moreover, a probabilistic model using Bayesian Networks was designed, in order to develop a condition-based maintenance model for the AM process. This technique and approach can represent a successful integration of a large number of data monitoring sets and complex modelling and analysis capabilities are achieved that can lead in the end at an optimisation of the AM process.

In conclusion, the thesis addresses complex fundamental and experimental researches with wide application in Industrial Engineering field, and specifically in Condition-Based Maintenance.

Algerian National Laboratory in Maintenance Education - ANLMED project

For Algerian economy, Africa's fourth economy, to be able to compete successfully both at national and international levels, production systems and equipment must perform at much better levels. Requirements for increased product quality, reduced throughput time and enhanced operating effectiveness within a rapidly changing customer demand environment continue to demand a high maintenance performance. Unfortunately, few companies in Algeria address the significant synergies of knowledge and skills in maintenance and maintenance operations. Currently, there are no any maintenance programmes at academic level while training in maintenance is isolated being performed solely in few large companies.

Today, the universities are further stressed by huge classes, overstressed infrastructures, inadequate and unskilled supervisors, insufficient and old equipment, and a lack of up-to-date educational and scientific materials. Vocational education suffers from problems with the language of instruction, poor teaching, haphazard job placement (lack of systematization), lack of industrial linkages, and lack of flexibility. These problems produce graduates with inadequate skills in unwanted areas and the inability to adapt. Investing in education and training in maintenance engineering and management at all professional levels, engineers, managers and technical personnel in various industries, will boost the Algerian economic competitiveness and will create thousands of new jobs in universities, training centres, and for engineers, managers and technicians in all economic sectors. Youth, men and women, will find a rewarded carrier path and professional satisfaction in Algerian economic sector.

The Algerian National Laboratory in Maintenance Education, ANL-MEd, has the mission to create the next generation educated workforce in industry. There are two major driving forces for the ANL-MEd project proposal: i) Matching the educational and training programmes at universities to the needs of industry and generally of the Algerian economy, for creation of new jobs. ii) Creation of a strong coalition between university - industry - governmental organizations for long-term collaboration in education, training and research, for revitalization of Algerian economy and in particular of Algerian industry.

ANL-MEd assembles for 36 months a consortium with 14 partners with unique combination of skills and expertise. The consortium, coordinated by USTHB, has a hierarchical structure that ensures an efficient communication and cooperation. Four European universities with solid competence in maintenance engineering and management will contribute to development of teaching material and training students, teacher, trainers and industry staff. The four Algerian universities will collaborate with EU partners and the Algerian industrial partners to develop and implement the specialization and training programmes, and to create the ANL-ORG, the national laboratory which will coordinates all activities related to maintenance education. The key factor for implementation of the project objectives is the active collaboration between academic and industrial partners. Therefore, important resources have been allocated for creating a harmonious working environment – ANL-ORG – with activities for creating synergies between project partners and stakeholders. This will contribute to strengthening the active cooperation between university and industry, as well between Algeria and EU. The project activities are distributed in 7 work packages according to a detailed work plan that adequately structures the efforts into manageable work packages with clear responsibilities and objectives. For improved effectiveness in the project for organization of implementation, the partners are grouped in three clusters: ANL-EDUC – cluster for education, ANL-VET – cluster for vocational education and training and ANL-ORG for organization of the ANL, coordinating the resources for integration, communication and exploitation.

The higher education institutions will collaborate to reach the following objectives

- To align the curricula in maintenance to the needs and structure of Algerian companies and to provide them with skilled maintenance personnel, especially at mid-level and high-level. Universities act as an important driver of economic development and catching-up through their role in education and technology absorption, adaptation, and diffusion.
- To create a national organization ANL-ORG with member universities and companies for coordinating the activities regarding maintenance education and training and active collaboration university-industry.
- To strongly involve the manufacturing companies to development of curricula in maintenance engineering. Joint development of co-op programs and defined research programs in industrial engineering; Effect: Innovative solutions for solving companies' maintenance problems.
- To develop the ANL-KNOWLEDGE Platform for education and training. Effect: A unified system for OER and communication between, students, teacher, staff in companies and stakeholders.
- Overall improvement of the company climate, performance and quality in education and training in maintenance engineering. Access to female students and employees to maintenance field.

In order to remain competitive on the international market, production personnel employed in Algerian companies and in International Corporations operating in Algeria has to accelerate the uptake of innovation in industrial maintenance and asset integrity. Key to the quality of production and product is improving understanding in maintenance engineering on all levels in manufacturing hierarchy. Many different studies undertaken in recent years to define the most important areas of future industrial research have placed maintenance engineering at or near the top of the list. In this respect, in today’s global world, generating new knowledge and turning it into new products and services is crucial to maintain and enhance the equipment integrity. Knowledge transfer between HEIs and industry in Europe is an excellent example of success story and one of Europe’s traditional key assets. The European HEIs and organizations will guide the knowledge transfer process between public research institutions and third parties, including industry and civil society organisations, ensuring a smooth implementation and a long-term impact. The EU partners will act together with Algerian partners, in a mutually reinforcing way, to overcome existing obstacles, in particular in terms of promoting the national dimension of knowledge transfer. Another important role of EU cooperation is to make better use of EU funds and to overcome a less systematic and professional management of education and training process.

EU partners will contribute for training of staff on a competitive basis and increased mobility between the public and private sectors while identify shared needs with industry.

The ANL-MEd project has to be regarded as an integrated concept where outputs/results are produced in incremental steps allowing for improvement, testing and quality assessment. The project outputs (OP) and results (RT) are associated to the ANL organization structure.

Source https://anlmed.com/.

Department of Manufacturing Engineering (UDJG)

The Department of Manufacturing Engineering (DME), a pillar structure of the Faculty of Engineering, manages the Manufacturing and Welding Engineering study programs with curriculum content closely connected to the manufacturing, metallurgy and shipbuilding industries, specific to this geographical region. DME focuses on combining cutting edge research with real world knowledge based on industrial needs and offers programs accredited by the Engineering Romanian Association for High Education Accreditation (ARACIS) in the field of:

- Bachelor of Science (B.S.) in Industrial Engineering (Manufacturing and Welding)
- Bachelor of Science (B.S.) in Economical Engineering
- Bachelor of Science (B.S.) in Robotics
- Bachelor of Science (B.S.) in Mechatronics
- Master of Science (M.S.) in Industrial Engineering (Manufacturing, Welding and Quality Management)

The objective of the *undergraduate* programs is to instil a strong background in mechanical engineering with applications in computer aided-design of the intelligent devices used to improve our daily life. Thus, computer aided design of the intelligent metallic and polymeric devices including knowledge from microelectronics, manufacturing, welding is our main professional goal in training the next generation of the Romanian engineers which will be employed by national, international or multinational companies.

The objective of the *graduate degree* program is to provide advanced training in Computer Integrated Manufacturing or Quality Management fields as for master, or PhD in Industrial Engineering. The students are encouraged to personally interact with the faculty throughout their program. These programs prepare individuals for a successful future professional career integrated in the globalized economy.

The DME characteristic is excellence due to a tradition of more than 50 years of training mechanical engineers with successfully carriers in Romania and abroad. The DME’s academic staff, involved in the didactical activities of both study programs, comprises 10 professors, 4 associate professors, 10 assistant professors. The most representative didactic laboratories are in connection with: Cutting Process Technologies, Cold Metal Forming, Cutting Tools, Fusion Welding and Pressure Welding Technologies and NDT Testing. Besides, the academic staff is developing research and scientific activities in the framework of the *Research Centre for Technological Engineering in Machine Building (ITCM)*, *Research Centre for Advanced Researches in Welding (SUDAV)* and *Center of Excellence Polymer Processing (CE-PP)*. The main research laboratories of the research centres are: Laboratory for Manufacturing Systems, Laboratory of Polymeric Materials Research, Laboratory for Modelling and Optimisation of Manufacturing Processes, Laboratory of Cold Metal Forming, Laboratory of Systems and Welding Technologies, Laboratory for Research and Investigation of the Welding Arc and Laboratory for Modelling and Simulation of Welding Processes. The results achieved, in the last 5 years, by the development and implementation of national/international projects have been disseminated in more than 90 articles published in journals and conferences proceedings indexed by Thomson Reuters (ISI), 15 patents and over 150 articles indexed in international databases.

Source http://www.if.ugal.ro.

Department of Mechanical Engineering (UMBB)

The Department of Mechanical Engineering, ex "National Institute of Mechanical Engineering" INGM, is a former Algerian institute created in 1973 under the supervision of the Ministry of Heavy Industry. In 1998, with the creation of the University of Boumerdes, INGM form three departments of the Faculty of Engineering Sciences (FSI): Department of Industrial Maintenance, Department of Mechanical Engineering and Department of Energy. Then, and with the restructuring of the FSI in 2017, the Department of Mechanical Engineering merged with several departments of the FSI.

Nowadays, there are eighty-five (85) Permanent Teachers / Researchers, including 9 Professors, 12 A Lecturers, 21 B Lecturers, 36 A Master Teachers and 06 B Master Teachers, which provide training and supervision of a total number of 1820 of students. With the advent of the L-M-D system, the department offers academic courses (Bachelor and Master) distributed in the tables below:

	Domain	**Study program**
Bachelor of Science (B.S.)	**Electromechanical**	Electromechanical
		Industrial Maintenance
	Mechanical Engineering	Energy
		Mechanical Construction
		Materials Engineering
	Industrial Engineering	Industrial Engineering

	Domain	**Study program**
Master of Science (M.S.)	**Electromechanical**	Industrial maintenance
		Mechatronics
		Electromechanical
	Mechanical Engineering	Energy
		Energy installation and turbomachines
		Mechanical construction
		Mechanical and manufacturing production
		Materials Engineering
		Pressure vessels and piping (P)
	Industrial Engineering	Industrial Engineering
	Renewable Energies	Renewable Energies in Mechanics

Bachelor's and Master's degrees in Mechanical Engineering fit into most industrial and service sectors, both in large industrial groups and in small and medium-sized enterprises.

Besides the didactics, the academic staff is developing research and scientific activities in the framework of three research laboratories: *Laboratory of Solid Mechanics and Systems*, *Laboratory of Energy, Mechanics and Engineering*, and *Laboratory of Dynamic Engines and Vibroacoustics*.

Sources:
https://fsi.univ-boumerdes.dz/;
https://fsi.univ-boumerdes.dz/index.php/formation-departements/genie-mecanique.

Chapter 1. Condition based Maintenance. State of the Art.

1.1. Introduction

Reliability has always been an important aspect in the assessment of industrial products and/or equipment. Good product design is essential for products with high reliability. However, no matter how good the product design is, products deteriorate over time since they are operating under certain stress or load in the real environment, often involving randomness. Maintenance has, thus, been introduced as an efficient way to assure a satisfactory level of reliability during the useful life of a physical asset [1].

The earliest maintenance technique is basically breakdown maintenance (also called unplanned maintenance, or run-to-failure maintenance), which takes place only at breakdowns. A later maintenance technique is time-based preventive maintenance (also called planned maintenance), which sets a periodic interval to perform preventive maintenance regardless of the health status of a physical asset. With the rapid development of modern technology, products have become more and more complex while better quality and higher reliability are required. This makes the cost of preventive maintenance higher and higher. Eventually, preventive maintenance has become a major expense of many industrial companies. Therefore, more efficient maintenance approaches such as Condition-Based Maintenance (CBM) are being implemented to handle the situation [1].

CBM is a maintenance program that recommends maintenance actions based on the information collected through condition monitoring. CBM attempts to avoid unnecessary maintenance tasks by taking maintenance actions only when there is evidence of abnormal behaviours of a physical asset. A CBM program, if properly established and effectively implemented, can significantly reduce maintenance cost by reducing the number of unnecessary scheduled preventive maintenance operations [1].

1.2. The Maintenance Process

1.2.1. Industrial Maintenance

The maintenance function is defined as the process that implements all the means available to keep the machines and devices working until they have to be removed from service [2]. The French standardization organization AFNOR has defined the maintenance by standard as [3]:

- all actions to maintain or restore a property in a specified state or able to provide a specific service;
- prevention on the operating system while reinstating supports and corrections after failure;
- service carry for pre-determination of the objectives to be achieved using quantification of the measurable parameters.

1.2.2. The Objectives of the Maintenance

According to the maintenance policy of companies, the objectives of the maintenance process are [4]:

- the availability and the life cycle of the assets/goods;
- the safety of people and assets/goods;
- the quality of the products;

- the protection of the environment;
- optimization of maintenance costs.

The maintenance policy leads, in particular, to make choices between:

- preventive and / or corrective maintenance, systematic or conditional;
- internalized and / or outsourced maintenance.

1.2.3. Maintenance Process Policy

The choice of a maintenance policy will be made by a company only after having defined the objectives of the technical-economic and human resources. While the main objective remains in the optimization of the cost / availability and security ratio, several decision support tools should be developed in order to choose the appropriate maintenance policy. The maintenance action plan consists in putting the right maintenance policy, where it is needed, and at the right time, at an optimal cost. The various types of preventive and reactive maintenance depend on the objectives and nature of the company [5].

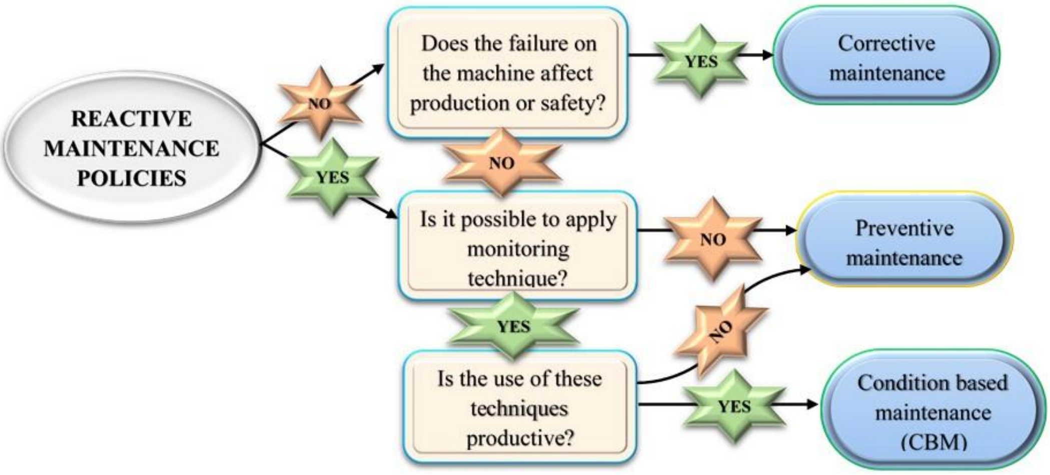


Fig. 1. Organization chart for choosing the maintenance policy

1.2.4. Maintenance Typology

The choice between the maintenance methods to be carried out, as part of the maintenance policy, must be done in agreement with the management of the company. In order to choose the maintenance process, it is necessary to be informed of the objectives, maintenance policy, but it is necessary to know also the operation and the characteristic of the materials, the behaviour of the equipment in exploitation, the conditions of application of each method, the maintenance costs and loss of production costs. There are two main types of maintenance used in industry: corrective maintenance and preventive maintenance.

1.2.4.1. Corrective Maintenance

Corrective maintenance, called sometimes curative (non-standardized term), is used for the process that the material its lost qualities, necessary for use.
Corrective maintenance is "the maintenance performed after the detection of a failure and it is intended to restore an object/device/machine its default property, with which can perform a required function". This maintenance is used when the unavailability of the systems have no major consequences or when the security constraints are low [6], [**7**].

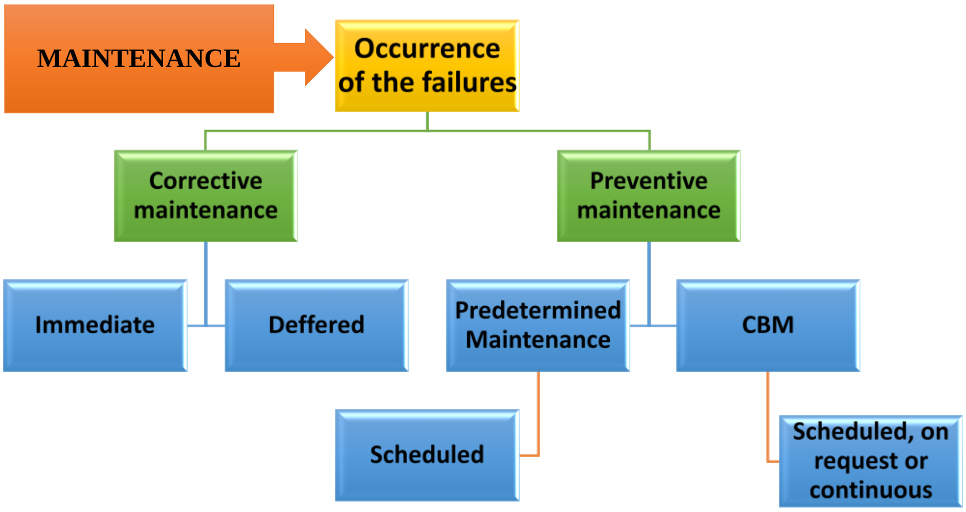


Fig. 2. Forms of maintenance according to standard [7]

a) **Corrective maintenance (palliative).** Corrective maintenance is used for curing a temporary problem caused by an object/device/machine without looking on the cause. Commonly called "troubleshooting", palliative maintenance consists mainly of temporary actions that are followed by curative actions.

b) **Corrective maintenance (curative).** Corrective maintenance actions are to restore a property of an object/device/machine, in a specified state, to re-enable it in order to perform a specified function.

1.2.4.2. Preventive Maintenance

Preventive maintenance (PM) process is the performed according to a predetermined criteria and its objective is to reduce the probability of failure of a property or degradation of a service rendered. This process is conducted in order to avoid failures of object/device/machine in use. The cost analysis will highlight a gain in relation to the failures that it avoids. The main goals of PM are:

- increase o the life cycle of the equipment;
- decrease the probability of service failures;
- decrease downtime in case of repairs or breakdowns;
- prevent and also anticipate corrective maintenance interventions;
- allow to decide corrective maintenance in good conditions;
- avoid abnormal consumption of energy, lubricant, spare parts, etc.;
- improve the working conditions of production staff;
- decrease the maintenance budget;
- decrease the risks of accidents.

a) Systematic preventive maintenance (NF EN 13306 standard). This is the preventive maintenance performed without prior checking of the condition of the object/device/machine properties, in accordance with an established schedule, the number of operating cycles, the number of produced pieces, periodic revisions or sensitive parts (lubrication, calibration, etc.). Systematic maintenance involves interventions, at scheduled dates, on a piece or on an equipment, whose importance can range from the simple replacement to the general overhaul:

- upgrading a production line by annual shutdown;
- general overhaul of the equipment;
- standard replacement of a part or assembly of a sensitive component;
- lubrication.

The working conditions reveals a systematic character of the preventive maintenance, opposite to what happens in conditional maintenance, which assume a perfect knowledge about the behaviour of the equipment, its operating modes and speed of degradation.

Table 1. Periodicity of systematic interventions

Periodicity T	Nature of operations	Criteria for choosing T
1/2 day per 1 week	• Visits • Shifts • Monitoring	•manufacturer's recommendation • empirical habits • experiments
1 week per year	• standard replacement • specific actions on a critical component	•manufacturer's recommendation • regulation • optimized by calculations, tests or experiments
1 year per 10 years	• partial or general revision • large periodic stops	• regulation •empirical habits often related to social constraints (annual holidays, etc.)

b) Conditional preventive or predictive maintenance [NF EN 13306 standard]. Conditional preventive or predictive maintenance it is the "maintenance subordinated to a predetermined type of event (self-diagnosis, information of a sensor, measurement, etc.) or to the analysis of the monitored evolution of significant parameters of the degradation and the decrease of performance of an entity". This monitoring of the degradation makes it possible to set an alarm threshold before an eligibility threshold. The main interest of such a strategy is to be able to use the entities to the maximum of their possibility but also to reduce the number of corrective maintenance operations.

- Condition-Based Maintenance (CBM) is a maintenance philosophy used by industry to actively manage the health condition of assets in order to perform maintenance only when it is needed and at the most opportune times. CBM can drastically reduce operating costs and increase the safety of assets requiring maintenance.

Corrective/reactive maintenance can have severe performance costs, and preventive/ scheduled maintenance replaces parts before the end of their useful life. CBM optimizes the trade-off between maintenance costs and performance costs by increasing availability and reliability while eliminating unnecessary maintenance activities

1.2.5. Planned Maintenance

Planned maintenance is a proactive approach to maintenance in which maintenance work is scheduled to take place on a regular basis. The type of work to be done and the frequency varies based on the equipment being maintained, and the environment in which it is operating. The primary objective of planned maintenance is to maximize equipment performance by keeping equipment running safely for as long as possible, without that equipment deteriorating or having unplanned outages.

Planned maintenance activities include any maintenance work scheduled in advance. For example, changing the oil in a vehicle because the oil light came on is not planned maintenance. Changing the oil because the vehicle had gone 3,000 miles would be planned maintenance. Planned Maintenance is a scheduled maintenance activity, or service visit, that is done to ensure that the equipment, or equipment components, are operating correctly and within the manufacturer's recommendations.

Planned maintenance includes preventive maintenance tasks such as checking oil levels, when those tasks are pre-planned. The schedule for planned maintenance tasks can be based on equipment running hours, number of items produced, distance travelled, or other measurable factors [8].

1.3. Condition-Based Maintenance (CBM)

Condition-based maintenance (CBM) is a maintenance technique that involves monitoring machine condition and predicting machine failure. Many CBM systems are controlled by computers. CBM systems can be used in aircraft as well as other high-tech industries for corrosion detection. Unlike periodic maintenance where services are based upon scheduled intervals, CBM relies upon actual machine health to dictate when and what maintenance is required. In simple words we can describe CBM as direction of maintenance actions based on indications of asset health as determined from non-invasive measurement of operation and condition indicators. CBM allows preventive and corrective actions to be optimized by avoiding traditional calendar or run based maintenance [9], [10].

CBM is based on using real-time data to prioritize and optimize maintenance resources. Through condition monitoring, a system determines the equipment's health, and action is taken only when maintenance is actually necessary. Ideally, condition-based maintenance allows maintenance personnel to:

- Perform only currently needed maintenance
- Minimize spare part costs
- Minimize system downtime
- Reduce time spent on maintenance

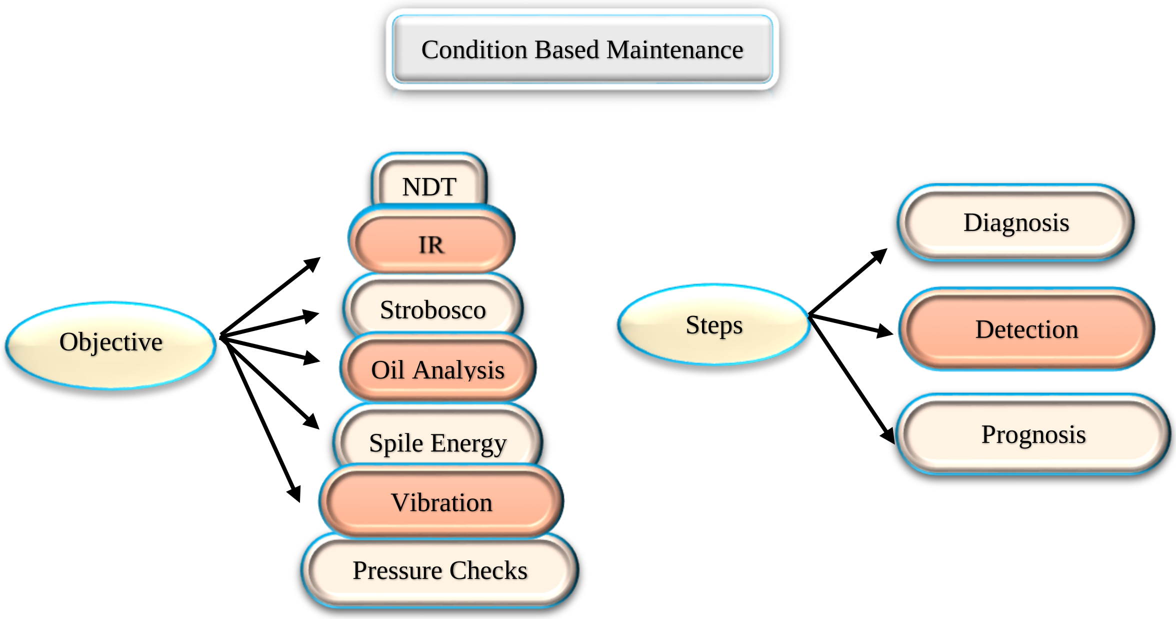


Fig. 3. Objective & steps of CBM [1]

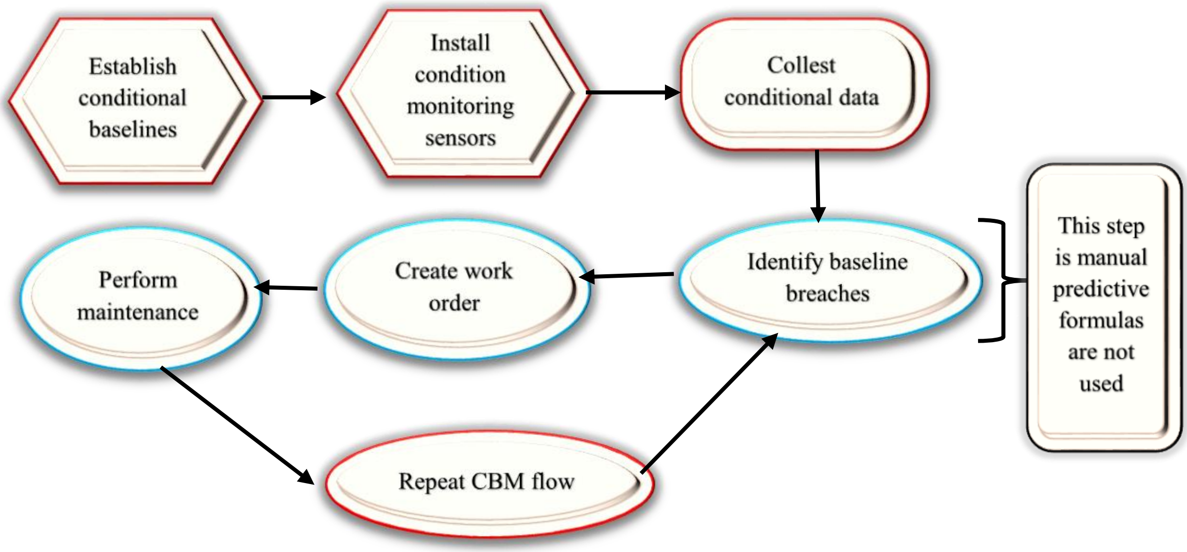


Fig. 4. Condition-based maintenance workflow

1.3.1. Objectives of CMB

The goal of Conditional Maintenance is to monitor and detect upcoming equipment failures so that maintenance can be scheduled proactively when needed - not before. Asset conditions must trigger maintenance long enough before the failure that the job can be completed before the asset fails or performance falls below the optimal level [11].

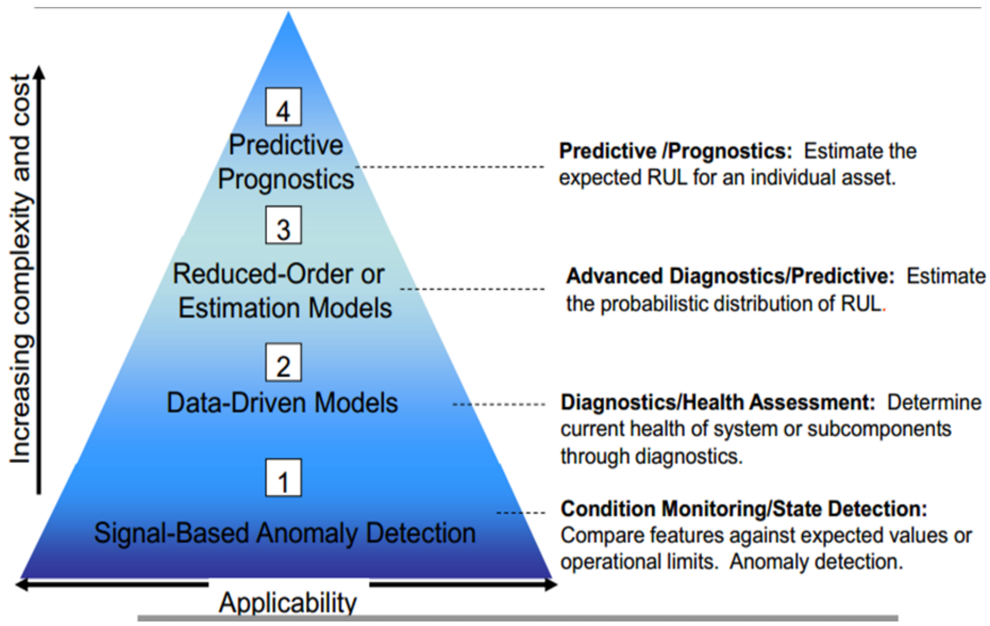


Fig. 5. The required level of capability depends upon the technical problem, the desired outcome and costs

In the following subchapters will be presented the pro and cons of the CBM highlighting the main objectives, types, elements etc.

1.3.2. Advantages of CBM

The CBM is performed while the asset is operating, which reduces the risk of disruption of normal operations:

- Reduces the cost of asset failures,
- Improves the reliability of the equipment,
- Minimizes unplanned downtime due to catastrophic failure,
- Minimizes the time spent on maintenance,
- Minimizes overtime costs by planning activities,
- Reduces the need for emergency spare parts,
- Optimizes maintenance intervals (more optimal than the manufacturer's recommendations),
- improves the safety of workers,
- Reduces the risk of collateral damage to the system

1.3.3. Disadvantages of CMB

- Condition monitoring test equipment is expensive to install, and databases cost money to analyse
- Cost to train staff–you need a knowledgeable professional to analyse the data and perform the work
- Fatigue or uniform wear failures are not easily detected with CBM measurements
- Condition sensors may not survive in the operating environment
- May require asset modifications to retrofit the system with sensors
- Unpredictable maintenance periods

1.3.4. CBM Elements and Techniques

CBM is a failure management strategy for a particular failure mode that meets criteria such as:

- The potential failure is clearly defined
- Failure interval is identifiable
- The maintenance task interval is less than the failure interval and physically possible.
- The time between the discovery of the potential failure and the occurrence of the function failure is long enough for the maintenance action to be taken to avoid, eliminate, or minimize the consequences of the failure mode [11].

Whereas PM addresses age-dependent failure probabilities, CBM addresses failures that can be measured by one or several indicators. When applying maintenance efforts (people, processes, and tools) in a CBM environment, maintenance is based on the actual condition of the equipment versus the age of the equipment, so that equipment in good condition does not need to be maintained as frequently as equipment that has reached the predicted age of deterioration. The core of CBM is using test equipment or statistically modelling data to predict the condition of equipment. The vision of the CBM application is to enable equipment to achieve nearly zero breakdowns. This will transform traditional maintenance practices from Run to failure (RTF) to predictive maintenance (PdM) and prevention of failures. CBM utilizes failure history to predict breakdowns before they happen to prevent future failures from occurring, where repairs are costly and operations are impacted [12].

1.3.4.1. CBM Elements. Run to Failure (RTM)

RTM monitoring is based on the idea that equipment can be evaluated while remaining in service, which will drive down the overall cost of maintenance. For example, a generator can be monitored based on a number of parameters in real time, such as temperature, cooling gas density, bearing vibration, lubricating oil condition, and others. Statistical analysis of the collected data allows diagnosis of impending failures. These failures, also known as incipient faults, cannot be predicted by human senses. Other equipment such as circuit breakers, relays, and switches are not readily assessable utilizing RTM techniques [11], [12]. The valid candidate for RTM must satisfy both the following criteria:

1. Equipment must be critical or expensive enough to warrant the cost, purchase and installation, of monitoring hardware and software.
2. Analysis of the parameters monitored must provide meaningful diagnostics and prognostics

1.3.4.2. CBM Elements (PdM)

PdM trending techniques have been used to confirm maintenance decisions that would have previously been based on expert opinions. PdM uses test results taken from PM techniques. Statistical analysis results are evaluated, and a prognosis is developed indicating the need for increased, decreased, or even elimination of maintenance intervals. While these techniques have often found problems that might not have been identified, PdM may actually slightly increase daily maintenance costs for some equipment due to the additional analysis required [11].

1.3.5. Applications

The CBM process can be applied to maintain activities in all industries, including: jet engines, wind turbine generators, marine diesel engines, natural gas compression, circuit card manufacturing, process optimization with complex input/output relationships, pattern recognition with incomplete data, anomaly detection for earliest indications of adverse performance shifts. In figures Fig. 6 - Fig. 10 are presented some application of CBM in different industries.

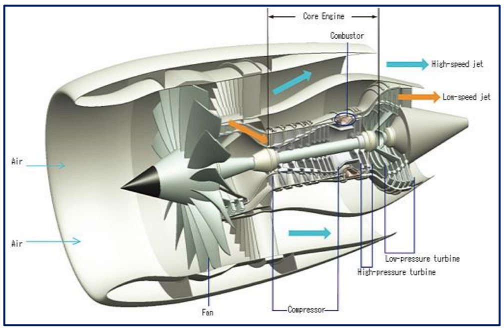


Fig. 6. Jet engines

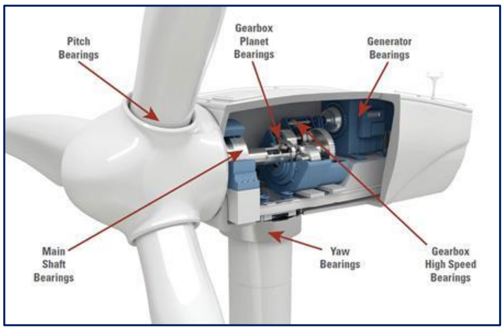


Fig. 7. Wind turbine generators

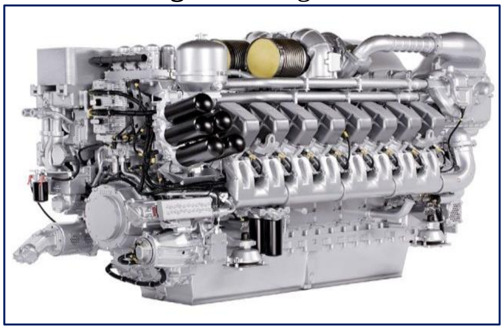


Fig. 8. Marine diesel engines

Fig. 9. Natural gas compression

Fig. 10. Circuit card manufacturing

1.3.6. Strategies Related to CBM

There are essentially three maintenance strategies that build off one another. Starting from the most basic maintenance practice:

- **Preventive Maintenance**: The facility takes a proactive approach to most maintenance practices and regularly schedules routine maintenance
- **Condition-based Maintenance**: The information collected isn't just manually documented by technicians during their daily routine, but also saved by the machines themselves. This gives the department even more information to help prevent downtime and bolster the bottom line
- **Predictive Maintenance:** All of the information stored is used to predict when downtime will occur. Algorithms take historical data and compare it to real-time data to determine what variables will cause a breakdown. This supplements the expert technician's role of analysing the data and making a decision on when maintenance will be required

1.3.7. Related Capabilities

CBM-related capabilities to include hardware, algorithms and tools: [13]

- ➢ Sensor suites (Octavis vibration sensor – VSExxx, VSA001 and VSE002(Pumps, Dry Running Protection and Bearing Diagnostics Octavis), SD6000 (Compressed air control), PIM series pressure sensor, TAD temperature transmitter)
- ➢ Data acquisition software and systems
- ➢ Data manipulation, repository and interface applications
- ➢ Automated condition monitoring and state detection algorithms
- ➢ Diagnostic algorithms
- ➢ Enhanced prognostic techniques
- ➢ Advisory tools and systems
- ➢ Business process analysis and automation
- ➢ Asset management and tracking systems
- ➢ Troubleshooting and maintenance aids
- ➢ Interactive and hands-on training

1.3.8. CBM Components and Technologies

CBM components are an optimized mix of:

- Maintenance technologies (diagnostics prognostics)
- Reliability-centred maintenance (RCM)-based processes
- Enablers (total asset visibility)

Condition-based maintenance is rooted in condition-based monitoring. This involves keeping tabs on the state of an asset using certain performance indicators. There are a number of different tools and techniques that allow maintenance teams to do this. These methods can include low-tech approaches, such as observation by a technician, or more technologically advanced processes, like gathering data through sensors.

One of the hallmarks of condition-based monitoring is that it is non-invasive. This means measurements are taken without shutting down a machine or adjusting the way it operates. Data is collected either at certain intervals or continuously through sensors, visual inspection, performance data, and/or scheduled tests.

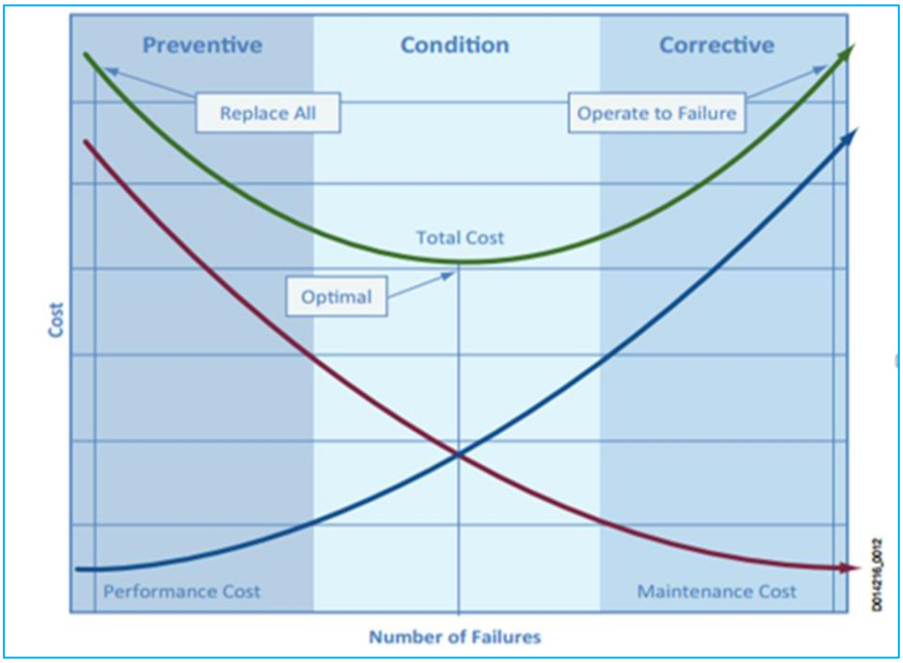


Fig. 11. CBM optimizes costs between preventive and corrective maintenance [14]

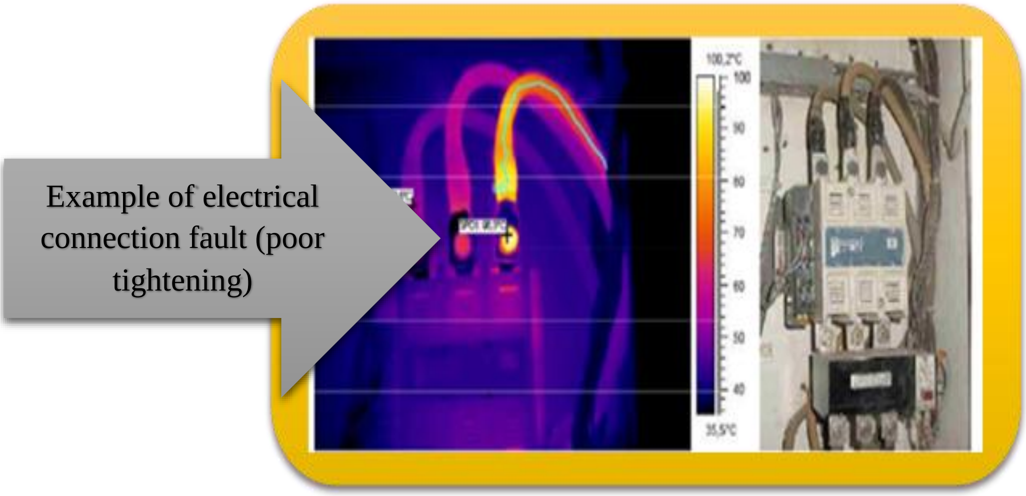
1.3.8.1. Oil Analysis

Oil analysis helps diagnose the internal conditions of oil-wetted components and their lubricants. This method can determine the health of an asset that uses oil, fuel or coolant and whether it is nearing failure. Oil analysis can be as thorough as testing blood samples. This type of condition monitoring can include testing for dozens of different elements, such as the level of wear metals or dirt contamination in oil. It also captures information on viscosity, acid levels, water content, and more to determine the effectiveness of the oil as a lubricant [14].

1.3.8.2. Infrared Thermography (IRT)

Infrared thermography is the science of acquiring and analysing thermal information using remote thermal imaging devices. The French standard A 09-400 defines infrared thermography as a technique that makes it possible to obtain the thermal image of a thermal scene in a spectral range of infrared by means of appropriate equipment. Infrared thermography is used in the field of condition monitoring to optimize maintenance tasks without disrupting the workflow, and to minimize maintenance costs.

Fig. 12. Visible image and correspondent thermogram of a roll



1.3.8.3. Vibration Analysis

This type of condition monitoring identifies potential failure by spotting changes in normal vibration signature. Vibration is affected by amplitude, intensity, and frequency. Sensors can detect abnormalities in these elements, which can be a sign that something is wrong with an asset. For example, rotating equipment, such as compressors and motors, exhibit a certain degree of vibration. When they degrade or fall out of alignment, the intensity of the vibration increases. Sensors can detect when the vibration becomes excessive and the component can be repaired or replaced [15].

1.3.8.4. Ultrasonic Analysis

Ultrasonic instruments help detect deep, subsurface defects. They do this by measuring sounds that are inaudible to us and converting them to a pitch we can hear. Once these sounds can be discerned by the human ear, it's easier to recognize anomalies in an asset and rectify them. For example, as ball bearings begin to wear out, they become deformed. This creates irregular surfaces on the bearing and increases the emission of ultrasonic sound waves. This can signal to a technician that the bearing is on its way to failure [15].

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1.3.8.5. Acoustic Analysis

Acoustic analysis is similar to vibration and ultrasonic analysis. It uses sensors and microphones to detect sounds that indicate an asset is not operating quite right. However, where the main use of vibration and ultrasonic analysis is to uncover deficiencies in rotating equipment, acoustic analysis has the added benefit of being able to target gas, liquid, or vacuum leaks. This is a key advantage for production facilities in the oil, energy and mining industries [15].

1.3.8.6. Electrical Analysis

When an electrical current is too strong or too weak, it can cause problems for an asset. Electrical analysis uses clamp-on ammeters to measure the current in a circuit. Using this tool, it's easy for maintenance teams to gauge when a machine is receiving an abnormal amount of electricity. The piece of equipment can then be shut down and serviced before a bigger, more expensive electrical problem occurs [14].

1.3.9. Simulation Tools for CBM

In order to find solutions for detecting failures, it is needed to analyse and understand the measured results. These analyses have some software with which the CBM can be simulated:

- **STAR-CCM+** is an all-in-one solution that delivers accurate and efficient multidisciplinary technologies in a single integrated user interface. STAR-CCM+ is a complete multidisciplinary platform for the simulation of products and designs operating under real-world conditions [16].

- **CHEMCAD** is an integrated suite of intuitive chemical process engineering software. It has the power and tremendous range of capabilities to meet an engineer's chemical process simulation needs, from day-to-day challenges to large, multifaceted projects.
- The **Petrel E&P** software platform brings disciplines together with best-in-class applied science in an unparalleled productivity environment. This shared earth approach enables companies to standardize workflows from exploration to production—and make more informed decisions with a clear understanding of both opportunities and risks.

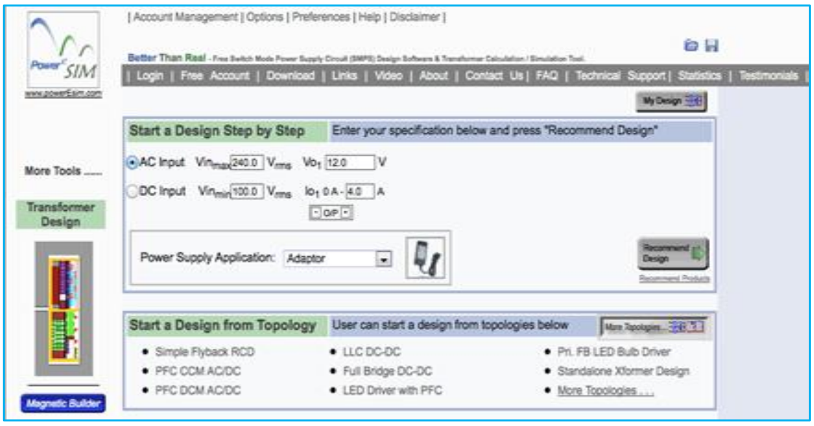


Fig. 13. Simulation with Power eSim

- **Circuit Simulator** is a handy tool for simulating electronic circuits using basic components. Intended for education purposes, Circuit Simulator is a good choice for people beginning to pursue electrical engineering or who are electrical engineering students [17].
- **FlexPro Acoustics** analysis option [18]. It determines the sound level and sound power in one easy, automatic step, analyse multiple channels of sound signals and their sound level at the same time and calculate the sound power. FlexPro includes standardized acoustic methods: sound power computation, sound level evaluation, loudness computation, octave analysis using time domain filters.

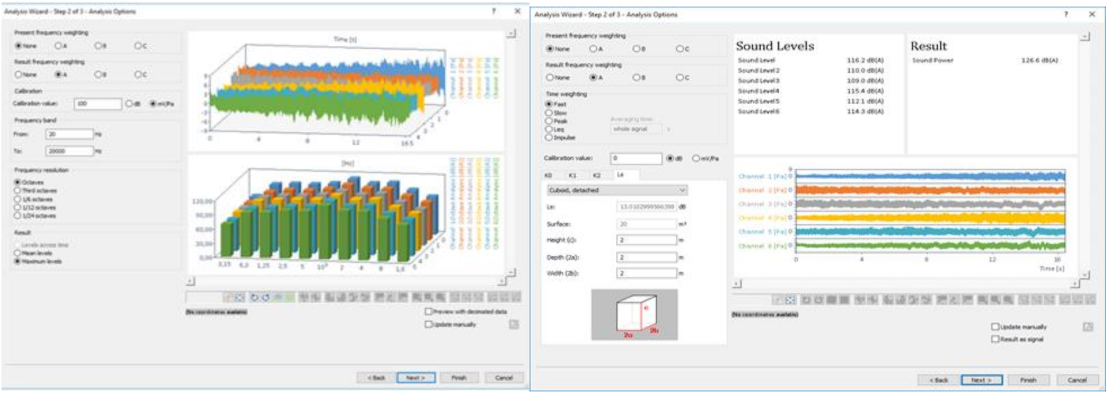


Fig. 14. FlexPro Acoustics analysis

- **UltraVision®** is the industry leading software for Ultrasonic Technology (UT) inspection applications. It offers many advanced features and tools that improve the efficiency of UT inspections for either on-site inspections or lab work. Inspection parameters and results are delivered in a comprehensive report. The ultrasonic inspection software is intuitive and allows users to easily design and simulate an inspection [19]

- **Vibration Analysis** with **Solidworks** 2018, concurrently introduces the reader to vibration analysis and its implementation in Solidworks Simulation using hands-on exercises. It helps users to learn vibration analysis as implemented in Solidworks Simulation, helps avoiding common mistakes, builds on user's experience with structural Finite Element Analysis, and quickly introduces to vibration analysis.
- The **DDS Software** (Digital Diagnostics System) is a powerful tool for storage and evaluation of vibration and technical diagnostics data. It allows the user to connect and work with data collected by portable data collectors and on-line monitoring systems. In the full configuration, it includes all the functions necessary for data transfer, analysis and data storage.

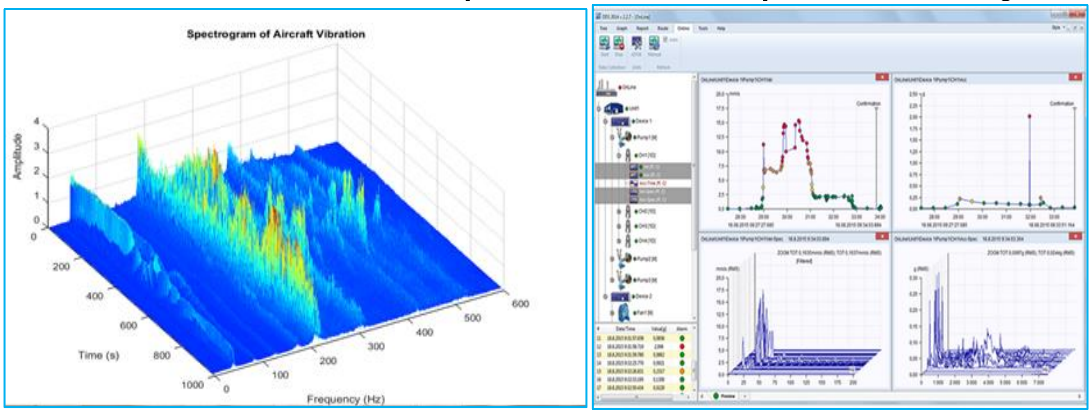


Fig. 15. Simulation of vibration analyse

- **FLIR Tools +** allows you to quickly edit and analyse infrared images, and integrate them into professional inspection reports [20];
- **SmartView® Software.** This powerful software is a modular suite of tools that allows you to view, optimize and analyse infrared images. You can produce fully customizable business reports in a few simple steps. Intuitive and easy to use, SmartView® software is ideal for customers with basic needs, while ensuring the performance needed for specialized thermographs for their advanced analysis and reporting [21].
- **IRT Cronista®** is a unique tool for the organization of infrared images, their analysis and the generation of complete reports. All functions necessary for image management, analysis and reporting are combined into one software [22].

1.3.10. Optimizing Operations and Maintenance with Predictive Analytics

The amount of data available today is requiring new utilities to operate more efficiently, effectively and safely. Predictive analytics solutions transform raw data into actions, allowing utilities to prioritize maintenance activities, while reducing operational and maintenance expenditures. Predictive asset analytics software detects subtle changes in equipment behaviour that are often the early warning signs of failure, enabling operations and maintenance personnel to address equipment issues before they become problems that significantly impact operations. Unscheduled downtime can be reduced because personnel receive early warning notifications of developing issues. These advanced analytics solutions can identify problems days, weeks or months before they occur, creating time for personnel to be proactive [25].

Instead of shutting down an asset or a section of the plant immediately, a problematic situation can be assessed for more controlled outcomes. Loads can be shifted to reduce asset strain, or the necessary maintenance can be scheduled during a planned outage. Predictive analytics software allows for better planning which in turn reduces maintenance costs. Parts can be ordered and shipped without rush and equipment can continue running while the problem is being addressed [25].

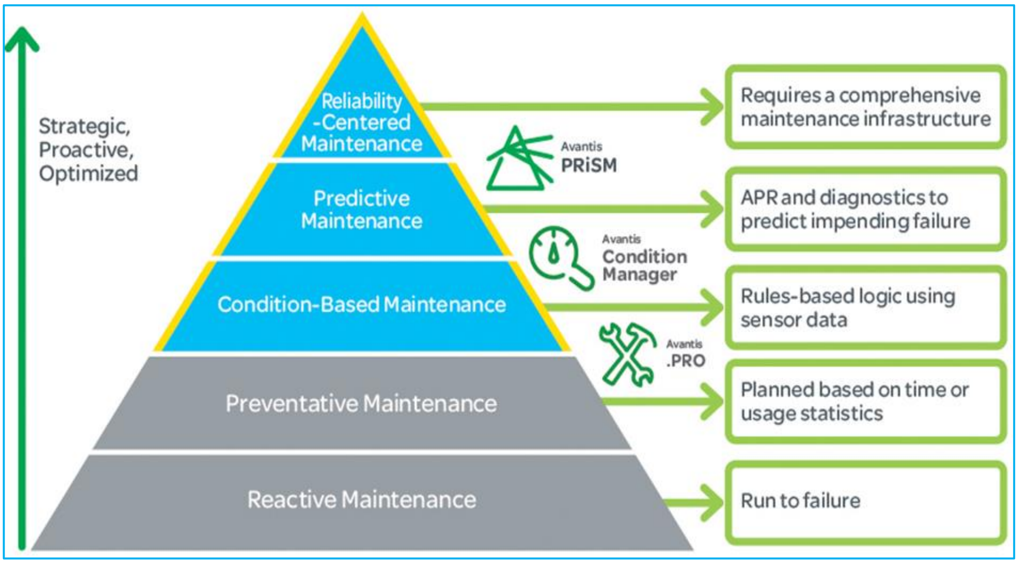


Fig. 16. Optimisation of the operations and maintenance with predictive analytics [25]

Predictive analytics tools also help personnel visualize actual and expected performance of an asset including detailed information on ambient, loading and operating conditions. Operations personnel become knowledgeable regarding where inefficiencies exist and their impact on financial performance. They can gauge the future consequences of the actions and decisions they make in the present. Risk assessment becomes an exact science and the potential behaviours of each monitored asset and can be used to better prioritize capital and operational expenditures. Additional savings are realized when considering the costs that "could have been," including loss of power, replacement equipment, lost productivity, additional man hours, etc., when a major failure is avoided [25].

1.3.11. Condition Based Monitoring vs. Planned Maintenance

Planned maintenance attempts to control unplanned downtime by performing maintenance at set intervals. This often results in waste as maintenance organizations have to replace materials and parts that still have life left in them. Traditional planned maintenance often embraces a time-based approach for their set intervals which consumes unnecessary resources and may actually cause failure by disrupting the equilibrium of stable assets. Unlike in planned maintenance, where maintenance is performed based upon predefined scheduled intervals, condition-based monitoring ensures maintenance is performed only after a decrease in the condition of the equipment has been observed.

For example, you have a motor the needs its oil changed on a regular basis to run efficiently. With planned maintenance, you would stop production every X number of hours and then change the oil. With condition-based monitoring, you would monitor the existing oil in the motor for indicators that the oil needs to be replaced, such as a change in viscosity or minute particles of certain substances being present. Only when those indicators are present is the oil change done [23].

In general, the practice of Condition Based Monitoring extends the time between maintenance shutdowns, because maintenance is done on an as-needed basis and as a result, has the potential to decrease maintenance costs.

1.4. Future Challenges and Considerations about CBM

Industrial maintenance has several challenges in order to provide productive and financial stability to industrial enterprises [24], [25]. Among the challenges we have:

- Data acquisition may involve various types of information: (Vibration, Temperature, Pressure, Speed Voltage/current, Stress/strain/shock, Position, Particulate count/composition).
- Feature extraction calculations may involve: (Fast Fourier, Transform, Data filtering/smoothing, Temperature/pressure ratio, Efficiency, Mass flow).
- Detection algorithms alert users to potential problems and otherwise unknown failures.
- Diagnostic algorithms isolate failures to specific components or subsystems.
- Prognostic algorithms estimate remaining useful life based on past and future operational profiles and physics of failure models.
- Supervisory reasoning algorithms reconcile conflicting information and provide recommendations such as: Inspections, Repairs, Parts ordering and Equipment shutdown.

1.5. Conclusion

Predictive asset analytics solutions help grid operators, systems engineers, controllers and many other plant personnel take advantage of the massive amounts of data and use it to make real-time decisions that have a significantly positive impact on equipment maintenance and reliability.

Early warning detection and diagnosis of equipment problems help personnel work more effectively by increasing lead time to plan necessary maintenance and avoid potential equipment failure.

Power utilities can transform their maintenance strategies by leveraging predictive asset analytics solutions to spend less time looking for potential issues and more time taking actions to get the most out of every asset. Using predictive asset analytics software, power utilities can monitor critical assets to identify, diagnose and prioritize impending equipment problems continuously and in real time.

Chapter 2. Infrared Thermography method used in CBM

2.1. Introduction

In many cases, it is almost impossible to detect faults in engineering electrical devices (electrical installations, valves, motors or electrical connections). Several methods have been used to detect damages in electrical and mechanical devices, including remote thermal imaging, through which high-quality portable infrared pyrometers are increasingly being used to identify certain vulnerabilities. In the field of non-destructive testing and evaluation, active **infrared thermography** is a widely used technique for evaluating material component part conditions and is a very important tool for ensuring the safety and reliability of installations, with a very wide range of applications. Offering an alternative to portable thermal imaging cameras, handheld or fixed infrared thermometers are becoming increasingly important in the field of preventive maintenance [26]. Infrared thermography is a tool that has become more and more widely used for preventive maintenance on mechanical and electrical systems over time. It takes advantage of the infrared radiation properties to extract useful conclusions for the condition of the equipment under test. It is neither non-destructive, nor an interrupting procedure and has no solid substitute [27].

2.2. Advantages & Disadvantages of IR Thermography

The main advantages of the infrared thermography are the following [27]:

- It is a non-contact type technique;
- Fast, reliable & accurate output;
- A large surface area can be scanned in a very short time;
- Presented in visual & digital form;
- Data can be stored for later image processing and analysis;
- Requires very little skill for monitoring (but not for evaluation, see disadvantages);
- Due to the mobility of modern IR cameras they can be made available at any time and at any place;
- No production interruptions, on the other hand all equipment should work at nominal load;
- Complies with legislation or insurance requirements;
- Easily prioritize emergencies.

Even if the method it has a large number of advantages, as a normal engineering technique, it has also some disadvantages. It can be mentioned the following ones [27]:

- Cost of instrument is relatively high (though you must take into account the time, labour costs and early warning savings).
- It is unable to detect the inside temperature if the test subject is separated by a non-transparent for IR radiation medium such as glass or other covers.
- Following the above it is a surface method and expertise and knowledge to evaluate the results is need.

2.3. Basic Concept about Thermography

Temperature and heat are not the same phenomena. Temperature is a measure of the intensity or degree of hotness in a body. Technically, it is determined by getting the average speed of a body's molecules. Heat is a measure of the quantity of heat energy present in a body. The spatial distribution of temperature in a body determines heat flow. Heat always flows from warmer to colder areas [28]. Heat is simply a form of energy that is transferred by a difference of temperature. Temperature is the measure of hotness expressed in terms of any of several scales, such as F, ^{o}C, or K. [29].

Heat is the energy associated with the number of molecules and atoms that make up matter, and which are assigned a certain random average speed. It is created by the conversion of other forms of energy, such as fuel combustion, movement or friction. Heat is a former of energy in transit due to a temperature. The heat transfer is the transmission of energy from one region to another region as result of the temperature difference between them. Whenever there exists a temperature difference in media or within a medium, heat transfer must occur [30]. The heat can be transferred by ***conduction***, ***convection*** and ***radiation***.

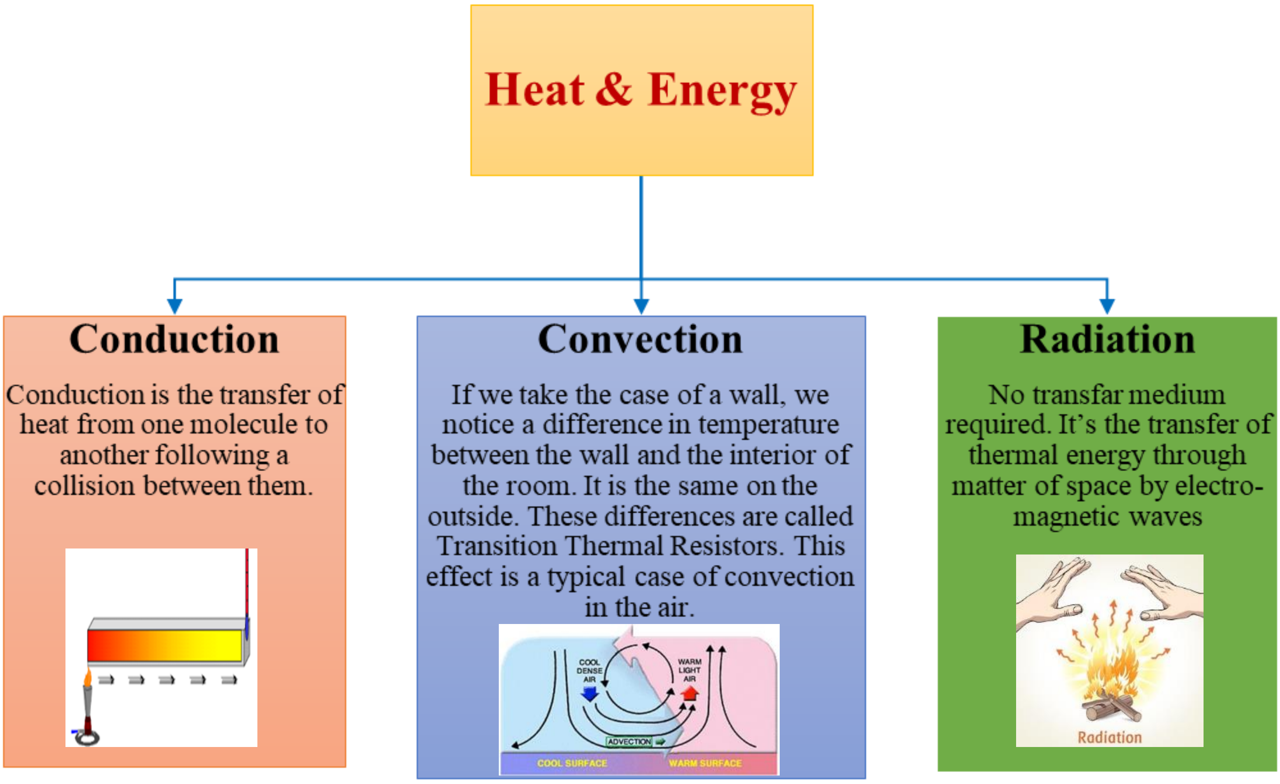


Fig. 17. Heat and energy transfer phenomena

Another important parameter is the spectrum. The entire electromagnetic spectrum highlighting the infrared part located between the visible and the radio waves, is depicted in **Fig. 18**. The IR spectrum can be subdivided into 5 regions [31], that are presented in Table 2.

Table 2. Infrared spectral bands

Spectral bands	Range [um]	Detector materials	Applications
NIR	0.74 6 – 1	SiO2	Telecommunications
SWIR	1 - 3	In, Ga, As, Pb, S	Remote sensing
MWIR	3 - 5	In, Sb, Pb, Se, Pt, Si, Hg, Cd, Te	High temperature inspection (indoors, scientific research)
LWIR	8 - 14	Hg, Cd, Te	Ambient temperature (outdoor, industrial inspection)
VLWIR	14 - 1000	----------------	Spectrometry, astronomy

Si: silicon; SiO2: Silica; In: Indium; As: Arsenic; Pb: Lead; S: Sulphur; Sb: Antimony; Ga: Gallium Se: Selenium; Pt: Platinum; Hg: Mercury; Cd: Cadmium; Te: Tellurium.

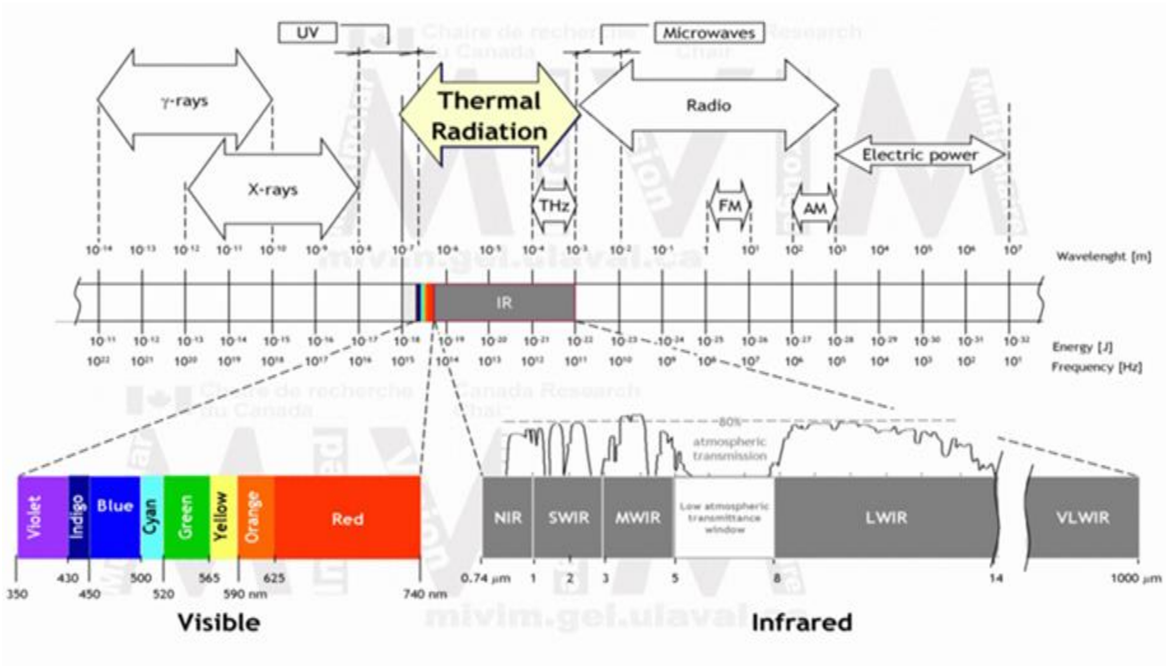


Fig. 18. The infrared bands in the electromagnetic spectrum

The spectral power distribution according to Planck´s Radiation Law exists in theory only. In practice, measuring objects or materials are existing as „grey bodies" or with an emissivity depending on then wavelength. Spectral thermography is detecting the infrared radiation in selected wavelength ranges, using those ranges with optimal emissivity – especially within the so-called absorption bands – or with a high transmissivity. For this purpose, the MWIR range (3...5) µm which contains many emissivity maxima of interesting materials is especially [32].

Black bodies. A blackbody is an ideal radiating element that absorbs 100% of incident radiation, which means that it does not reflect or transmit any radiation. This does not exist in reality, since there is always a little something considered for example. For a black body, the emissivity $\varepsilon = 1$ (and $\rho + \tau = 0$) [33].

Real (Grey) bodies. In a real measurement situation, we will never meet black bodies. Our objects will not be black bodies, but so-called "real" or "grey" bodies. Real bodies can have the ability to emit, absorb, reflect and transmit. However, most target objects are not transmissive but opaque, so $\tau = 0$. For opaque target objects of bodies other than black, such as real non-transmissive bodies, the sources emanating from the object are reflected radiation and the one issued. This remark is important and must be taken into account when interpreting an infrared image [33].

The black body is the body of reference in the theory of infrared radiation: it is capable of absorbing any incident radiation regardless of its wavelength and in turn emit radiation at all wavelengths. This reference body transfers the energy captured to the environment until the establishment of a thermodynamic equilibrium: the black body is an ideal radiator [32]. In thermal radiation theory, blackbody is considered as a hypothetical object which absorbs all incident radiations and radiates a continuous spectrum according to Planck's law as follows [34].

$$W\lambda = \frac{2\pi \cdot h \cdot c^2}{\lambda^5 \cdot \exp\left(\frac{h \cdot c}{\lambda \cdot k \cdot T}\right) - 1}$$

λ is the wavelength of the radiation (µm);

$W\lambda$: the power radiated by the blackbody per unit surface and per unit solid angle for a particular wavelength;
c speed of light = 3.10^{10} cm/s;
h: Plank constant = $6.6 \cdot 10^{-34}$ Watt.s^2;
k: Boltzman constant = $1.4 \cdot 10^{-23}$ Watt.s^2/°K;
T: Absolute temperature of the black body in Kelvin.

These complex mathematical formulations are represented by curves (Fig. 19). From these curves, it can be noticed that:

- The electromagnetic power emitted increases with the temperature of the black body;
- The emission of radiation passes by a maximum: this maximum occurs at wavelengths of increasingly weak when the temperature of the black body grows;
- From a temperature of the order of 520 ° C, the emission of the infrared radiation appears in the visible spectral range (0.4-0.8µm): the objects heated at least to this temperature become visible to the human eye by the dark red color;
- Below this temperature, we do not "see" the temperatures because the emission of radiation is beyond the spectral band on which are calibrated our eyes. Therefore, to visualize bodies whose T ° is lower than 520 ° C, it is necessary to use devices whose detection threshold is lower than that of the human eye.

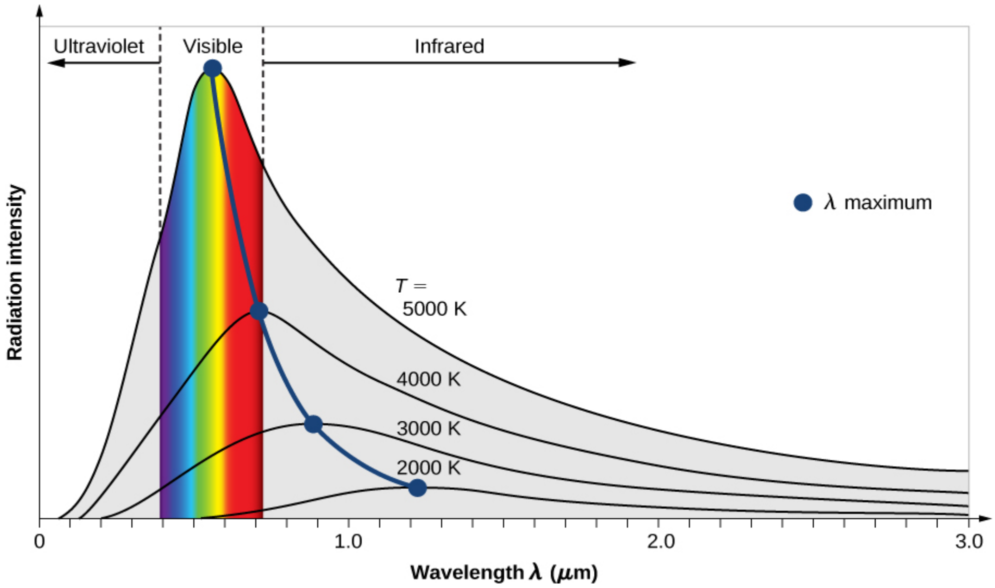


Fig. 19. Plank Law curves

2.3.1. Emission, Reflection and Transmission

The radiation recorded by a thermal system consists of the emission, transmission and reflection of the IR radiation which is emitted from objects in the surroundings to the thermal systems [35]:

- **Transmission (t).** Transmission is the ability of a material to allow IR radiation to pass through it (transmit). A thin plastic sheet, for example, has a very high transmissivity – meaning that if one wants to use a thermal imager to record the temperature of a thin plastic sheet hanging in front of a house wall, one measures the temperature of the wall and not that of the sheet. Most materials do not allow IR radiation to pass through, so that the degree of transmissivity of a material is as a rule almost 0 and can thus be neglected.
- **Emission (ε).** Emission is the ability of a material to emit IR radiation. This ability is expressed in the level of emissivity. It depends on, among other things, the material itself and its surface structure. The sun, for example, has an emissivity of 100 %. However, this value

never otherwise occurs. Concrete, on the other hand, is close, with an emissivity of 93 %. This means that 93 % of the IR radiation is emitted by the concrete itself.

- **Reflection (ρ).** The other 7 % are reflections from the surroundings of the material / the object which one wishes to measure, i.e. the temperature which is reflected from the object. One can enter the degree of emissivity and the reflected temperature into a thermal imager in order to obtain as precise a thermal image as possible.
- **Connection between emission and reflection.** Measurement objects with high emissivity ($\varepsilon \geq 0.8$) [35]:
  - have a low reflectivity (ρ): $\rho = 1 - \varepsilon$;
  - their temperature can be very well measured with a thermal imager Measurement objects with medium emissivity ($0.6 < \varepsilon < 0.8$);
  - have a medium reflectivity (ρ): $\rho = 1 - \varepsilon$;
  - their temperature can be well measured with a thermal imager Measurement objects with low emissivity ($\varepsilon \geq 0.6$);
  - have a high reflectivity (ρ): $\rho = 1 - \varepsilon$;
  - temperature measurement with a thermal imager is possible, however you should critically question the results;
  - a correct setting of the reflected temperature compensation is indispensable, as it makes a large contribution to the temperature calculation.

2.4. IR Equipment

2.4.1. Infrared Cameras

Thermography is a method of inspecting electrical and mechanical equipment by obtaining heat distribution pictures. This inspection method is based on the fact that most components in a system show an increase in temperature when malfunctioning. The increase in temperature in an electrical circuit could be due to lose connections or a worn bearing in the case of mechanical equipment. By observing the heat patterns in operational system components, faults can be located, and their seriousness evaluated. The inspection tool used by Thermographs is the Thermal Imager. These are sophisticated devices which measure the natural emissions of infrared radiation from a heated object and produce a thermal picture. Modern Thermal Imagers are portable with easily operated controls. As physical contact with the system is not required, inspections can be made under full operational conditions resulting in no loss of production or downtime [36].

The infrared camera captures through a transmitting medium (i.e. the atmosphere) the radiation emitted by a thermal scene. The radiometric system converts the power of radiation into digital or analogue signals: these are transcribed into temperature by the computer and converted into light spots on a screen. The image thus obtained is called "Thermogram".

2.4.2. Infrared Camera for CBM

Several parameters must be considered before choosing an infrared camera as the ability of producing a sharp and accurate thermal image largely depends on these performance parameters. A few important parameters are discussed below [37].

Spectral range. Spectral range is defined as the portion of the infrared spectrum in which the infrared camera will be operationally active. As temperature of an object increases, the thermal radiations emitted by the object are more in the shorter wave length bands. For observing objects at ambient temperature long wave length band (7.5–14 μm) is preferable. This is because of two reasons, bodies at ambient temperature emits predominantly at these wavelengths and secondly measurements performed at these wavelengths are not affected by the radiation from sun (valid for outdoor measurements), as radiation from sun is predominantly in the shorter wave length bands. Short wave systems (2–5 μm) may be preferred during overcast days and night times [38].

Spatial resolution. Spatial resolution of a thermal imaging system is defined as the ability of the camera to distinguish between two objects within the field of view. A better spatial resolution will result in superior image quality. Spatial resolution of an infrared camera primarily depends on object to camera distance, lens system and detector size. Spatial resolution decreases with increasing object to camera distance. Lens system with small field of view has higher spatial resolution. For example, a 10° × 7° lens system has superior spatial resolution than a 20° × 16° lens system. Finally, detectors with larger number of array element will produce thermal images with better spatial resolution. For example, 640 × 512 elements detector will have better spatial resolution than 320 × 256 elements detector. Typical spatial resolution value for a 320 × 256 elements detector with 20° × 16° at 1 m object to camera distance will be 1.1 mm/pixel and 1.09 mm/pixel respectively in the horizontal and vertical directions respectively [39].

Temperature resolution. Temperature resolution is defined as the smallest difference in temperature in the field of view which can be measured by the infrared camera. Temperature resolution depends on several experimental parameters like object temperature, ambient environmental temperature, object to camera distance, presence of filters, etc. The most common parameters used as a measure of temperature resolution are noise equivalent temperature difference (NETD), minimum resolvable temperature difference (MRTD) and minimum detectable temperature difference (MDTD).these quantities are in general determined as per the ASTM standards E 1543-94, E 1213-92 and E-1311-89 respectively. Typical values of NETD for modern Stirling cycle cooled cameras are less than 0.025 K at room temperature [39].

Temperature range. Temperature range signifies the maximum and minimum temperature values which can be measured using an infrared camera. Typical values are within the range −20 to 500°C. The range can be extended up to 1700°C using various filters [39].

Frame rate. Frame rate is defined as the number of frames acquired by an infrared camera per second. Higher frame rate cameras are in general preferable for monitoring moving objects or dynamic events like propagation of thermal fronts. Typical frame rate values are 50 Hz, i.e. 50 frames per second

Apart from the above-mentioned performance parameters, the selection of an infrared camera also depends on the inherent parameters such as power, size, weight, image processing capabilities, calibration, storage capacity, computer interface, cost and service. Some of the infrared cameras (along with the spectral range, temperature resolution and detector elements) used for condition monitoring applications [39].

2.4.3. Spectral Filters

The use of spectral filters requires a special calibration of the thermographic system in the desired temperature range. Narrow-band filters are leading to a significantly lower response of the thermographic camera (worse signal/noise ratio), whereby the thermal resolution in lower temperature ranges can decrease. In spectral thermography so called longwave-pass filters (LWP), shortwave-pass filters (SWP), bandpass filters (BP) and narrow bandpass filters (NBP) are used.

Fig. 20. Spectral filters for thermographic cameras

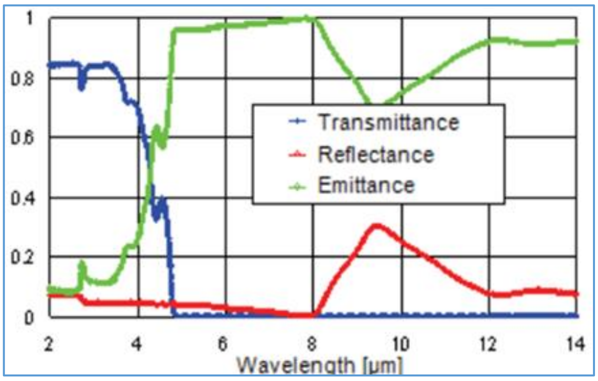


Fig. 21. Glass Spectral transmissivity, reflectivity and emissivity

2.4.3. Signal Processing in IR Cameras

The main elements of thermal systems are [40]:

1. **Image** can form by the optical system using radiation in infrared wavelength range;
2. **Thermal detector** convert radiation into electrical signal which are falling on them;
3. Some system requires **scanning mechanism** or some system not. Most of the time large detector array can be used to completely cover the field of view of the imager;
4. Conversion of electrical signal into a video signal is done by an **electronic processor** and then visual image from the video signal generated by display.

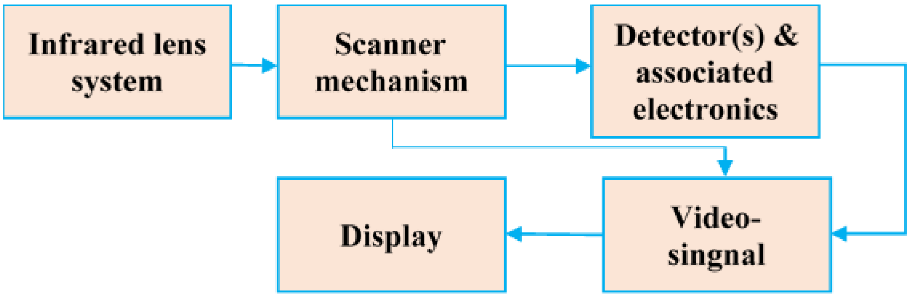


Fig. 22. Block diagram of signal process in infrared camera

The Fig. 22 shows that processing of infrared signal from optical system to display. The different subassembly of an infrared scanning system is presented below.

Optical System. The design of optical system for visible wavelength is same in thermal imager only difference is that different materials are used. This is fact that 3-5m band or 8-14m band optical materials are different [41].

Thermal Detectors. In cameras, the thermal detector is most important element. It is required to determine potential level of heat or thermal and spatial resolution. The types of infrared thermal detectors are [42]:

1. Rising in the temperature due to IR radiation heating the detector element and after that triggering some other physical mechanism that is taken as a measure of the radiation falling on the element. This detector called as thermal detector;
2. To produce charge carriers which are generated across the detector element, it is necessary for photons, which are the incident radiation, to interact at atomic or molecular level with the material of the detector. In this mechanism, electron always absorbing a photon and therefore quantum energy is moving from one level to another. This detector called as a photon or quantum detector.

Scanning Mechanism. The image formed on detector element by the lens system which is move in well-controlled fashion. There are three classes of scanner system as represented by one-dimensional (1D) oscillating mirror scanner arrangements. In the first arrangement, space between optical system and the detector take place by scanner. In the next arrangement, space between the external object and the image forming optical system take place by scanner and in the third arrangement scanner is place between focal front end and image-forming back end of optical System. For scanning IR image, one type of scanning mechanism is shown in figure below. In figure, there are two mirrors with its respective motors and at the bottom of image there is IR lands with detector. There is one way to scan FOV (field of view) by IR camera with single IR detector that is left mirror scans the vertical axis and right mirror scans the horizontal axis. Therefore, for scan all FOV (field of view) motor with mirror is used [43].

Displays. External display like computer screen or a small display that forms part of the camera is required to view the image generated by a thermal imager. LCD having flat screen, s mall and direct view display and it is a part of camera. It is also used in eyepiece displays. Display may be monochromatic or colour. To show temperature difference as colour difference, image can be colour coded in latter case [44].

The quality of the measurements is based on two main criteria [45]:

- Thermal resolution: This is the ability of the camera to discern from slight differences in luminance or temperature. It is essentially limited by the electronic noise of the detector assembly and processing line of the signal (analogy and digital). Which explains the extreme cooling of the detector and the very good noise performance of the preamplifier (<0.6 nV / Hz).
- Spatial resolution: This is the ability of the camera to show the distinction between spatially very close luminance values. She is limited by the quality of optics and the response time of the entire chain electronic. Hence the choice of the bandwidth of the amplifier and the sampling frequency. Other characteristics are also important:
- The operating range: The temperature range covered is usually divided into sub-ranges. The low limit is not well known (between - 50 and - 30 ° C depending on the wavelengths).
- Dynamics: It is equal to the maximum signal-to-noise ratio that the camera can present.
- Drift in the short and long term.

Suitable for spectral thermography are the MWIR thermographic systems. *Infracted* offers of the Image IR®-series that are equipped with motorized filter wheel and allows software-controlled insertion of different filter positions directly into the optical path of the detector. An alternative solution are manual filter slides – for example for the uncooled micro bolometer camera Vario CAM® hr head – for on glass measurements, protection against CO_2 – laser and measurements on plastic foils [32].

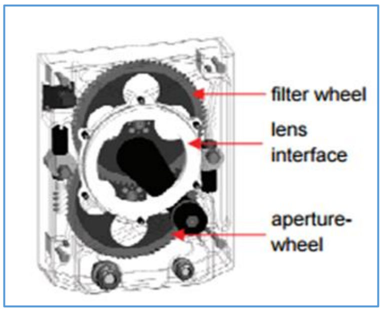


Fig. 23. Opto-mechanism of ImageIR [32]

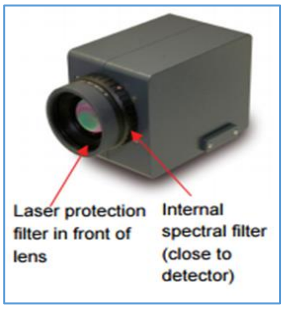


Fig. 24. Hr head with filter slide close to detector [32]

Fig. 25. Camera Image IR® series with motorized filter wheel [32]

2.5. Applications of IRT

Some applications of spectral thermography are the following [32]:

- IR-reflectography (only MWIR). IR-reflectography is used for the detection of lower painting layers due to its spectral behaviour (upper layer transmissivity, lower drawings reflective).
- Humidity detection (only MWIR). With the help of humidity detection, for example for the analysis of building materials in case of claims, the spectral absorption factor of water band is defined.
- Leakage (only MWIR). Another interesting application is the detection of leakages on tanks using IR-detectable gases. A suitable and available gas is CO_2, having a strong absorption band at 4,25 µm. A tempered background helps to recognize the leaving gas flow.
- Temperature measurement of flames (only MWIR). Temperature of flames can be estimated by measuring selectively within the absorption band of CO_2 at 4.25 µm. Thermography at objects behind the flame is possible using the spectral range of (3.75 … 4) µm (for example furnace walls or pipes).
- Film extrusion process (LWIR und MWIR). Film surface temperature can be measured using a band pass filter at 3.4 µm (applicable for various plastics, e.g. polyethylene, polypropylene, polyamide, polyvinyl). For some plastics an absorption band at 8 µm (LWIR).

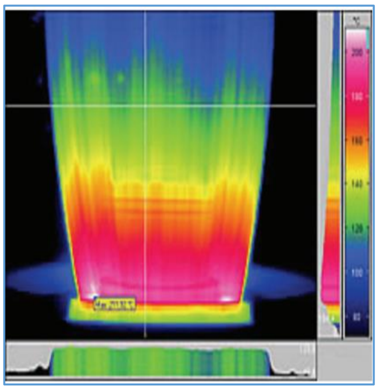


Fig. 26. Film surface temperature measurement [32]

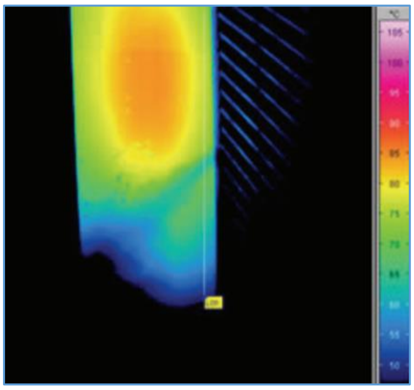


Fig. 27. CO_2 – gas flow on a car cooler [32]

IR thermography is divided into two broad areas, imaging and measurement, which encompass a lot of subdomains that has a lot of application also in industry.

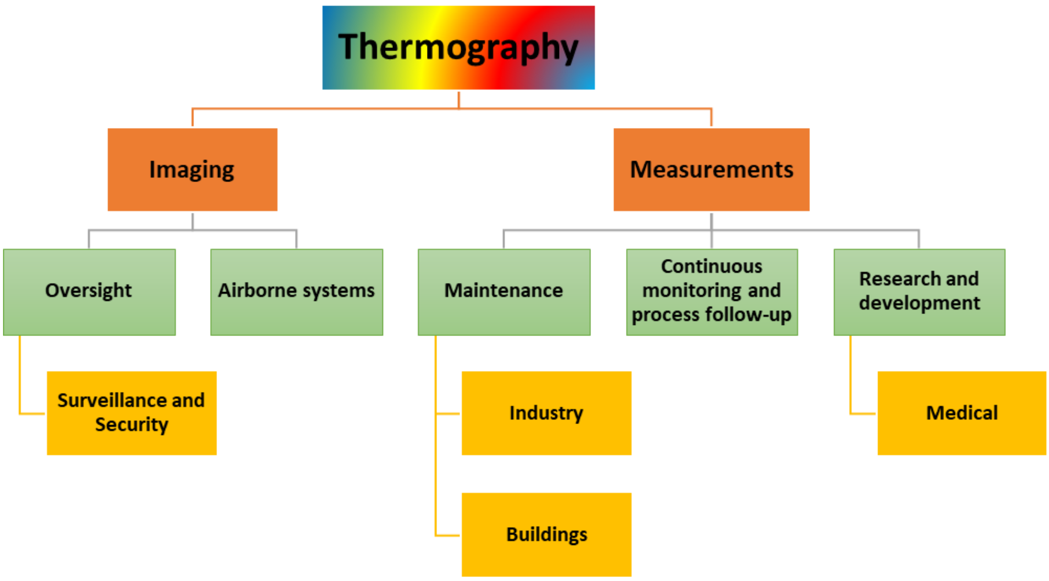
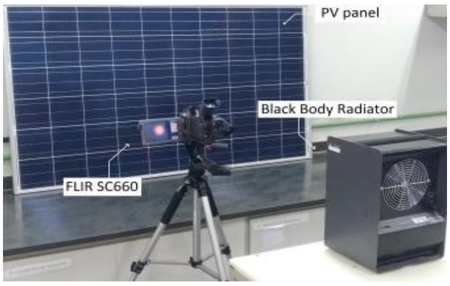
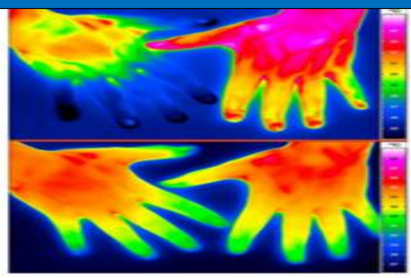
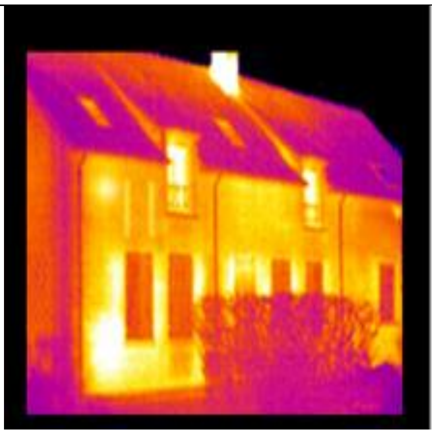
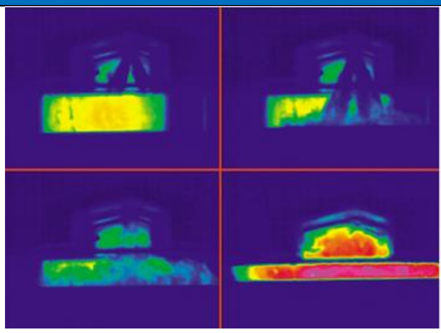
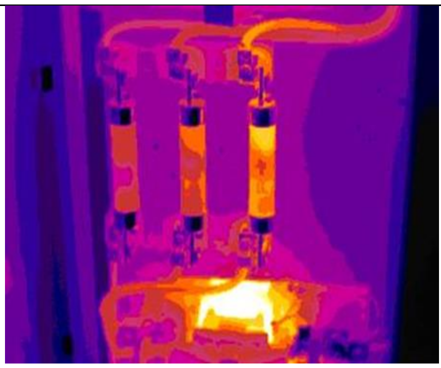


Fig. 28. Main filed of application of the IR thermography

The applications of thermography are numerous and can be enumerated as following [46]:

Solar Panels [15]	**Solar panels**: Infrared thermography (IRT) has become one of the most important techniques to study thermal behaviour of PV panels. Thermography is used to detect hot spots, to investigate the effect of shadows and soiling, also to determine performance of PV panels inside laboratories and outdoor Usually, studies are qualitative in essence, and do not intend to measure temperature effectively, only to observe temperature gradients. If temperature measurements are needed, the inspector must choose between making the inspections from the back side or from the front side. From the back side, the surface is usually opaque, diffuse and possess high emissivity then accurate measurements of temperature can be made. But, most of the times, inspections are made from the front side (or from above using unmanned aerial vehicles - UAV) In the front side perspective, the scenario is completely different. Panels are multilayer structures reflecting the sky, which makes the problem non-gray, and the IR camera's software does not cover this condition. Thermal imagers and commercial post processing tools consider a scenario in which the target object is gray, and the reflected component has spectral distribution proportional to a blackbody.	 
Medical and Veterinary	Using infrared thermography, you can detect cancer, arthritis and circulation issues. Doctors find muscular and skeletal problems. Vets to discover muscular and skeletal problems can use the technology. Infrared technology is even used to fit horses with saddles.	 Thermal image of hands before and after regulation therapy
Surveillance and Security	Infrared cameras deliver more to the field of security than simple threat detection and enemy movements on the field of battle. Thermal imaging applications in security can be used to detect smoke-filled rooms, provide effective home security, or even to locate weapons and chemicals being smuggled into prisons or county jails	 Surveillance of garden

Buildaing	The most common infrared thermography applications are found being use by business owner and home owners alike to save energy cost in residential, commercial and industrial sectors, including infrared thermography home energy surveys and electrical inspections. Common industrial infrared application is performing infrared industrial electrical system surveys and reliability engineering like PdM and RCM. In process and manufacturing, maintenance can view systems under a load with non-invasive infrared inspection to spot a problem before it occurs and even improve the process performance. Also infrared thermography is commonly used in building and construction for moisture detection, on the other end of the spectrum, used for fire safety. Also testing of equipment are common infrared applications, including the following.	
Industry	**A. Mechanical Equipment Infrared Applications:** - Detecting blocked air coolers and radiator tubes in internal combustion engines - Finding air leaks and clogged condenser tubes in refrigeration systems - Locate and identify overheating bearings, increased discharge temperatures, and excessive oil temperatures in pumps, compressors, fans, and blowers **B. Boilers and Steam Systems Infrared Applications:** - Examine insulation breakdown. - Check leakage of the link or valve. - To check the effectiveness of insulation **C. Thermography in Electronics and Electrical Industry** **D. Thermography in industrial application (welding monitoring, manufacturing processes like milling, machining etc.)**	 

2.6. Thermal Imaging for Industrial Maintenance

Thermal imaging is widely accepted (maintenance, repairs & operations) tool in both electrical and mechanical systems. Over the past few years, thermal imaging has been growing in popularity. Uses include:

- Proactive equipment monitoring. Manual use of thermal imaging tools can identify weakening components before they fail, based on the abnormally high temperature of the materials in those components. Easily adapted for pumps, valves, belts, motors and more.

- Checking equipment remotely. Thermal imaging allows a properly trained technician to conduct routine maintenance without opening a control panel and/or without shutting down an entire line. This is an advantage for electricians and electrical contractors.
- Automated condition monitoring. Thermal imaging also lets you configure automated systems that can identify problems, create signals and alert your team before a failure happens [47].

Various condition monitoring applications of infrared thermography [39]:

a. Monitoring of machineries where abnormal surface temperature distribution is an indication of a probable flaw.
b. (Inspection of liquid levels in industrial components.
c. Inspection of printed circuit boards. Localized defects like short circuits or current leakages produce hot-spots which can be easily detected by infrared thermography.
d. Typical thermal images of a transformer circuit breaker where the faulty regions can be clearly seen as hot-spots.
e. Inspection of shaft belt where the thermal anomaly is due to over-tightening of a belt.
f. Condition monitoring of three phase electrical panel where local hot spots are developed due to load imbalance.

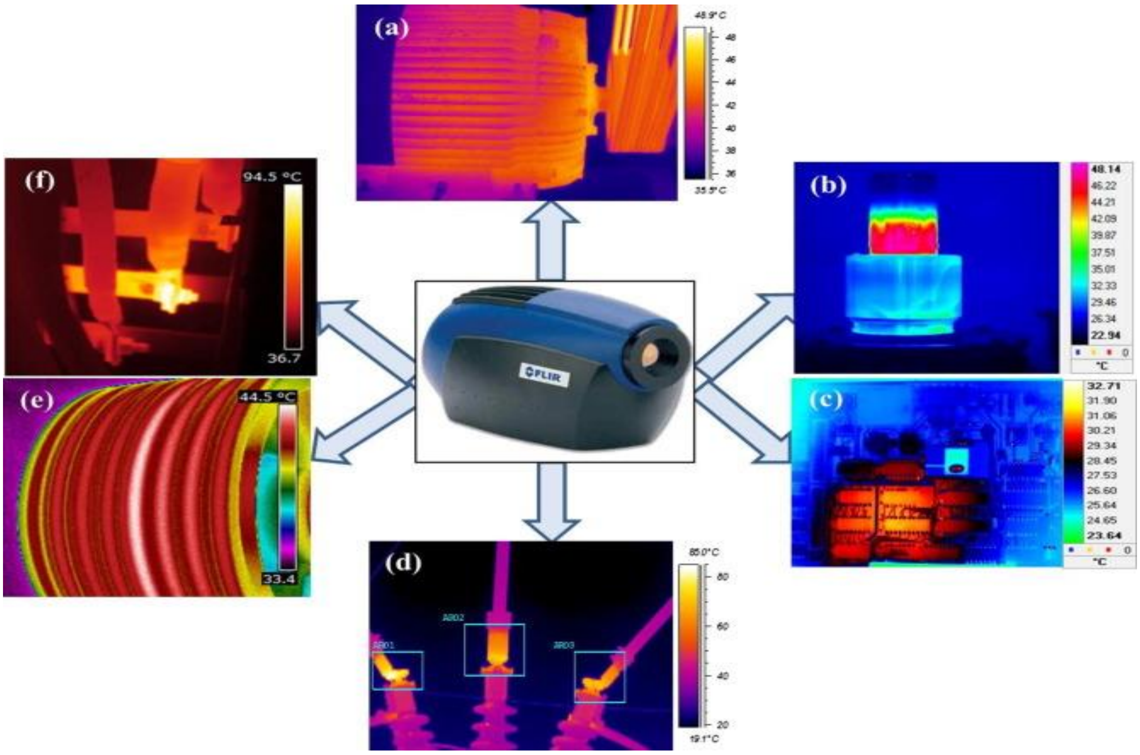


Fig. 29. Thermal Imaging for Industrial Maintenance

We have other application of thermography in maintenance [48]:

- Monitor and measure bearing temperatures in large motors or other rotating equipment.
- Identify "hot spots" in electronic equipment.
- Identify leaks in sealed vessels.
- Find faulty insulation in process pipes or other insulated processes.
- Locate overloaded circuit breakers in a power panel.
- Identify fuses at or near their current rated capacity.
- Identify problems in electrical switch gear.
- Capture process temperature readings

2.7. Data Analysis Methods for IRT-based Condition Monitoring

The quantitative analysis of IRT data enables accurate determination of the temperature of a point or a region. On the other hand, in qualitative analysis relative value of a local hotspot with respect to a reference point is considered. In majority of condition monitoring applications like inspection of electrical components and machineries qualitative data analysis is performed as the methodology is fast and does not warrant rigorous evaluation of the acquired thermal images and provides quick decisions using the difference in temperature of the region of interest and the reference region (ΔT) criteria [49], [51].

The severity of the incident is in general represented in terms of ΔT tables, where, three to four different priority classes are present, and each class represents a level of severity. Several standards are available, which provide such ΔT tables for qualitative measurement of temperature using IRT for electrical equipment. Some of the commonly used standards are International Electrical Testing Association (NETA) American Society for Testing & Materials (ASTM): E 1934-99a [50], National Fire Protection Association (NFPA) military standard: MIL-STD2194 and Allen-Bradley motor control centre standard. Introspection institute standard specifies the experimental methodologies and data analysis techniques for electrical components as well as rotating components Maximum allowable temperature of several mechanical components (like bearing, rolling elements, lubricants, grease, synthetic coils, seals, gaskets, gear drives, chain drives, etc.) are listed in this standard.

Under normal operational conditions temperature of a particular component must not rise beyond the maximum allowable value enlisted in the above-mentioned standard. Table 3 shows the salient features of the NETA, MIL-STD2194 and Infraspection institute standards. As qualitative monitoring suffers from several drawbacks like non-availability of standard data tables and lack of accuracy, detection of systematic equipment failures requires rigorous quantitative analysis [51], [52], [53], [54], [55], [56], [57].

Table 3. Salient features of NETA [39]

Standards	Temperature (°C)	Difference (ΔT)	Recommended action
NETA	Between similar components under identical loading	Between components and ambient air temperature	
	1–3	1–10	Possible deficiency, warrants investigation (priority: 4)
	4–15	11–20	Indicates probable deficiency, repair as time permits (priority: 3)
	–	22–40	Monitor continuously until corrective measures can be accomplished (priority: 2)
	>15	>40	Major discrepancy, repair immediately (priority: 1)

Table 4. Salient features of MIL-STD2194 [39]

Standards	Temperature (°C)	Recommended action
MIL-STD2194	10–20	Component failure unlikely but corrective measures required at next scheduled routine maintenance period
	24–40	Component failure probable unless corrected

Standards	Temperature (°C)	Recommended action
	40–70	Component failure almost certain unless corrected
	>70	Component failure imminent

Table 5. Salient features of standards for IRT based inspection of electrical equipment [39]

Standards	Temperature (°C)	Recommended action
Infra-spection institute standard for electrical and/or mechanical components	1–10	Corrective measures should be taken at the next maintenance period
	>10–20	Corrective measures required as scheduling permits
	>20–40	Corrective measures required ASAP (as soon as possible)
	>40	Corrective measures required immediately

2.8. IR Devices Used for the Experiments

2.8.1. Equipment

In the present thesis, the equipment used for IR thermography monitoring, that can be applied in CBM process is the ThermoVision A20M. This is an affordable, accurate, intelligent infrared imaging and temperature measurement camera for industrial process monitoring, product verification, and security applications. Some technical specifications and characteristics are presented in chapter 3.

2.8.2. IR Camera Measurements

The measurements of the camera it will be described in this sub-chapter. The camera receives radiation not only from the object itself. It also collects radiation from the surroundings reflected via the object surface. Both these radiation contributions become attenuated to some extent by the atmosphere in the measurement path. To this comes a third radiation contribution from the atmosphere itself [58].

This description of the measurement situation, as illustrated in the figure below, is so far a fairly true description of the real conditions. What has been neglected could for instance be sun light scattering in the atmosphere or stray radiation from intense radiation sources outside the field of view. Such disturbances are difficult to quantify, however, in most cases they are fortunately small enough to be neglected. In case they are not negligible, the measurement configuration is likely to be such that the risk for disturbance is obvious, at least to a trained operator. It is then his responsibility to modify the measurement situation to avoid the disturbance e.g. by changing the viewing direction, shielding off intense radiation sources etc. Accepting the description above, we can use the figure below to derive a formula for the calculation of the object temperature from the calibrated camera output [58].

Assume that the received radiation power W from a blackbody source of temperature T_{source} on short distance generates a camera output signal U_{source} that is proportional to the power input (power linear camera). We can then write (Equation 2.1) [58]:

$$U_{source} = CW(T_{source}) \tag{2.1}$$

or, with simplified notation:

$$U_{sources} = CW_{source} \tag{2.2}$$

where C is a constant.

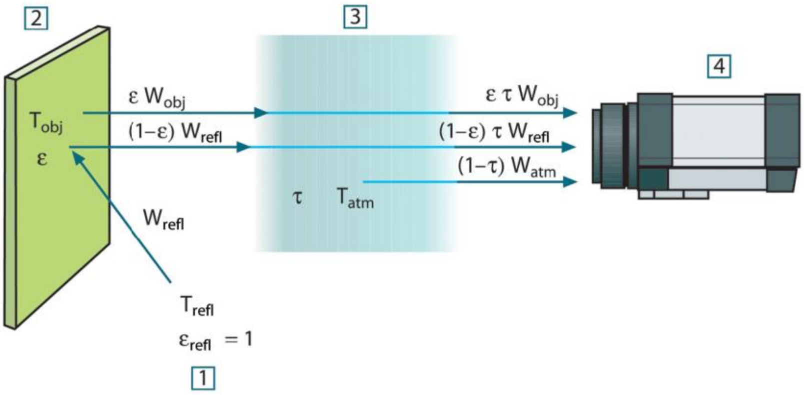


Fig. 30. A schematic representation of the general thermographic measurement situation
1: Surroundings; 2: Object; 3: Atmosphere; 4: Camera [58]

Should the source be a graybody with emittance ε, the received radiation would consequently be εW_{source}.

1 – Emission from the object = $\varepsilon\tau W_{obj}$, where ε is the emittance of the object and τ is the transmittance of the atmosphere. The object temperature is T_{obj}.

2 – Reflected emission from ambient sources = $(1 - \varepsilon)\tau W_{refl}$, where $(1 - \varepsilon)$ is the reflectance of the object. The ambient sources have the temperature T_{refl}.

It has here been assumed that the temperature T_{refl} is the same for all emitting surfaces within the halfsphere seen from a point on the object surface. This is of course sometimes a simplification of the true situation. It is, however, a necessary simplification in order to derive a workable formula, and T_{refl} can – at least theoretically – be given a value that represents an efficient temperature of a complex surrounding.

It can be noticed also that it has been assumed that the emittance for the surroundings = 1. This is correct in accordance with Kirchhoff's law: All radiation impinging on the surrounding surfaces will eventually be absorbed by the same surfaces. Thus, the emittance = 1. (Note though that the latest discussion requires the complete sphere around the object to be considered.)

3 – Emission from the atmosphere = $(1 - \tau)\tau W_{atm}$, where $(1 - \tau)$ is the emittance of the atmosphere. The temperature of the atmosphere is T_{atm}.

The total received radiation power can now be written (Equation 2.2) [58]:

$$W_{tot} = \varepsilon\tau W_{obj} + (1-\varepsilon)\tau W_{refl} + (1-\tau)W_{atm} \tag{2.3}$$

We multiply each term by the constant C of Equation 2.1 and replace the CW products by the corresponding U according to the same equation, and get (Equation 2.3):

$$U_{tot} = \varepsilon\tau U_{obj} + (1-\varepsilon)\tau U_{refl} + (1-\tau)U_{atm} \tag{2.4}$$

Solve Equation 2.3 for U_{obj} (Equation 2.4):

$$U_{obj} = \frac{1}{\varepsilon\tau}U_{tot} - \frac{(1-\varepsilon)}{\varepsilon}U_{refl} - \frac{(1-\tau)}{\varepsilon\tau}U_{atm} \tag{2.5}$$

This is the general measurement formula used in all the FLIR Systems thermographic equipment. The voltages of the formula are:

Table 6. Voltages of the formula [58]

U_{obj}	Calculated camera output voltage for a black body of temperature T_{obj}, i.e. a voltage that can be directly converted into a true requested object temperatur

U_{tot}	Measured camera output voltage for the actual case
U_{refl}	Theoretical camera output voltage for a black body of temperature T_{refl} according to the calibration
U_{atm}	Theoretical camera output voltage for a black body of temperature T_{atm} according to the calibration

The operator has to supply a number of parameter values for the calculation:

- the object emittance ε,
- the relative humidity,
- T_{atm}
- object distance (D_{obj})
- the (effective) temperature of the object surroundings, or the reflected ambient temperature T_{refl}, and
- the temperature of the atmosphere T_{atm}

This task could sometimes be a heavy burden for the operator since there are normally no easy ways to find accurate values of emittance and atmospheric transmittance for the actual case. The two temperatures are normally less of a problem provided the surroundings do not contain large and intense radiation sources.

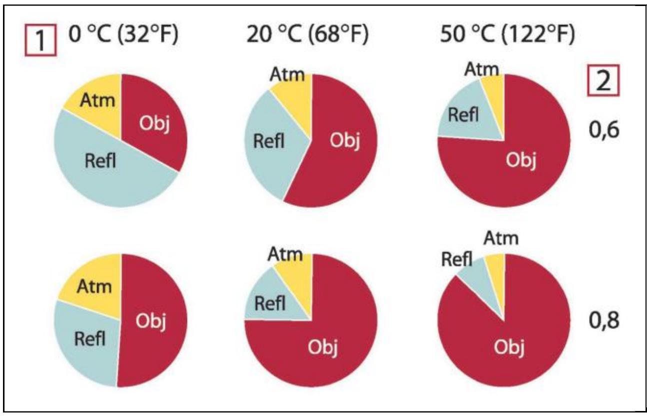
The figures below illustrate the relative magnitudes of the three radiation contributions for three different object temperatures, two emittances, and two spectral ranges: SW and LW. Remaining parameters have the following fixed values:

- $\tau = 0.88$;
- T_{refl} = +20°C (+68 °F);
- T_{atm} = +20°C (+68 °F).

It is obvious that measurement of low object temperatures is more critical than measuring high temperatures since the ‘disturbing’ radiation sources are relatively much stronger in the first case. Should also the object emittance be low, the situation would be still more difficult.

We have finally to answer a question about the importance of being allowed to use the calibration curve above the highest calibration point, what we call extrapolation. Imagine that we in a certain case measure U_{tot} = 4.5 volts. The highest calibration point for the camera was in the order of 4.1 volts, a value unknown to the operator. Thus, even if the object happened to be a blackbody, i.e. $U_{obj} = U_{tot}$, we are actually performing extrapolation of the calibration curve when converting 4.5 volts into temperature.

Let us now assume that the object is not black, it has an emittance of 0.75, and the transmittance is 0.92. We also assume that the two second terms of Equation 4 amount to 0.5 volts together. Computation of U_{obj} by means of Equation 4 then results in U_{obj} = 4.5 / 0.75 / 0.92 – 0.5 = 6.0. This is a rather extreme extrapolation, particularly when considering that the video amplifier might limit the output to 5 volts! Note, though, that the application of the calibration curve is a theoretical procedure where no electronic or other limitations exist. We trust that if there had been no signal limitations in the camera, and if it had been calibrated far beyond 5 volts, the resulting curve would have been very much the same as our real curve extrapolated beyond 4.1 volts, provided the calibration algorithm is based on radiation physics, like the FLIR Systems algorithm. Of course, there must be a limit to such extrapolations.



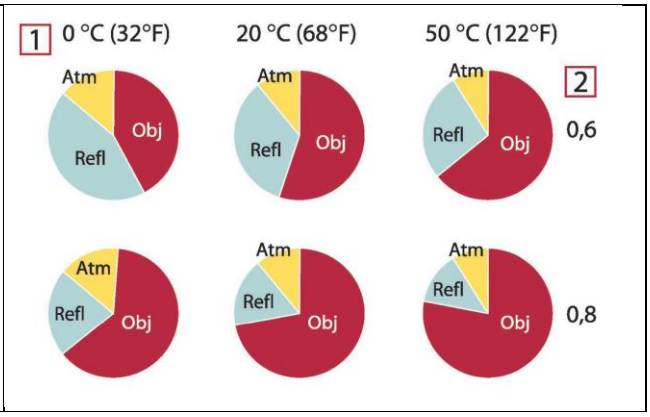


Fig. 31. Relative magnitudes of radiation sources under different measurement cond. (SW cam).

Fig. 32. Relative magnitudes of radiation sources under different measurement cond. (LW camera).

1: Object temperature; **2:** Emittance; **Obj:** Object radiation; **Refl:** Reflected radiation; **Atm:** atmosphere radiation. Fixed parameters: $\tau = 0.88$; $T_{refl} = 20°C$ (+68°F); $T_{atm} = 20°C$ (+68°F) [58]

For using the IT camera in measurements of radiation sources, that should be considered the emissivity values of various materials. Table 7 shows the emissivity values of some common materials used for setting up the monitoring conditions [59].

Table 7. Emissivity values of common materials [59]

Material	Emissivity	Material	Emissivity
Aluminum, polished	0.05	Electrical tape, black plastic	0.95
Aluminum, rough surface	0.07	Enamel	0.90
Asbestos board	0.96	Bronze, polished	0.10
Asbestos fabric	0.78	Carbon, purified	0.80
Brass, dull,	0.22	Glass	0.92
Brick, common	0.85	Glass, polished	0.02
Clay, fired	0.91	Steel Oxidized	0.79
Copper, polished	0.01	Steel Polished	0.07

Conclusion

Infrared thermography has evolved as an effective condition monitoring tool for real-time temperature monitoring of objects or processes in a non-contact way. It provides pertinent information regarding the health and efficiency of equipment or processes which are very crucial to prevent catastrophic breakdown or emergency shutdown. The applications of modern image processing tools on the acquired infrared thermal images along with artificial intelligence-based approaches can further augment the decision-making process faster and without human interference. Unlike other condition monitoring methodologies, infrared thermography provides a real-time pseudo colour coded image of the object and visual manifestation of defects. Applications of IRT as a condition monitoring technique in civil structures, electrical installations, machineries and equipment, material deformation under various loading conditions, corrosion damages, welding processes, nuclear, aerospace, food, paper, wood and plastic industries are reviewed. This review would also enable non-specialist in industries to adopt this technique for various condition monitoring applications, which would reduce down-time, maintenance cost, risk of accidents and enhance the productivity and growth.

Chapter 3. Condition-Based Maintenance for the Optimization of Smart Manufacturing Processes (SMP) using Infrared Thermography

3.1. Smart Manufacturing Processes

3.1.1. Introduction

The manufacturing is undergoing a transformation through the progress of automation, using of cyber Physical Systems (CPS), Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL) etc. There are a lot of discussion about manufacturing systems that focuses around terms such as big data and digital manufacturing. There is no doubt that the volume of data generated in manufacturing is increasing, however, the volume of the data collected and its usage varies across different industries, their scale, and production areas [60], [61]. For example, collecting large volumes of data is common in the semiconductor industry. Yet, in majority of discrete manufacturing companies, one would have difficulty identifying a machining centre with a dozen sensors installed. In addition, the utilization of data generated in manufacturing tends to be low. Some research organizations have retrofitted machine tools with multiple sensors to study the utility of the generated data, e.g., vibration, oil temperature, pressure [62].

Some manufacturing industries have shown interest in installing sensors on the legacy equipment. Since the research around data-driven modelling has been limited, equipment manufacturers have been reluctant to install sensors. Once benefits from the manufacturing data are fully demonstrated, the mainstream discrete manufacturing industry is likely to follow the data collection practices of other industries. For example, a typical wind turbine that has about the same order of complexity as a machine tool may streams over 100 data points at 0.1 Hz frequency. The data is collected in SCADA (supervisory control and data acquisition) systems that are transaction based. This practice differs from the storage in relational data bases used in many industries. The main developments in smart manufacturing are conditioned by data, and therefore of the assessment of the main data sources and usage, is needed across its technologies. Fig. 33 shows a part of the technologies with importance to smart manufacturing [62].

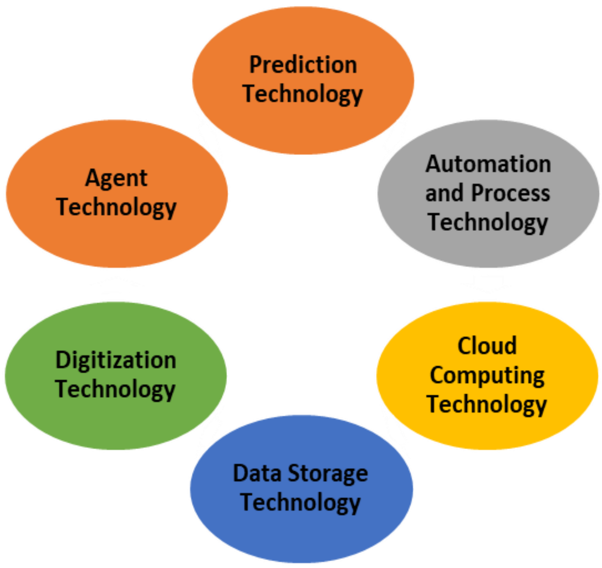


Fig. 33. Sources and consumers of data in smart manufacturing [62]

3.1.2. Materials

The basic idea of smart manufacturing involves flexibility in systems, monitoring, and adaptation to changing needs. Advancements in material technologies become critical for the varied applications of smart manufacturing systems which include sensors for the Industrial Internet of Things (IIoT), CPS, and robot-human interactions. In most sensors used for sensing of stimuli such as forces, temperature, humidity, one type of material is not enough for all applications. Hence, multi-material sensors become necessary. With shrinking volume of sensing systems, and reducing costs and energy required for running the sensors and collecting data – making compact, highly efficient sensor systems would require innovative materials. Nanotechnology and smart material systems would be the key to helping overcome challenges in material aspects of smart manufacturing [63].

Concerning huge data being generated in machining systems [64], the storage of data would require innovation such as optical storage arrays [65]. Multi-material systems consisting of combinations of ceramic materials, conductors, and insulating materials, along with piezoelectric materials and semiconductors would be important areas to explore for novel sensor systems [66]. Materials that would demonstrate a change in phase, and tenable properties for sensor systems [67], [68], would be important tools towards achieving full capabilities of IoT technologies. More targeted research on materials for the sensors targeted at monitoring manufacturing processes would involve rapid innovation in material systems for the scalable and sustainable development of the technology.

3.1.3. Sensors, Control, Platforms and Models for Smart Manufacturing

A 2014 NSF Workshop President's Council of Advisors on Science and Technology (AMP Report, 2014) focused on contrasting smart manufacturing with digital manufacturing and adopted the acronym ASCPM (Advanced Sensors, Control, Platforms, and Modelling) for manufacturing. Modelling is the underlying foundation of ASCPM, as the lingua franca for simulating and analysing a physical system. Models can be used at every point in the product life cycle. Design models are used to optimize a product and investigate product quality, reducing the requisite amount of expensive or impossible experimental validation. Models are also used in manufacturing for control and operation and optimization of supply chains. Models may also be used post-production to examine equipment degradation, product quality, and disposal issues. During the manufacturing process, mathematical models tied to advance sensing provide decision support. Models are also necessary for control of the manufacturing process, use of online fault monitoring methods, and implementation of state estimation techniques. At a higher level, plant-wide or industrial-scale models can also tie into product and process models to improve quality and efficiency by supporting business decisions. Models are currently used for many different applications, but there is still a need to integrate modelling efforts across multiple scales, from the molecular level to macro plant level, and to blend empirical (data driven) models with high fidelity models. The NSF Workshop on Smart Manufacturing discussed key research areas in ASCPM, which are summarized as follows [69]:

a) ***Sensors and Monitoring.*** Low-cost sensing technology will play a key role in future development for smart manufacturing. This measurement data is key to making improvements in the manufacturing process. Smart sensing includes new sensing methods, real-time process analysis, wireless connectivity, and sensors integrated with new cyber technologies. These advanced sensors may be able to autonomously manage and evaluate sensor health, continuously quantify measurement uncertainty, and support efficient calibration procedures. Smart sensors enable a wide range of advanced manufacturing capabilities. Product sampling for quality control testing can be reduced when advanced measurement information is properly integrated into the production process. Sensors provide information for validation and improvement of models. A mathematical model has limited use until measurements are used for model validation. As a system changes with time, process sensor values can be used to update the process models, allowing for various advanced manufacturing improvements. Additionally, better sensing leads to quantification of process variability and uncertainty. Improvements in sensor capabilities and industrial networking will provide large amounts of data. This "big data" problem leads to issues related to visualization and informatics. Without strong visualization and analysis techniques, big data can result in limited usefulness. Data cleaning, compression, and data security are also relevant issues that must be addressed. Practical concerns include integration of new sensor systems with legacy machines and processes. Data and models can be used to diagnose abnormal situations while helping in mitigation of negative consequences.

b) ***Control and Automation.*** Opportunities exist for smart control and automation to support optimal decision-making, enterprise modelling, and process analytics, but current technologies do not readily support rapid integration across various business and production applications. Simulation-based control strategies such as nonlinear model predictive control can be used to improve the production process. Future control methods should better support short-term scheduling, longer-term planning, and economic optimization. Supply chain management and scheduling challenges include improving the models used to represent the manufacturing systems. More efforts should be directed towards capturing, characterizing and mitigating uncertainty in the operation of manufacturing systems (caused, e.g., by variability of orders and deliveries, but increasingly, by fast fluctuations such as those observed in, e.g., energy prices). The use of historical data for improving system models and uncertainty models should be extended, and methods for verifying the quality of solutions obtained by accounting for uncertainty should be developed. Moreover, these modelling and analysis efforts should be directed towards systems of ever-larger scale; as a complementary direction, significant work will be required to expand the capabilities of current numerical optimization algorithms, such that very large-scale problems can be addressed in practical amounts of time.

c) ***Platforms and Standard.*** Machine-to-process-to-plant to-enterprise-to-supply-chain aspects of sensing, instrumentation, monitoring, control, and optimization include hardware and software platforms for industrial control and automation. A new generation of networked-based information technologies, data analytics and predictive modelling is providing unprecedented capabilities as well as access to previously unimagined potential uses of data and information not only in the advancement of new physical technologies, materials and products but also the advancement of new, radically better ways of doing manufacturing, processing materials and interoperating with material and energy resources. The platform is the informatics infrastructure that allows industry to develop and deploy relevant smart applications. This allows consistent applications to be joined together, even between businesses. Open interfaces, protocols, and standards will aid in platform development, allowing for plug-and-play interoperability in the platform. A vendor-agnostic Smart Manufacturing (SM) platform could support reuse and ready application of models and analytics at the level of need and readiness. The SM Platform similarly should support a mechanism to identify, exercise, and evaluate emerging manufacturing technologies from research organizations, as model elements of larger scale commercial system design emerge. The infrastructure allows for virtual test and analysis in early design phases using model representations in a free market library available to qualified commercial entities

d) ***Modelling.*** Process models and product models are moving toward more complexity. Large-scale models attempt to provide a much higher level of detail. Efforts to extend models from 1D or 2D to 3D often lead to computational complexity. Increased sensing and access to data leads to problems related to unstructured information, correctness verification, model clarity, and model resilience. Development of large-scale, hierarchical, high fidelity models presents challenges for process control and optimization. Specifically, advancements could be made in control of difficult (nonlinear, stochastic, hybrid) systems, planning, and use of unstructured information. There is a perceived gap between models used for process scheduling and for process control. Methods should also attempt to account for uncertainty in operations in order to allow for robust operations. For example, historical data could potentially be used for determining the extent of model uncertainty. Uncertainty leads to difficulty in verification of process control and optimization solutions. Additionally, uncertainty in cost variability is rarely included in scheduling and optimization work.

3.1.4. Artificial Intelligence (AI)

Artificial intelligence (AI) is the simulation of human intelligence processes by machines, especially computer systems. These processes include learning (the acquisition of information and rules for using the information), reasoning (using rules to reach approximate or definite conclusions) and self-correction. Particular applications of AI include expert systems, speech recognition and machine vision. AI can be classified as either weak or strong. Weak AI, also known as narrow AI, is an AI system that is designed and trained for a particular task. Virtual personal assistants, such as Apple's Siri, are a form of weak AI. Strong AI, also known as artificial general intelligence, is an AI system with generalized human cognitive abilities. When presented with an unfamiliar task, a strong AI system is able to find a solution without human intervention. While AI tools present a range of new functionality for businesses, the use of artificial intelligence raises ethical questions. This is because deep learning algorithms, which underpin many of the most advanced AI tools, are only as smart as the data they are given in training. Because a human select what data should be used for training an AI program, the potential for human bias is inherent and must be monitored closely.

Some industry experts believe that the term artificial intelligence is too closely linked to popular culture, causing the public to have unrealistic fears about artificial intelligence and improbable expectations about how it will change the workplace and life in general. Researchers and marketers hope the label augmented intelligence, which has a more neutral connotation, will help people understand that AI will simply improve products and services, not replace the humans but use them [70]. The principal components of artificial intelligence system are presented in the Fig. 34. Artificial intelligence has made its way into a large number of areas, with the following six examples.

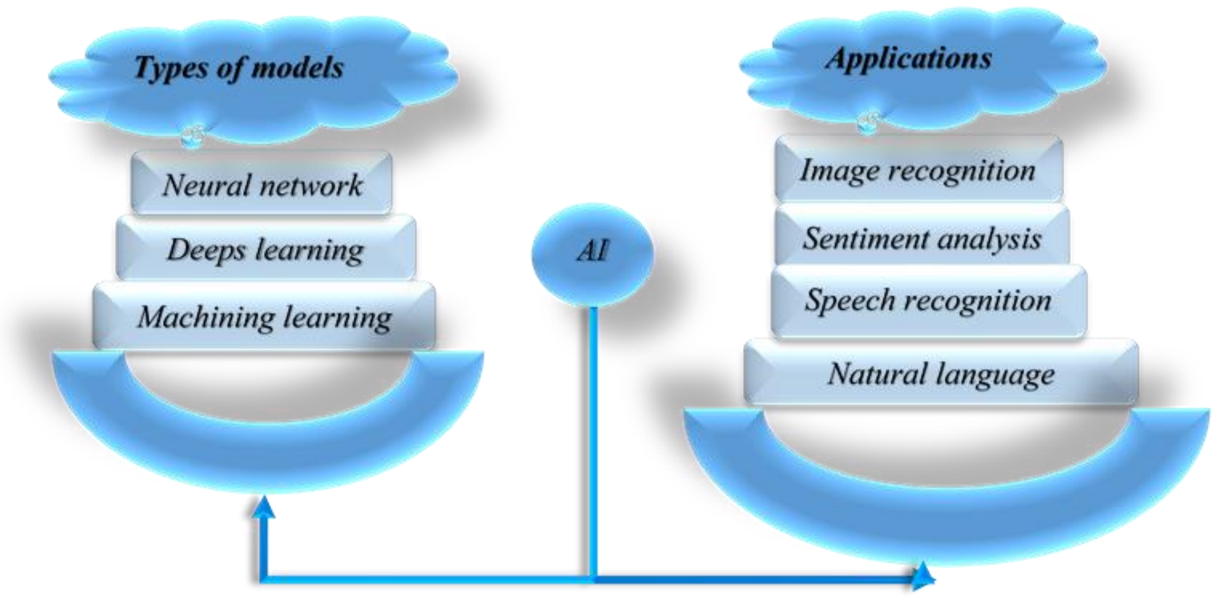


Fig. 34. Components of AI

The AI applications can be in a various number of fields. This can be in manufacturing, healthcare, business, education, finance and law. The software that AI is based on is doing the following issue:

- Collects information from sensors;
- Monitors anomalies and uses predictive models;
- Use this information to request human intervention;
- Maintenance of an industrial tool.

For predictive maintenance, artificial intelligence monitors information from machines in two different ways:

- Anomaly: The system reads data generated from the equipment and detects any variation from normal operating conditions.
- Failure: The system focuses on data models to detect potential failure based on similarities to predefined failure modes.

These two modes of operation generate alerts to inform the maintenance team that there is a problem. When combined, they form the basis of advanced maintenance strategies, such as condition monitoring and predictive maintenance.

Predictive maintenance is now used to monitor a wide variety of equipment. It has the major advantage of detecting defects that a human would miss or simply not be able to inspect or test. Better still, companies in the manufacturing, mining, oil, gas, and utilities sectors use this technology to remotely monitor critical assets scattered around the world, on land and under water. This saves them from having to send their staff for routine inspections, as has been the practice so far [71].

3.1.4.1. Artificial Intelligence in Maintenance

Today, companies have more than ever, the possibility of accessing quantities of data related to the exploitation of their machine park. The cost of connected devices is falling steadily; their exploitation is of interest to larger and smaller companies to optimize their process. As might be expected, one of the objectives relates to one of the strategic points of a company with physical assets effective management of maintenance. The fact that these technologies allow the communication of machine-to-machine (M2M) and machine to staff (M2H) is particularly interesting. However, the fact that machines are now able to think intelligently, to learn, to teach, to make decisions and to react as (or even better) than man, has launched an unprecedented opportunity to improve problems, Recurring in maintenance. New technologies such as AI, ML, virtual reality (VR) and the IIoT are attracting significant interest in order to reduce costs.

The most popular AI tools that can be applied in CBM are powerful optimisation methods that can deal with complex maintenance planning problems. Both *knowledge-based systems* (KBS) and *fuzzy-logic* (FL) show moderate interest with fewer studies using *case based reasoning* (CBR) and *neural networks* (NN). No studies were found on using DM the author expects interest in using *data minening* (DM) in maintenance should be forthcoming. FL, KBS and CBR applications cover both policy type as well as operational type maintenance decision problems while *generic algorithms* (GA) and NNs are mainly focused on operational problems such as project management planning and scheduling. The study of publications' trends GAs showed large increase in rate of publication with both FL and Hybrid system publications increased significantly. CBR sustained its moderate number of publication with interest started in NNs [72].

3.1.3. Machine Learning (ML)

Machine learning is the scientific study of algorithms and statistical models that computer systems use to effectively perform a specific task without using explicit instructions, relying on patterns and inference instead. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task [73]. ML algorithms are used in a wide variety of applications, such as email filtering, and computer vision, where it is infeasible to develop an algorithm of specific instructions for performing the task. Machine learning is closely related to computational statistics, which focuses on making predictions using computers. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a field of study within machine learning, and focuses on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics [73], [74], [75], [76]. There are many applications for machine learning, including [73]:

- Agriculture
- Anatomy
- Adaptive websites
- Affective computing
- Banking
- Bioinformatics
- Brain–machine interfaces
- Cheminformatics
- Computer Networks
- Optimization
- Recommender systems
- Robot locomotion
- Search engines
- Sentiment analysis
- Time series forecasting
- User behaviour analytics
- Computer vision
- Credit-card fraud detection
- Data quality
- DNA sequence classification
- Economics
- Financial market analysis
- General game playing
- Handwriting recognition
- Information retrieval
- Insurance
- Syntactic pattern recognition
- Telecommunication
- Theorem proving
- Structural health
- Internet fraud detection
- Linguistics
- Machine learning control
- Machine perception
- Machine translation
- Marketing
- Medical diagnosis
- Natural language processing
- Natural language understanding
- Online advertising
- Sequence mining
- Software engineering
- Speech recognition
- monitoring

3.1.4. Cyber-Physical Systems (CPS)

A CPS is a mechanism that is controlled or monitored by computer-based algorithms, tightly integrated with the Internet and its users. In cyber-physical systems, physical and software components are deeply intertwined, each operating on different spatial and temporal scales, exhibiting multiple and distinct behavioural modalities, and interacting with each other in a lot of ways that change with context [77], [78]. Helen Gill proposed this term in 2006 at the National Science Foundation (NSF) CPS Workshop conducted by the US NSF. Now CPSs are included in the priority lists of innovations of the US and several European countries [79]:

- The novelty and fundamental difference of CPS from existing embedded systems or automated process control systems (APCS), even though they are similar in appearance, is that CPS integrate the cybernetic beginning, computer hardware and software technologies, qualitatively new actuators, embedded in their environment and able to perceive its changes, respond to them, learn and adapt themselves;
- From the computer science point of view CPS are the integration of computing and physical processes. They include embedded computers, network monitors, and controllers, usually with feedback, where physical processes affect computations and vice versa;
- From the automation technologies point of view, CPSs are specialized systems, which activities are controlled by computing and communication cores embedded in objects and structures of the physical environment;
- According to the US NSF, the CPS of the future will far exceed the existing systems in performance, adaptability, fault tolerance, security, and ease of use.

The CPS architecture often consists of two main layers [80], [81]: the cyber layer and the physical layer. The current state of the CPS includes variables that represent data obtained by sensors and control variables representing control signals [82]. The normal value of a certain process parameter is called a set point. In CPS, the controllers calculate the distance between the values of the process variables and the corresponding control points. After calculating this offset, the controllers, using a complex set of equations, develop a local actuation, and compute new actuation and control variables.

The received control value is sent to the corresponding actuator to keep the process closer to a specific set point [83]. Controllers also send the received measurements to the main control servers and execute the selected commands from them. In CPS, system operators should be aware of the current status of the controlled objects. Thus, the graphical user interface (GUI), called the human-machine interface (HMI), and provides the current state of the controlled object to the human operator.

3.2. 3D Printing as part of Smart Manufacturing Processes

3D printing is nothing but a three dimensional view of the object is created or printed. This process of printing an object is simple. People can easily create the image with the help of computer software. These software helps in designing your imagination and the printers will help you in making them into object. There are two key components necessary for creating the objects and them are3D printers and 3D scanners. 3D printer is similar to a normal printer except that it layers atoms on top of each other to produce/create three-dimensional objects. Sounds magic, right? However, that is exactly what it does. Creating 3D prototypes of various designs produced by engineers and other experts. This technology was not invented overnight. It took many a years before the first successful prototype was made with the help of a 3D printer. Though this technology requires much more time to evolve completely, many organizations have already started using it to create may astounding things. There are a few instances where this technology has made remarkable contributions, especially, in the medical field where it has been able to save lives of many people. This provides us with a hint as to how 3D printing can change the world [84].

The continued development in the field of 3D technology has led to numerous developments. In the past, 3D printing made use of cheap materials such as plastic to produce the prototypes of the real parts that were to be manufactured at a later date. Today, this technology has developed to create the original machine parts using the same raw material that is used in manufacturing them, without the need of creating any prototypes. This led to a host of companies that started to manufacture nanocomposites, blends of different plastics, and blends of different powdered metals that have the capacity to mimic original metals such as steel. This paved the way to create mechanical parts that can be directly used in the machines. For example, companies like Jaguar have already started using this technology for rapid product development.

3.2.1. Types of 3D printing

The ISO/ASTM 52900 standard categorized all different types of 3D printing under one of these seven groups [85]:

- Material Extrusion (FDM): Material is selectively dispensed through a nozzle or orifice;
- Vat Polymerization (SLA & DLP): Liquid photopolymer in a vat is selectively cured by UV light;
- Powder Bed Fusion (SLS, DMLS & SLM): A high-energy source selectively fuses powder particles;
- Material Jetting (MJ): Droplets of material are selectively deposited and cured;
- Binder Jetting (BJ): Liquid bonding agent selectively binds regions of a powder bed;
- Direct Energy Deposition (LENS, LBMD): A high-energy source fuses material as it is deposited;
- Sheet Lamination (LOM, UAM): Sheets of material are bonded and formed layer-by-layer.

It all starts with the creation in a 3D model computer. This digital design is for instance a CAD (Computer Aided Design) file. A 3D model is either created from the ground up with 3D modelling software or based on data generated with a 3D scanner. It is possible to create a digital copy of an object with a 3D scanner [25].

3.2.2. 3D Printing Materials

Each 3D printing process is compatible with different materials. Plastics both thermoplastics and thermosets) are by far the most common followed by metals. Some composites and ceramics can also be 3D printed [86].

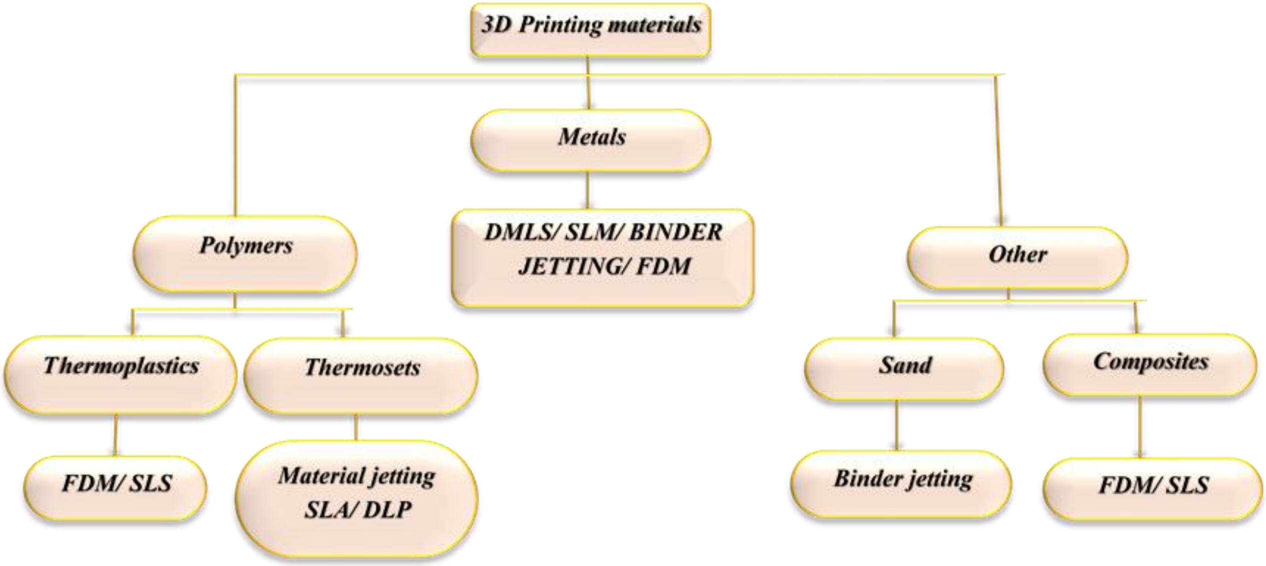


Fig. 35. The common materials used in 3D printing

3.2.2.1 Plastics

3D printing plastics are lightweight materials with a wide range of physical properties, suitable for both prototyping purposes and some functional applications. Plastics are either thermoplastics (with FDM or SLS), which are generally more suited for functional applications or thermosets (with SLA/DLP or Material Jetting), which are generally more suited for applications that require good visual appearance for example [86]:

- **PLA** High stiffness, good detail, affordable.
- **ABS** Commodity plastic, improved mechanical and thermal properties compared to PLA.
- **Resin** High detail and smooth surface, injection mold-like prototyping.
- **Nylon** Used to substitute functional injection moulded parts, good chemical resistance.
- **PETG** Good for mechanical parts with high impact resistance and flexibility. Sterilizable.
- **TPU** Rubber-like material, suitable for tubes, grips, seals and gaskets.
- **ASA** UV stability and high chemical resistance, preferred material for outdoor applications.
- **PEI** Engineering plastic, high performance applications, flame retardant.

3.2.2.2 Metals

3D printing metals are mainly used in applications that require high strength, high hardness or high thermal resistance. When 3D printing in metal, topology optimization is critical to maximize part performance and mitigate the high cost of the technology for example [86]:

- **Stainless steel** - High tensile strength, temperature and corrosion resistance.
- **Aluminium** - High machinability and ductility, good strength-to-weight ratio.
- **Titanium** - Used in aerospace, automotive and medical industries, excellent strength-to-weight ratio.
- **Cobalt-chrome** - Super alloy used in extreme environments, aerospace and biomedical applications.
- **Nickel alloy** - Super alloy used in extreme environments, aerospace applications.

3.2.3. Software for 3D printing

Different software packages can aid you in each different stage of the design process: from CAD design, to STL repair and preparation. In this section we list the best software for 3D printing to help you get started. The CAD software recommended for 3D design is: Solidworks, Rhinoceros, Fusion 360, Onshape, TinkerCAD. For fixing or modifying the STL files it can be used: Netfabb or Meshmixer. In the end, for turning the STL files into G code it can be used Cura or Simplify 3D [87].

3.3. Experimental Setup and Used Devices

The experiments were conducted in the Laboratory of Mechatronic Systems from "Dunarea de Jos" University of Galati, Faculty of Engineering, Manufacturing Engineering Department. This includes the analysis of the CBM based on Infrared thermography, vibration analysis and acoustics.

3.3.1. Thermal camera ThermoVision™ A20M

For the IRT monitoring, in the experiments was used the ThermoVision A20M thermo camera, a device that allows to measure temperature differences as small as 0.12° C in a range from -20° C up to +900°C. It produces high-resolution images (320 x 240 pixels), offering more than 76,800 individual measurement points per image at a refresh rate of 50/60 Hz. The data can then be used by the operators to monitor or control the production processes, or can be processed by the camera’s on-board intelligence to autonomously generate multiple independent digital alarms or even control process equipment [20].

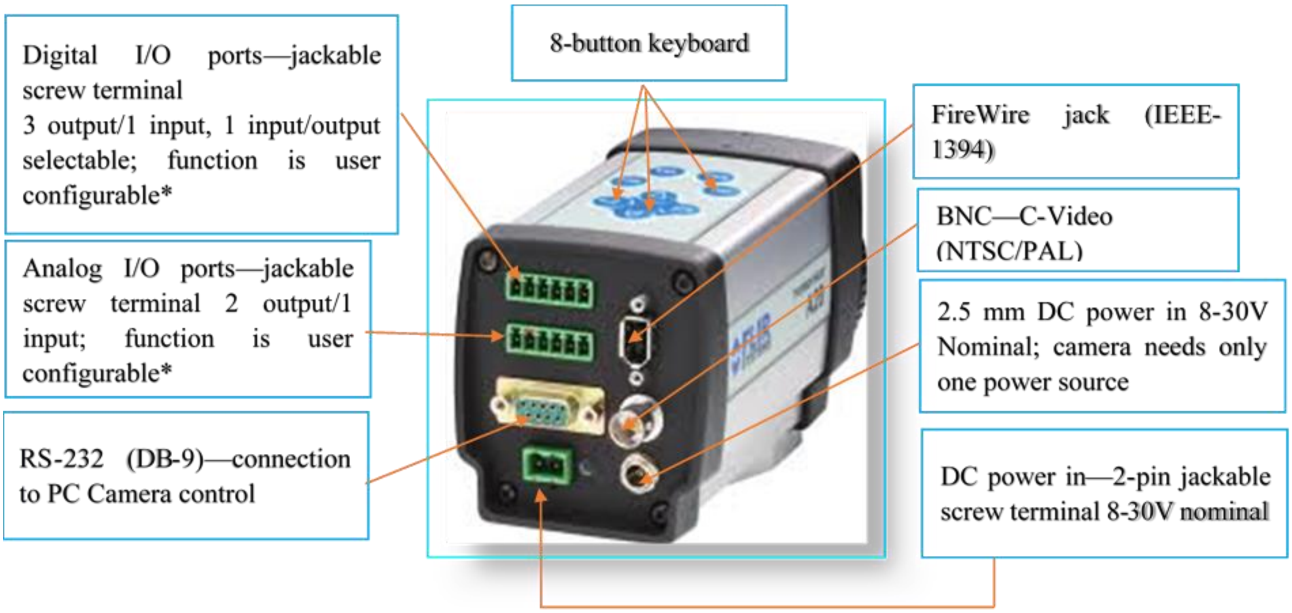


Fig. 36. ThermoVision™ A20M

3.3.2. Sonometer Larson Davis 831

The Larson Davis Model 831 Class 1 Sound Level Meter, with its high definition display, is a versatile device, performing the functions of several instruments. It puts the combined features of a precision Class 1 sound level meter, environmental noise analyser, personal noise dosimeter, and a real-time frequency analyser in the palm of your hand. The Model 831 is a fifth generation Larson Davis sound level meter, designed for simple, single-handed operation, yet is fully featured, smart and versatile with an ever-expanding firmware platform. The design of the Model 831 was based on countless inputs from customers. It expands upon the Larson Davis tradition of delivering value, innovation and function in a rugged, single-handed, expandable package and is backed by a 2-year factory warranty, 24-hour application support and accredited factory service/calibration [88].

Fig. 37. Sound Meter Larson Davis 831

3.3.3. Vibration meter Quest VI-100

The VI-100 can be used to evaluate machine vibrations and isolation effectiveness. The VI-100 is designed to be used for general-purpose investigations in industrial or environmental applications. Investigations may consist of shock or pulsation checks, basic machinery condition monitoring, comparative studies, quality specification checks and general engineering work [89].

- Machinery condition monitoring
- Production quality control checks
- Noise control engineering
- Basic occupational exposure measurements
- Design, R & D, shock test measurements
- Portable, rugged, easy to use.
- Simple 4-button operation
- Lightweight durable metal case
- Clear easy-to-read LCD readout
- Direct readings of acceleration
- Velocity and displacement

Fig. 38. Vibration meter Quest model VI-100

3.3.4. Creality CR-10S PRO 3D Printer

The Creality CR-10S PRO is a 3D printer that has many functions and features [90]:

- ✓ Both automatic levelling and auxiliary levelling modes;
- ✓ Resume printing function, restart and continue printing
- ✓ Double gear extrusion mechanism, has a large extrusion to make sure feeding smoothly
- ✓ Filament detection, the transparent filament can also be detected
- ✓ V2.4.1 Motherboard, four-layer PCB board, TMC ultra-quiet drive 256 subdivision, print more precision
- ✓ With high-quality Teflon tube, high temperature resistant makes the feeding smoother, improves the printing quality
- ✓ 5 minutes quickly heating up to 110°C

The technical specifications are presented in the Table 8 and the components of the printer in Fig. 39.

Table 8. Technical specification of the Creality CR-10S PRO is a 3D printer [90]

Specification	Type
Moulding technology	FDM
Printing size	300*300*400mm
Printing speed	< 180mm /s, normal 30-60 mm/s
Precision	± 0.1 mm
Slice thickness	0.1 - 0.4mm
Nozzle diameter	Standard 0.4 mm, can be in 0.3, 0.2 mm
Nozzle number	1
Nozzle temp	< 260°C
Bed temp	<110°C
Working mode	Online or SD card offline
File format	STL, Obj, amf
Slice software	Cura, Repetier-host, Simplify 3D
Power supply	INPUT/ 100-240 V, 5.9 A 50/60Hz Output: DC 24V - 21 A
Total power	480W
Filament	PLA, ABS, WOOD, TPU, carbon fiber, gradient color,
Filament diameter	1.75mm

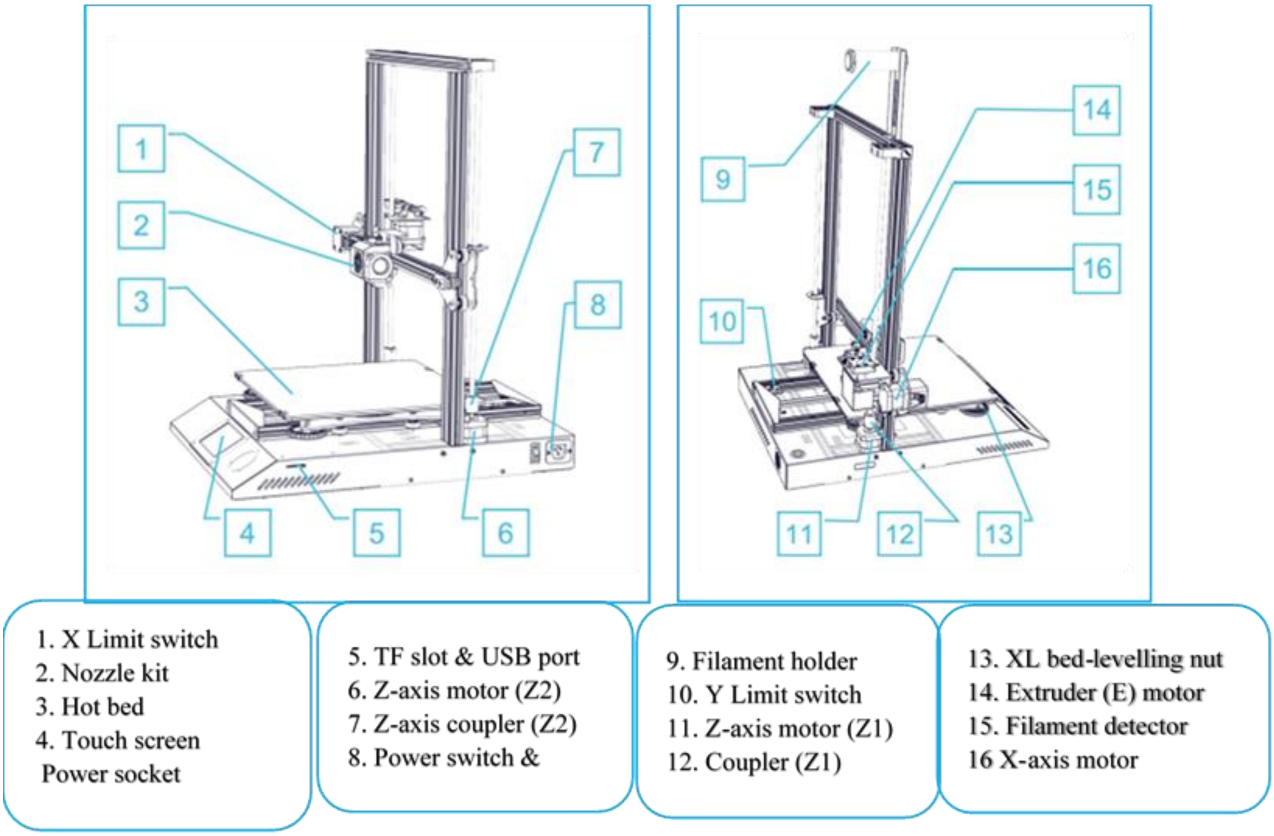


Fig. 39. Creality CR-10S PRO 3D Printer components [90]

In the experiments, the monitored motors within the Creality 10S Pro 3D printer are the Nema 17 stepper motors. The stepper motors are DC motors that have multiple coils allowing them to move in small increments. These coils are organized in groups called phases. By energizing each phase in sequence, the motor will rotate, one step at a time. By having a computer control these movements, they can be very precise. They are best used for positioning, speed control, and low speed torque. While they can be very useful, they do have their limitations. To start, "stepper motor current consumption is independent of load." When a motor is not moving, it will still consume a large amount of current. This can make them run hot. Stepper motors also tend to lose torque the faster they spin. Some stepper motors are designed for high speed torque, but the performance of these motors is also greatly dependent on the stepper drivers paired with them.

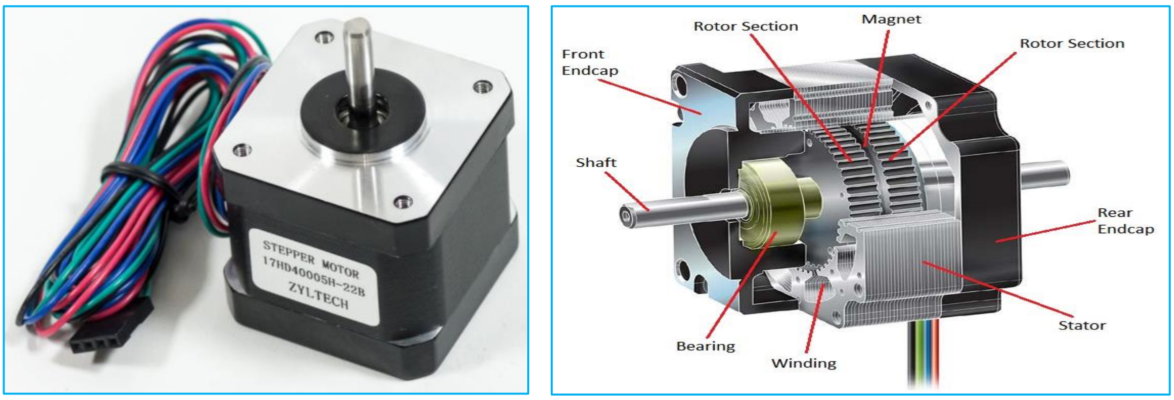


Fig. 40. Nema 17 stepper motors [90]

3.3.4. Ultimaker 2+ 3D Printer

The Ultimaker 2+ is reliable, efficient and user-friendly 3D printer. Thanks to its support of a wide range of materials, it is suitable for a huge variety of applications, from prototypes to customized tools. It is a great all-around 3D printer that delivers consistent results [91]. In Fig. 41 are presented the main models of 3D printers from the Ultimaker series, in Fig. 42 the main components of the Ultimaker 2+ model, used in the experiments and in **Table 2** the specification of the printer.

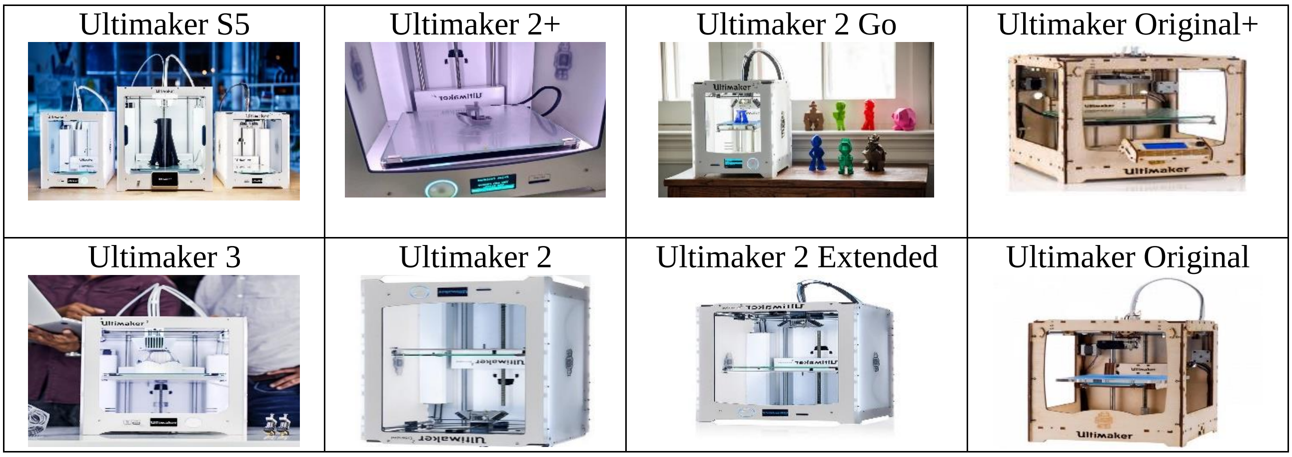


Fig. 41. 3D printers of the Ultimaker series

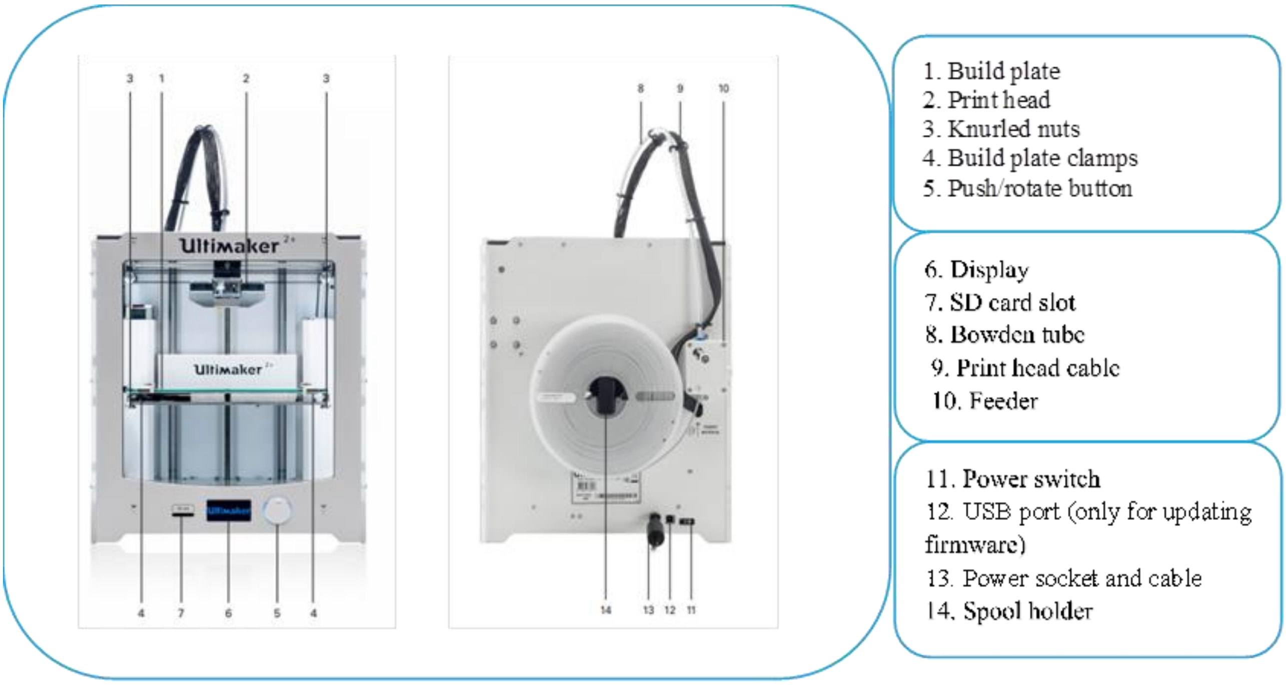


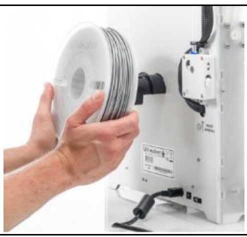
Fig. 42. Ultimaker 2+ 3D printer components [91]

Table 9. Technical specification of Ultimaker 2+ 3D printer [91]

Specification	Type
Technology	Fused filament fabrication (FFF)
Print head	Single extrusion print head with swappable nozzles
Filament diameter	2.85 mm
Layer resolution	0.25 mm nozzle: 60 - 150 micron

Specification	Type
	0.4 mm nozzle: 20 - 200 micron 0.6 mm nozzle: 20 - 400 micron 0.8 mm nozzle: 20 - 600 micron
XYZ accuracy	12.5, 12.5, 5 micron
Print head travel speed	30 - 300 mm/s
Build speed	0.25 mm nozzle: < 8 mm³/s 0.4 mm nozzle: < 16 mm³/s 0.6 mm nozzle: < 23 mm³/s 0.8 mm nozzle: < 24 mm³/s
Build plate	Heated glass build plate
Build plate temperature	20 - 100 ºC
Build plate leveling	Assisted leveling
Supported materials	PLA, ABS, Nylon, CPE, CPE+, PC, PP, TPU 95A
Nozzle diameter	Included are 0.25, 0.4, 0.6 and 0.8 mm nozzles
Nozzle temperature	180 - 260 ºC
Nozzle heat up time	~ 1 min
Build plate heat up time	< 4 min (20 - > 60 ºC)
Operating sound	50 dBA
Connectivity	Standalone 3D printing from SD card (included)
Supplied software	Ultimaker Cura
Supported OS	MacOS, Windows, and Linux
Plugin integration	SolidWorks, Siemens NX, Autodesk Inventor
File types	Ultimaker Cura: STL, OBJ, X3D, 3MF, BMP, GIF, JPG, PNG; Printable formats: GCODE

The Ultimaker 2+ is supplied with several hardware accessories, for example [91] as follows:

			
1. PLA (750g)	2. Nozzle kit	3. Power adapter & cable	4. Glass plate
			
5. Calibration card	6. Hex wrenches	7. Spool holder	8. Glue stick
			
9. Magnalube (for lead screw Z motor)		10. USB cable (only for updating firmware	

The Ultimaker 2+ comes with one spool of PLA material that we referred to above, but does support the use of various materials; each material requires different settings for optimal results [91]. Some materials used in 3D printing supported of Ultimaker 2+:

	PLA (polylactic acid) is one of the most widely used 3D printing materials and the recommended material for beginners. It prints fast, is safe, and can be used for a broad range of models and applications. Temperatures: between 200-210°C
	ABS (acrylonitrile butadiene styrene) is a frequently used 3D printing material. It has good mechanical properties and can be used for a wide range of applications. Ultimaker ABS shows exceptionally low warping and consistent layer bonding, making it more reliable Temperatures: between 225 and 260°C.
	Nylon (polyamide) is widely used by manufacturers to 3D print strong end-use parts and functional prototypes that require durability and abrasion resistance. Temperatures: between 230 and 260°C.
	CPE (co-polyester) is a chemical resistant and relatively tough material widely used for functional prototyping and modelling. Temperatures: between 230 and 260°C
	Ultimaker TPU 95A (thermoplastic polyurethane) is a semi-flexible material that can be used in a wide variety of engineering applications Temperatures: between 220 - 235°C
	Ultimaker PC (polycarbonate) is a very strong and tough material that can be used for various engineering applications Temperatures: between 260 and 280°C.
	PP (polypropylene) is a commonly used polymer in the industry. Properties of Ultimaker PP include exceptional layer bonding and good adhesion to the build plate. Temperatures: between 205 and 220°C.

3.4. Results and Discussions

The experimental results consist of three tests of the smart manufacturing process, by means of 3D printing, that was monitored in order to corelate the three methods presented above for having more complex data for achieving CBM.

- First test (*Test 1*) was related to the CBM of the 3D printing process on the Creality CR-10S PRO 3D Printer (***Piece 1***)
- Second test (Test 2) was related to the CBM of the 3D printing process on the Creality CR-10S PRO 3D Printer (***Piece 2***)
- Third test (Test 3) was related to the CBM of the 3D printing process on the Ultimaker 2+ 3D printer (same piece as in *Test 1* - ***Piece 3***)

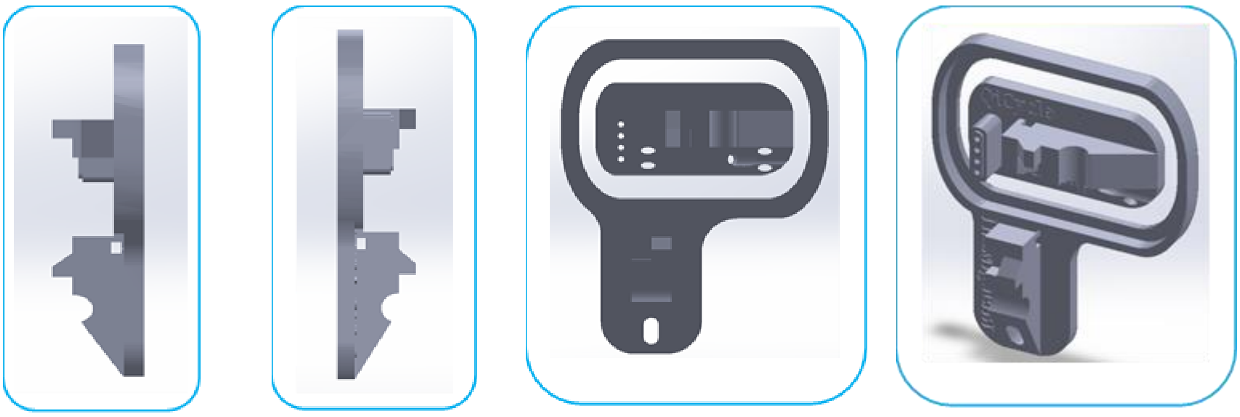
In the experiments, several programs have been used for the design, analysis and monitoring of the smart manufacturing process, in this case the 3D printing process:

- **ThermaCAM® Researcher™** from Flir: monitor and analyse changes and temperature degradation in both motors (1&2) from the 3D printing process. The software analyses the thermal performance with ThermaCAM® Researcher™ that is one of the most robust real-time digital storage, measurement, and analysis software available. It digitally stores and retrieves static and real-time infrared images, live IR digital video sequences, dynamic high-speed events and data directly from ThermaCAM IR cameras allowing in-depth and precise analysis of thermal events.

- **Noise & Vibration Works (version 2.4.1)**: analyse the results of vibratory and acoustic monitoring. Nwwin is designed specifically for handling Noise and Vibration data. It provides reporting and application modules for Environmental, Workplace, Sound Power, Architectural, and Automotive Passby. NWwin can handle the native files from all Larson-Davis and Sinus instruments as well as any meter that can export.csv format.
- **VibSensor** for vibration mobile recording, analysis and data storing. The software came as a mobile application for live displaying of the tilt and vibration data in real time. The data will be compared with industrial measurements using professional vibration device.
- **Cura printing software for 3D printing** (for Ultimaker 2+ 3D Printer): creates the integration between compatible 3D printers, software and materials and it is an open source cross-platform. It has plugins for any CAD software and optimized profiles for third-party materials and supports STL, OBJ, X3D, and 3MF file formats
- **Simplify 3D** (for Creality CR-10S Pro 3D printer) is a software that includes a realistic pre-print simulation, allowing to see the exact actions of the 3D printers that will perform before starting the printing. The simulation includes information about the exact speeds, sequences, and settings that are used for the printing so that can quickly verify the settings very easily.

3.4.1. CBM of 3D Printing Process – Test 1

In the first test, the experimental part included the condition-based monitoring of two ***Nema17 stepper motors*** and the ***printer nozzle***, that are parts of the Creality CR-10S Pro 3D printer. The 3D printing is a smart manufacturing process that should be very well monitored and controlled, in order to achieve good final products using the technology. The main scope of the research was to analyse three different methods of condition-based monitoring for achieving CBM, using one method, by measuring: the temperature (by thermal camera & IR thermography. In the experiments, the piece P1 (Fig. 43) was printed using the Creality CR-10S Pro 3D printer, process that took place in about 3h and 50 minutes. The 3D model was created in SolidWorks and exported like STL file. After, using the *Simplify 3D* software was created the G-code file, and imported in the 3D printer flash-drive.



a) b) c) d)

Fig. 43. Left, right, front and isometric view views of the 3D model of piece P1(clamping system)

The setup of equipment, devices and software used in the experiments from test 1 are presented in the diagram from Fig. 44 and the real setup in the Fig. 71. It can be observed the positioning of the devices, the connection between these and the main methods of monitoring used in the real conditions for CBM. The material used in the experiments was PLA.

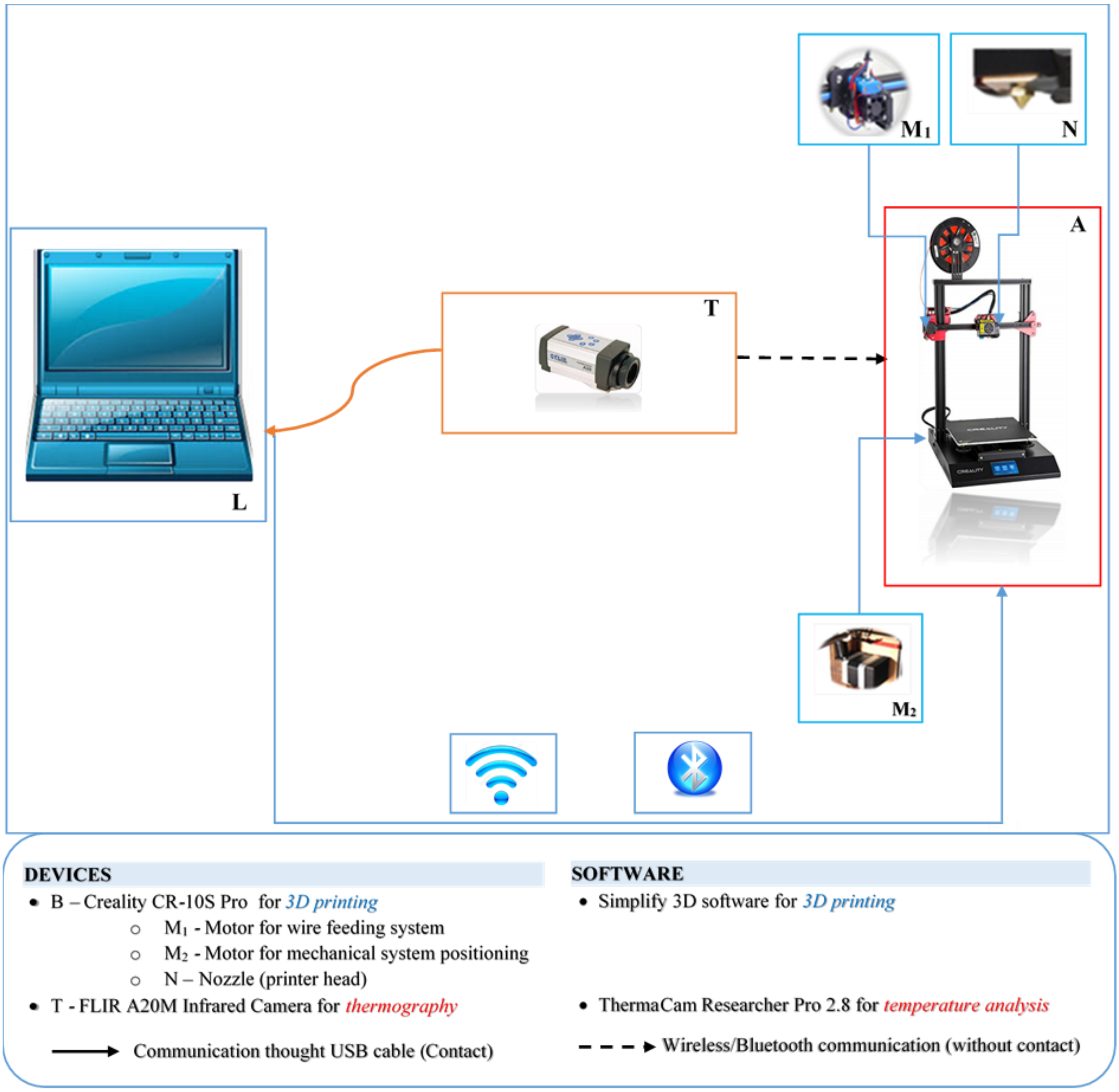


Fig. 44. The setup of the experimental test 1. Schematic diagram.

One method of monitoring was used in Test 1, respectively the infrared thermography (IRT). The IRT was achieved using ThermoVision™A20M thermal camera from FLIR. This was positioned in front of the Creality CR-10S Pro 3D printer (A) for framing the two motors (M1 – for wire feeding system and M2 for the 3D printer mechanical system positioning) and the printer head (nozzle). The ThermoVision™ A20M camera and ThermaCAM® Researcher™ software was used for the data analysis and processing of thermal field monitoring during the 3D printing process, as represented in the Fig. 71a and b. The final piece – P1, that was achieved using the 3D printing process, is presented in Fig. 71c. This was showed good visual aspect and characteristics. In the pictures Fig. 45 and Fig. 46 is presented the experimental setup for the 3D printing process with the main areas were thermography method was used in order to monitor and analyse data necessary for CBM.

In the Test 1 experiment, temperature fields of the two Nema 17 step motors and 3D printer nozzle area were analysed using infrared thermography and the ThermaCAM® Researcher™ software 2.8. It was chosen to analyse three points from the motor M_1 used for the wire feeding system, respectively the spots SP1, SP2 and SP3 and the motor M_2 used for the mechanical system positioning, respectively the spots SP4, SP5 and SP6. Moreover, the zone from the 3D printer nozzle (printer head) was marked using an area, AR1 respectively.

Fig. 45. 3D printing process monitoring using thermography. Experimental test 1

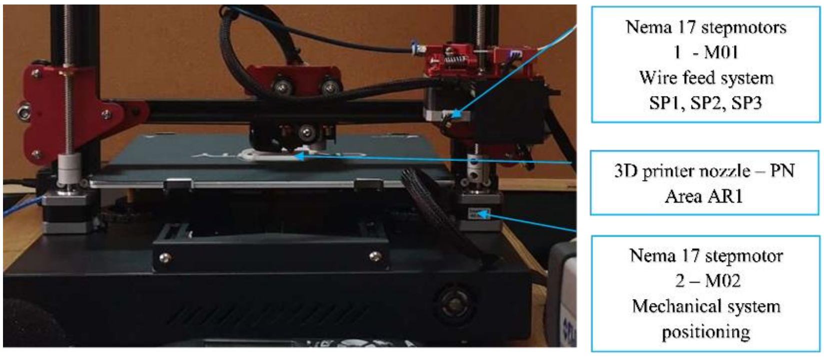


Fig. 46. Monitored areas during the 3D printing process

In the Fig. 47 - Fig. 66 are presented the temperature field distributions, in multiple phases of the 3D printing process, on the surface of the two step motors and nozzle area. In the pictures were chosen where the minimum and maximum temperature were encountered, on each three spots from the two motors. Furthermore, the area in which the highest temperature in the nozzle zone was reached.

Fig. 47. Temperature field distribution at min 62:02, when SP01 from the M_1 reached the maximum temperature of 46.067°C

Fig. 48. Temperature field distribution at min 235:02, when SP01 from the M_1 reached the minimum temperature of 32.641°C

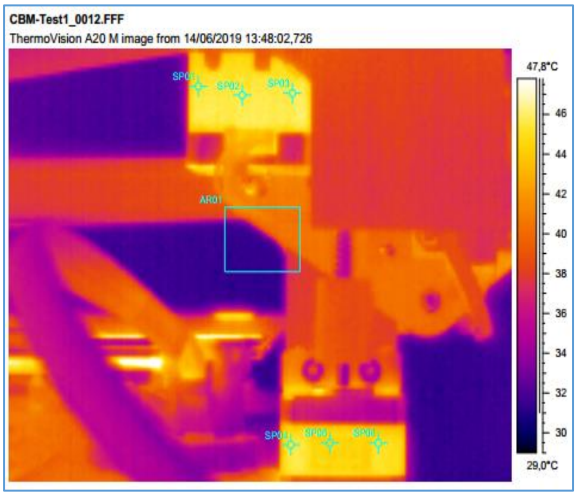


Fig. 49. Temperature field distribution at min 49:02 min, when SP02 from the M_1 reached the maximum temperature of 44.165°C

Fig. 50. Temperature field distribution at min 235:02, when SP02 from the M_1 reached the minimum temperature of 32.373°C

Fig. 51. Temperature field distribution at min 60:02, when SP03 from the M_1 reached the maximum temperature of 44.444°C

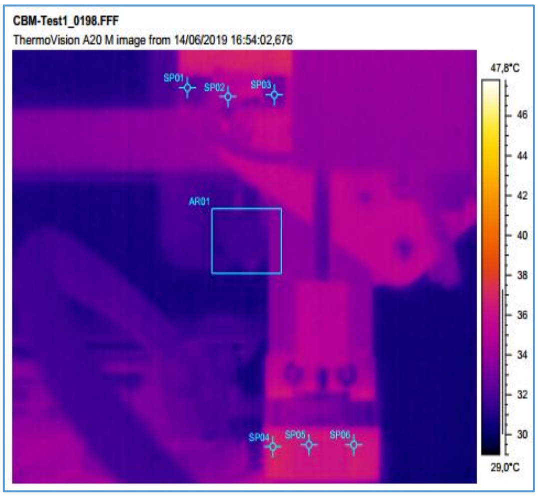


Fig. 52. Temperature field distribution at min 235:02, when SP03 from the M_1 reached the minimum temperature 30.971°C

Fig. 53. Temperature field distribution at min 61:02, when SP04 from the M_2 reached the maximum temperature of 44.472°C

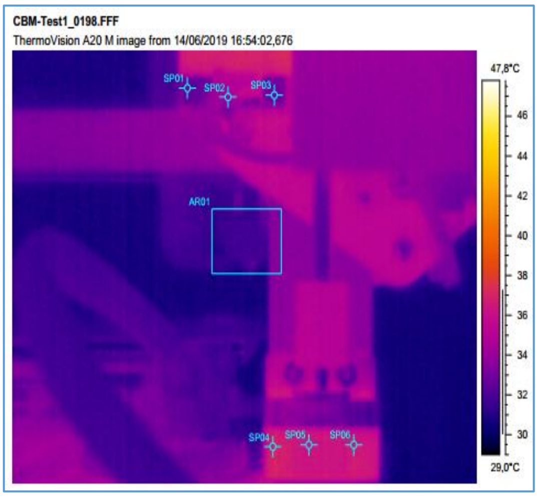


Fig. 54. Temperature field distribution at min 235:02, when SP04 from the M_2 reached the minimum temperature of 34.640°C

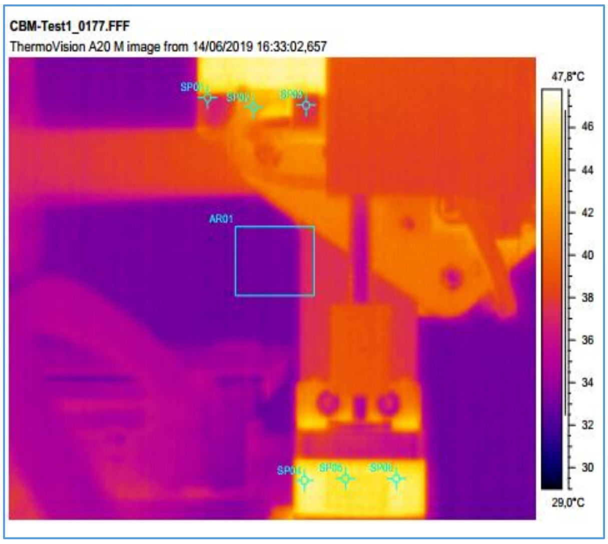


Fig. 55. Temperature field distribution at min 241:02, when SP04 from the M_2 reached the maximum temperature of 45.493°C

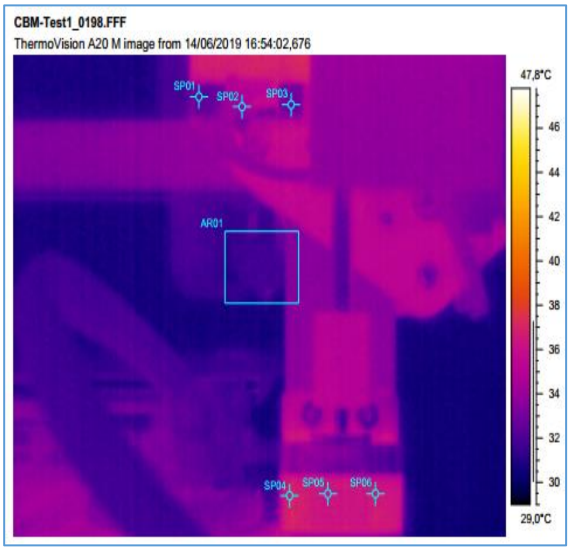


Fig. 56. Temperature field distribution at min 235:02, when SP05 from the M_2 reached the minimum temperature of 36.138°C

Fig. 57. Temperature field distribution at min 62:02, when SP06 from the M_2 reached the maximum temperature of 44.109°C

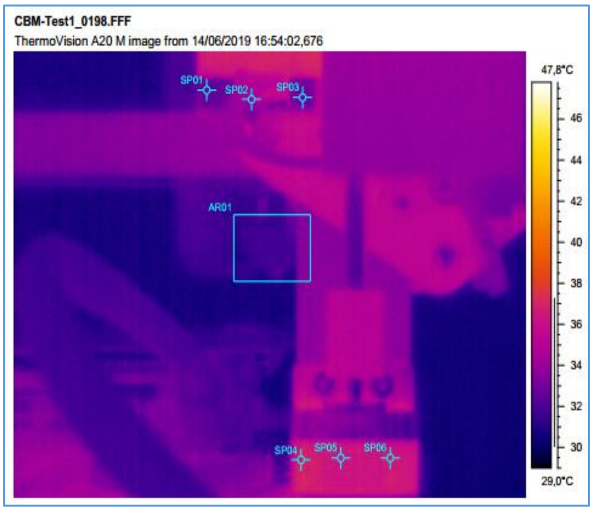


Fig. 58. Temperature field distribution at min 235:02, when SP06 from the M_2 reached the minimum temperature of 34.336°C

Fig. 59. Temperature field distribution at min 222.02 during the cooling phase

Fig. 60. Temperature field distribution at min 233.02 during the cooling phase

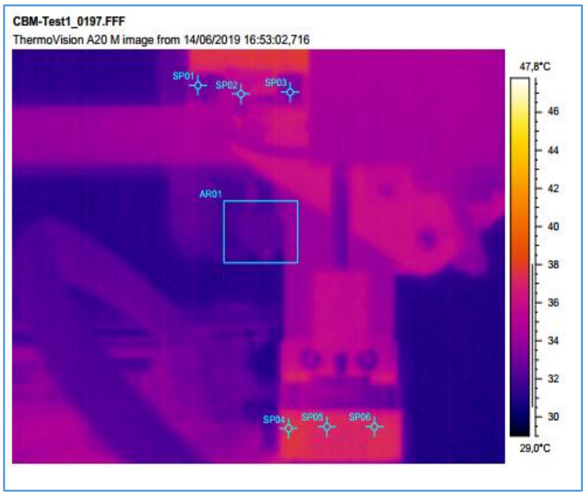


Fig. 61. Temperature field distribution at min 234.02, during the cooling phase

Fig. 62. Temperature field distribution at min 237.02, during the cooling phase

Fig. 63. Temperature field distribution in the nozzle area AR1 when maximum temperature was reached

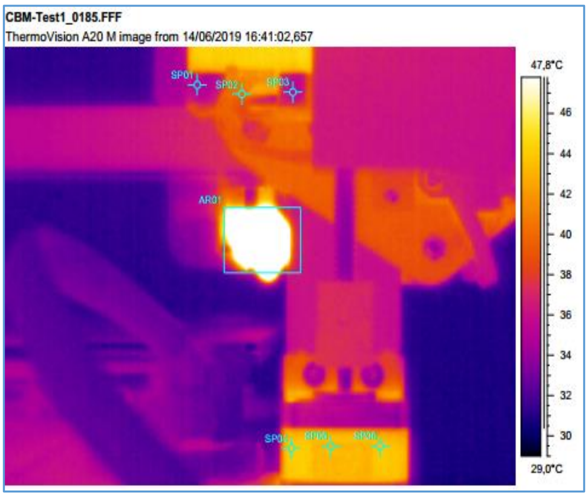


Fig. 64. Temperature field distribution in the nozzle area AR1 when maximum temperature was reached

Fig. 65. Temperature field distribution in the nozzle area AR1 when maximum temperature was reached

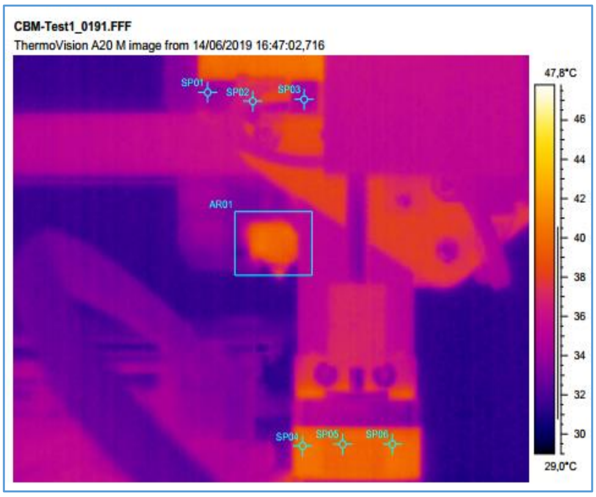


Fig. 66. Temperature field distribution in the nozzle area AR1 when maximum temperature was reached

In the Fig. 67 is presented the processed data related to the temperature variation during the 3D printing process on the M_1 in spots SP1, SP2 and SP3 and in Fig. 68, the processed data related to the temperature variation during the 3D printing process on the spots M_2 in SP4, SP5 and SP6. It can be noticed that the trend of temperature is relatively similar, that means that both motors M_1 for the wire feed and M_2 for the mechanical positioning are corelated during the 3D printing process. The maximum temperatures, for both motors are reached when the 3D printer is performing faster operations and the piece P1 is printed on the largest contours. Because the thermography monitoring started after the beginning of the 3D printing process, it can be noticed that the first values are relatively high. However, the thermography monitoring was achieved also during the cooling phase, hence after the 3D printing process stopped.

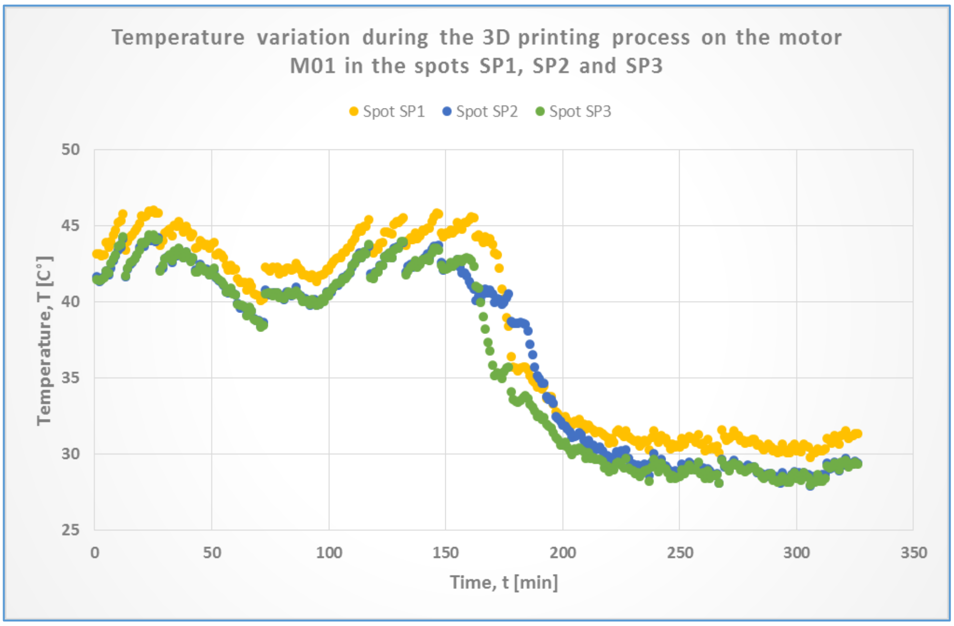


Fig. 67. Temperature variation during the 3D printing process on the M_1 in SP1, SP2 and SP3

Analysing the data obtained using thermography, it can be noticed that the temperature of the motors does not exceed 50ºC, that is an optimal temperature for a proper functioning of the 3D printer.

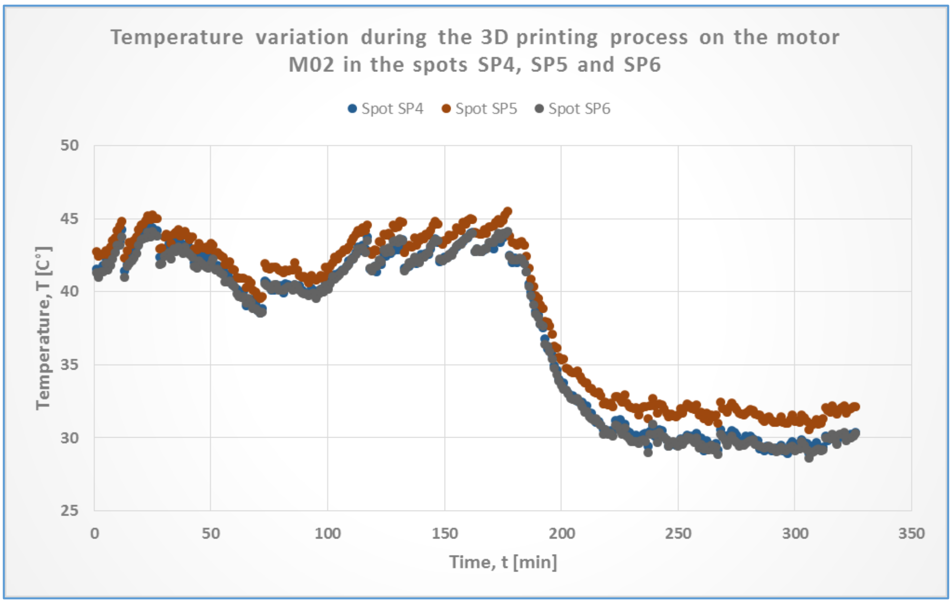


Fig. 68. Temperature variation during the 3D printing process on the M_2 in SP4, SP5 and SP6

In the Fig. 69 is presented a screenshot from the ThermaCam Researcher 2.8 software, from the data analysis and processing operations, for the area AR01 positioned on the printer head/nozzle area. The measurement function will automatically display the hottest spot within the AR01 in the nozzle area, the maximum temperature of 137,2°C, and the difference between the maximum temperature in the specific area and a reference, respectively the ambient temperature.

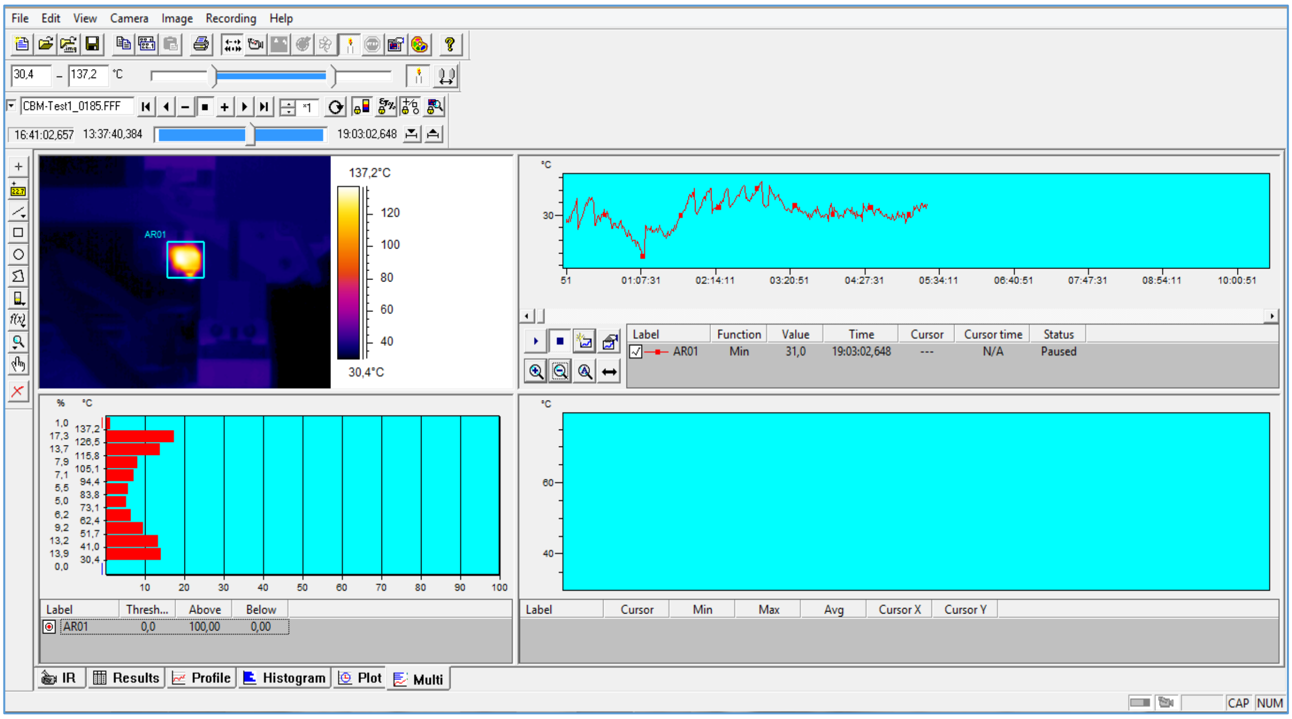


Fig. 69. Temperature variation during the 3D printing process on the nozzle area, AR01

3.4.2. CBM of 3D Printing Process – Test 2

In the second test, the experimental part included the condition-based monitoring of the same *Nema17 stepper motors* and the *printer nozzle*, that are parts of the Creality CR-10S Pro 3D printer. The main scope of the research conducted in *Test 2* was to analyse **three** different methods of condition-based monitoring for achieving CBM, using three methods, by measuring: the **temperature** (by thermal camera & IR thermography), the accelerations/**vibrations** (by vibration meters), and the **sound** (by sound meters). In the experiments, the same piece P1 (Fig. 43) was printed using the Creality CR-10S Pro 3D printer, using the same conditions.

The setup of equipment, devices and software used in the experiments from Test 2 are presented in the diagram from Fig. 70 and the real setup in the Fig. 71. It can be observed the positioning of the devices, the connection between them and the main methods of monitoring used in the real conditions for obtaining the CBM. The IRT was achieved using ThermoVision™A20M thermal camera from FLIR. This was positioned in front of the Creality CR-10S Pro 3D printer for framing the two motors (M_1 – for wire feeding system and M_2 for the 3D printer mechanical system positioning) and the printer head (nozzle). Near the printer, the sonometer Larson Davis 831 was positioned for performing the sound monitoring. Furthermore, a Huawei P20 smartphone was positioned on the printer, in order to measure the acceleration/vibrations of the 3D printer during the process using VibSensor mobile application, as represented in the Fig. 71a and b. The smartphone accelerometer sensors measure data were compared with an industrial vibrometer Quest VI-100 from Larson Davis, in order to achieve a calibration of the vibration measurement system.

Fig. 70. The setup of the experimental Test 2. Schematic diagram

In the Test 2 experimental, temperature fields of the two Nema 17 step motors and 3D printer nozzle area were monitored, using infrared thermography and the ThermaCAM® Researcher™ software 2.8. Same with Test 1, it was chosen to be analysed three points from the motor M_1 used for the wire feeding system, respectively the spots SP1, SP2 and SP3 and three points from the motor M_2 used for the mechanical system positioning, respectively the spots SP4, SP5 and SP6. Moreover, the zone from the 3D printer nozzle (printer head) was marked using an area, AR1 respectively. It can be noticed the maximum temperature of 46.249°C on the motor M_1 was achieved at time t=77:32min from the beginning of the process, in the spot SP02. The minimum temperature of 32.516°C on the motor M_1 was achieved at time t=43:32min from the beginning of the process, in the spot SP01. It is obvious that SP01 achieves minimum temperature due to the fact that this point was chosen on margin of the motor M_1.


a)

b)

c)

Fig. 71. The setup of the experimental Test 2. 3D printed piece – P1

The maximum temperature of 45.352°C on the M_2 was achieved at time t=77:32min from the beginning of the process, in the spot SP06. The minimum temperature of 34.543°C on the M_2 was achieved at the same time as M_1, at t = 43:32min from the beginning of the process, in the spot SP05.

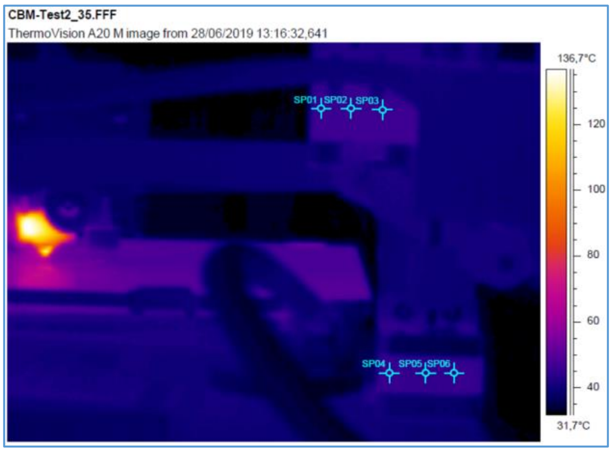


Fig. 72. Temperature field distribution at min 77.32, when SP01 from the M01 reached the maximum temperature of 46.109°C

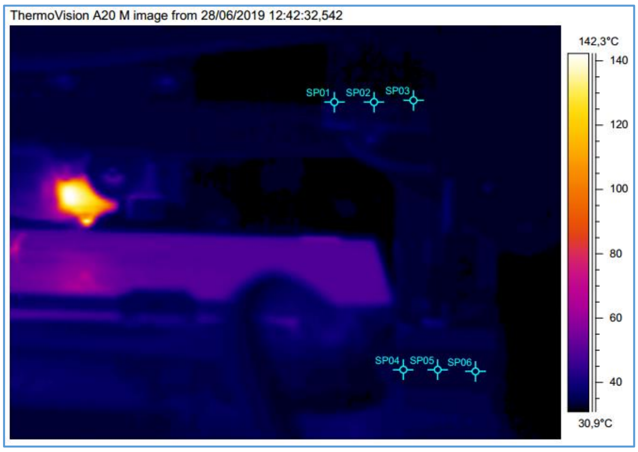


Fig. 73. Temperature field distribution at min 43:32, when SP01 from the M01 reached the minimum temperature of 32.516°C

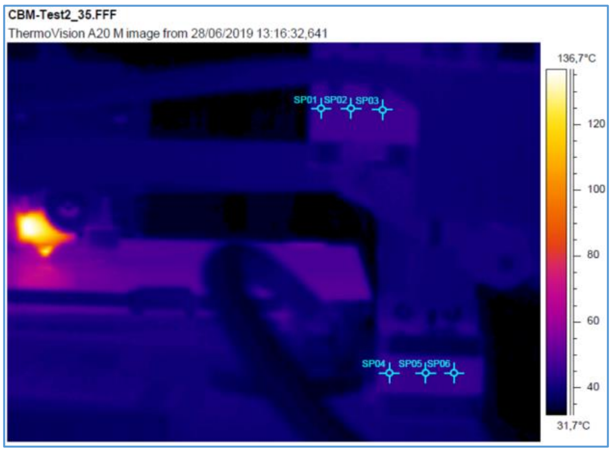


Fig. 74. Temperature field distribution at (35) 77.32 min when SP02 from the M01 reached the maximum temperature of 46.249°C

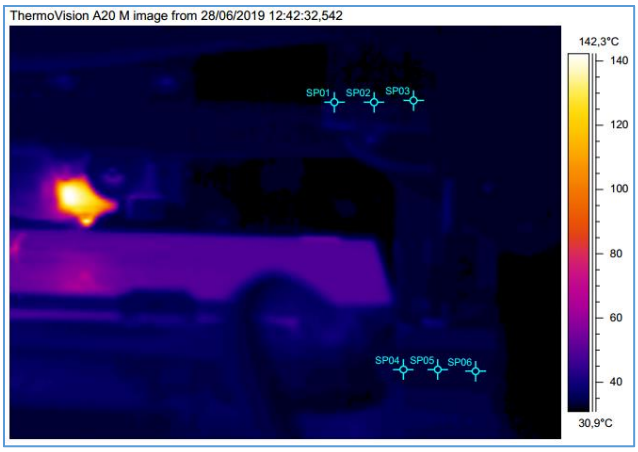


Fig.75. Temperature field distribution at min 43:32, when SP02 from the M01 reached the minimum temperature of 32.579°C

Fig. 76. Temperature field distribution at min 77.32, when SP03 from the M01 reached the maximum temperature of 46.249°C

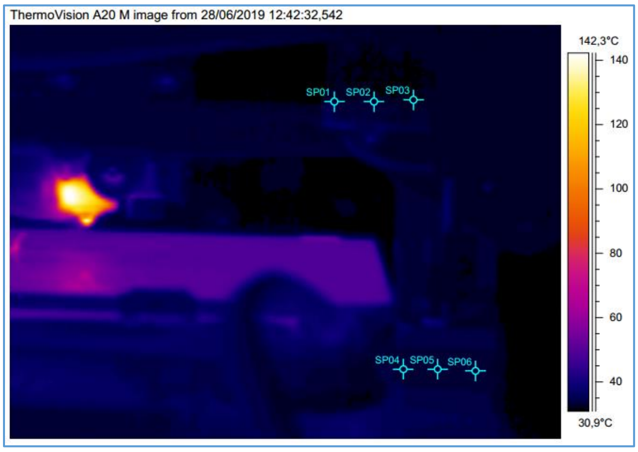


Fig. 77. Temperature field distribution at min 43:32, when SP03 from the M01 reached the minimum temperature of 32.689°C

Fig. 78. Temperature field distribution at min 77.32, when SP04 from the M02 reached the maximum temperature of 46.305°C

Fig. 79. Temperature field distribution at min 45:32, when SP04 from the M02 reached the minimum temperature of 34.836°C

Fig. 80. Temperature field distribution at min 77.32, when SP05 from the M02 reached the maximum temperature of 44.830°C

Fig. 81. Temperature field distribution at min 45:32, when SP05 from the M02 reached the minimum temperature of 34.543°C

Fig. 82. Temperature field distribution at min 77.32, when SP06 from the M02 reached the maximum temperature of 45.352°C

Fig. 83. Temperature field distribution at min 45:32, when SP06 from the M02 reached the minimum temperature of 34.558°C

Fig. 84. Temperature field distribution in the nozzle area AR01, when maximum temperature was reached, at the beginning of 3D printing

Fig. 85. Temperature field distribution in the nozzle area AR01, when maximum temperature was reached, at the end of the 3D printing

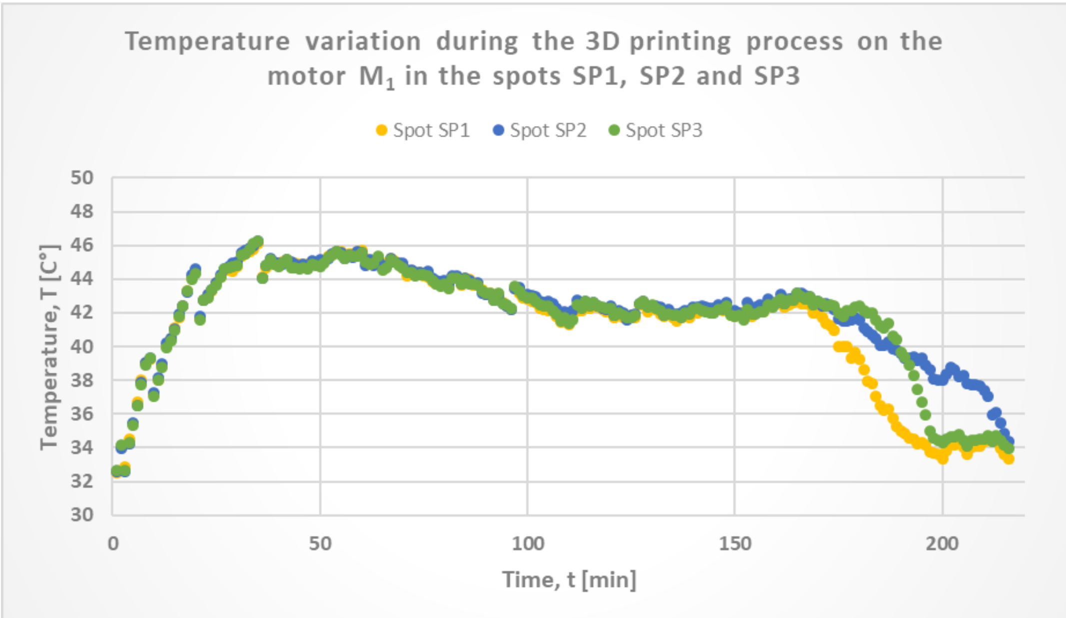


Fig. 86. Temperature variation during the 3D printing process on the M_1 in SP1, SP2 and SP3

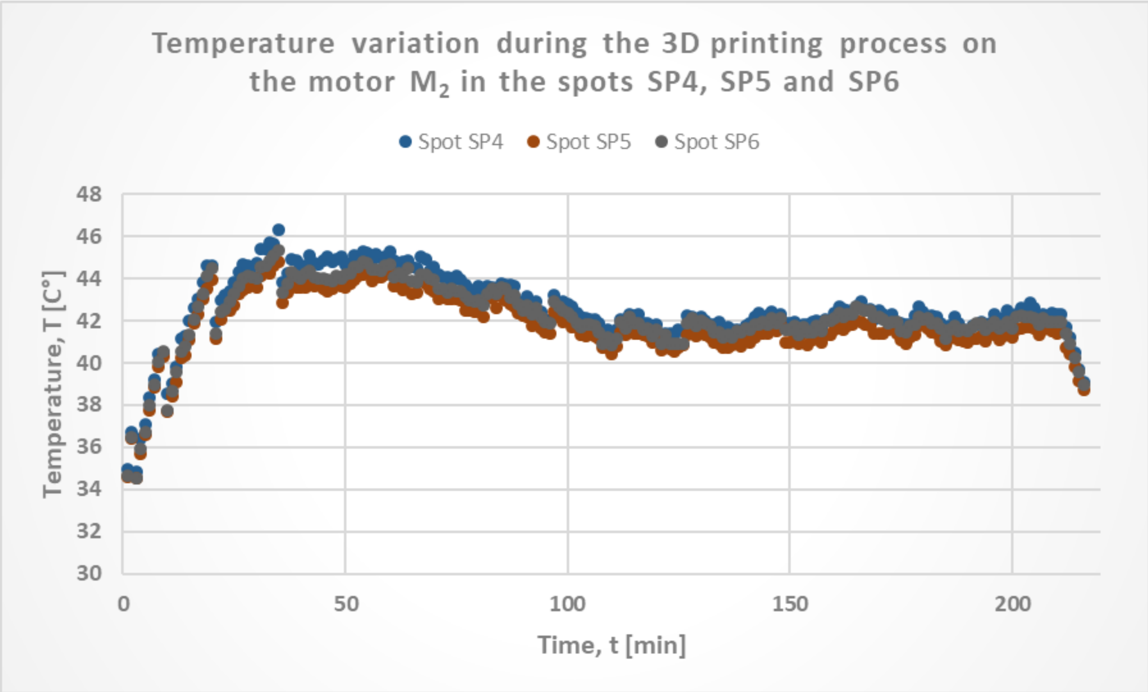
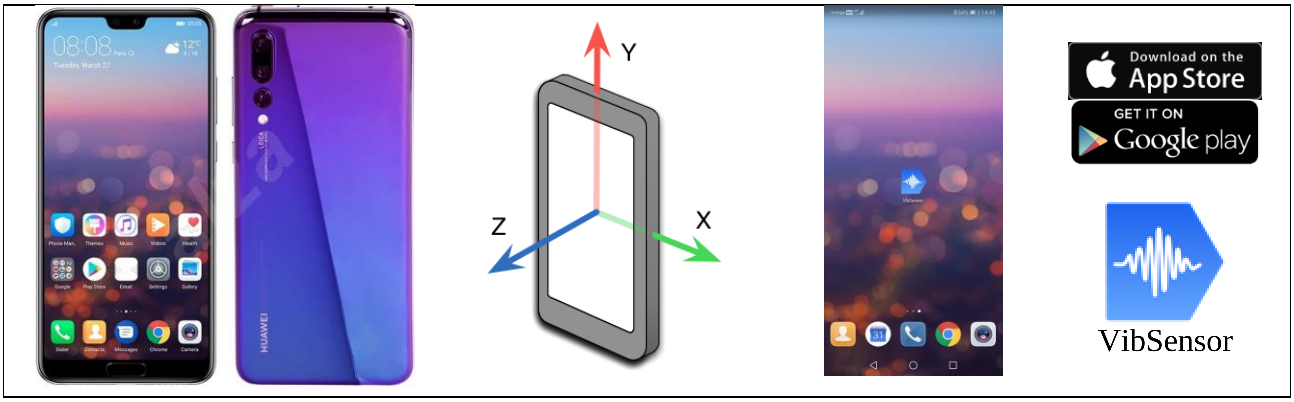


Fig. 87. Temperature variation during the 3D printing process on the M_2 in SP4, SP5 and SP6

The second part of Test 2 experiment was related to the vibration encountered during the 3D printing process. The measurements were achieved using a smart phone, Huawei P20 (Fig. 88a) with accelerometer sensors, that measures along each of the main axes of the device. By convention, the axes are labelled as follows (Fig. 88b) presents. On the device, a mobile application called VibSensor was downloaded from Google Play and installed on the smart phone (Fig. 88c). VibSensor record, analyse, store, and email accelerometer and vibration data offering, live display of the tilt and vibration data in real time, acquisition (timed acquisition, with settable delay and duration; it collects raw accelerometer data for up to 10 minutes at max rate allowed by device), data storage (on the device, with date and time stamp for later retrieval, analysis (data collection can be viewed to see the raw accelerometer data, processed tilt and vibration, and calculated power spectral densities, both in graphical and report format) and email access features, in which users can email raw or processed data in text (csv or tab-delimited) or MATLAB format.



a) b) c)

Fig. 88. Device for real time vibration monitoring

In the Fig. **89** are presented the main vibration analysis parameters measured and logged using the Huawei P20 device and VibSensor mobile application.

Start: 28 Jun 2019 (12:23:00.970 pm)

Length: 229 min 57 sec

Points: 46,173 Gaps: 10 (13377 sec total)

Data rate: 100.0 Hz Units: m/s^2

Peak raw: X (LIMIT) Y (11.64) Z (LIMIT)

Integrated Spectral Density - ISD:

X (0.28) Y (0.41) Z (0.28)

Resonances:

X: 0.13 Hz (0.078), 4.5 Hz (0.0068)

Y: 0.085 Hz (0.59), 7.4 Hz (0.021)

Z: 0.024 Hz (0.033), 32 Hz (0.026)

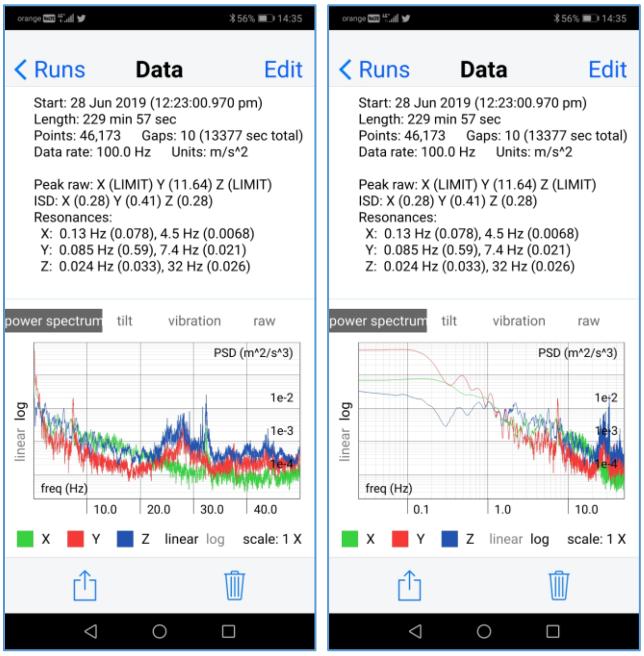


Fig. 89. Measured and logged vibration parameters using the Huawei P20 and VibSensor in Test 2

The raw accelerometer data contains the effects of gravity plus any other accelerations the device may be experiencing. In Live View, this data is split into slowly varying Tilt and quickly varying Vibration data. For tilt data, a full hemisphere means one g of acceleration. The scale for vibration data is indicated by the small-scale bar, and ranges from 0 to 0.5g. Typical devices actually have a full range of -2g to +2g. The smaller range in Live View is chosen to emphasize smaller vibrations. The data acquisition related to the vibrations of the 3D printer was triggered at the beginning of the manufacturing process. Each data consisted of raw, time-stamped acceleration information, that were automatically saved into a database, with a date and time stamp that allows later viewing, analysing, and exporting in different formats, like, *.csv, *.txt or *.m files. The frequency range of acquisition can be modified in the settings. The "high" range collects at the maximum rate supported by the device and allows analysing vibrational frequencies between 0.03 and 50 Hz. The "low" range extends this by averaging to allow analysis of vibrations with periods as long as 5 minutes. The resulted data were compared with the Vibration meter Quest model VI-100 industrial vibration meter in order to calibrate the sensors and also to validate the measurements. VibSensor application installed on the Huawei P20 smartphone has proven to be reliable and accurate for the proposed measurements for monitoring the 3D printing process.

The third part of Test 2 experiment was related to the sound encountered during the 3D printing process. In the field of non-destructive testing, acoustic emission is a method that allows to perceive in real time the appearance of a signal resulting from a cohesion in a material. It is also a method of voluminal control due to the emission and propagation of elastic waves. The measurements were performed using a Larson Davis 831 Sonometer model. In Fig. 90 are presented the measured and logged sound signals during the 3D printing processes from the Test 2.

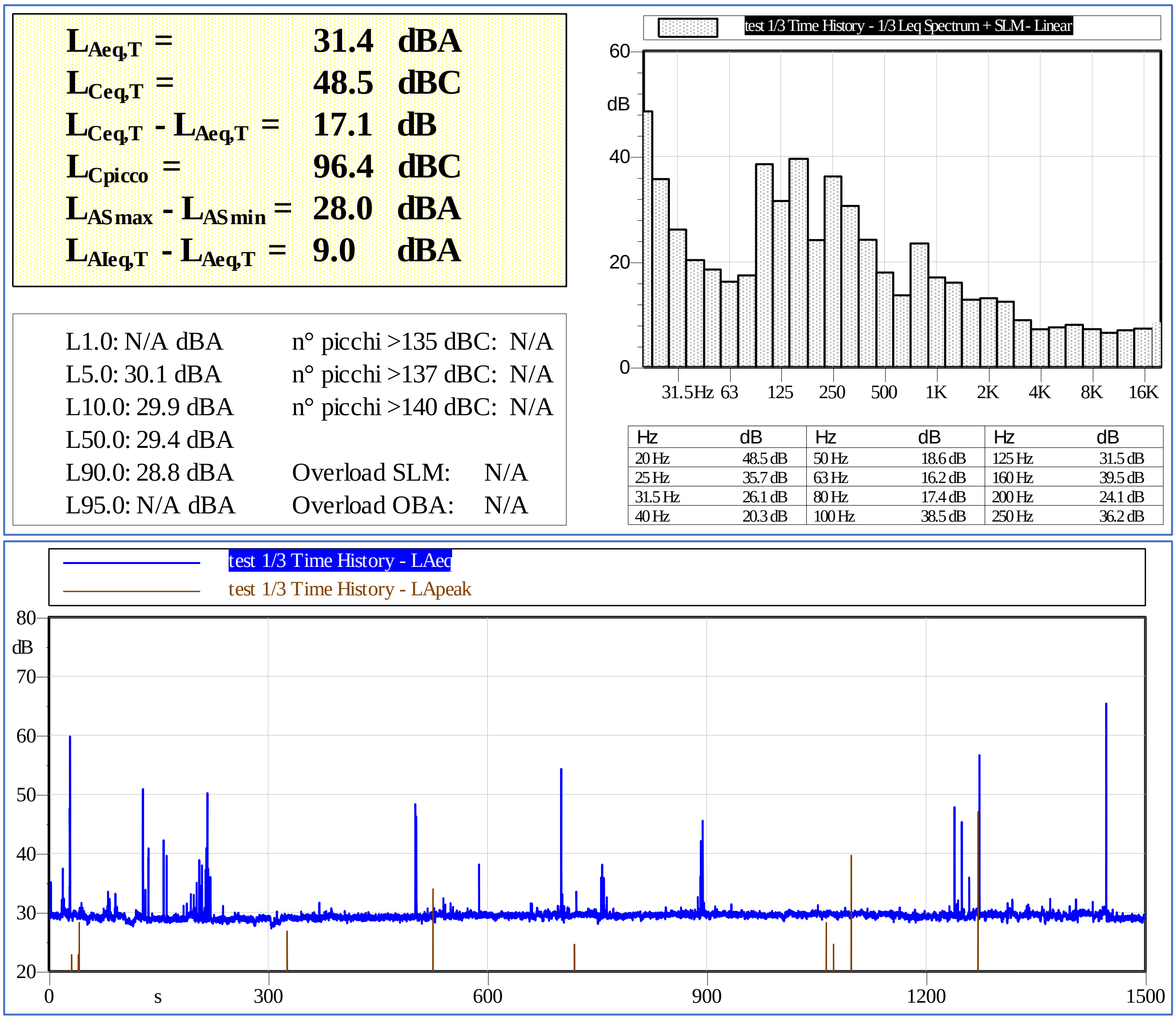
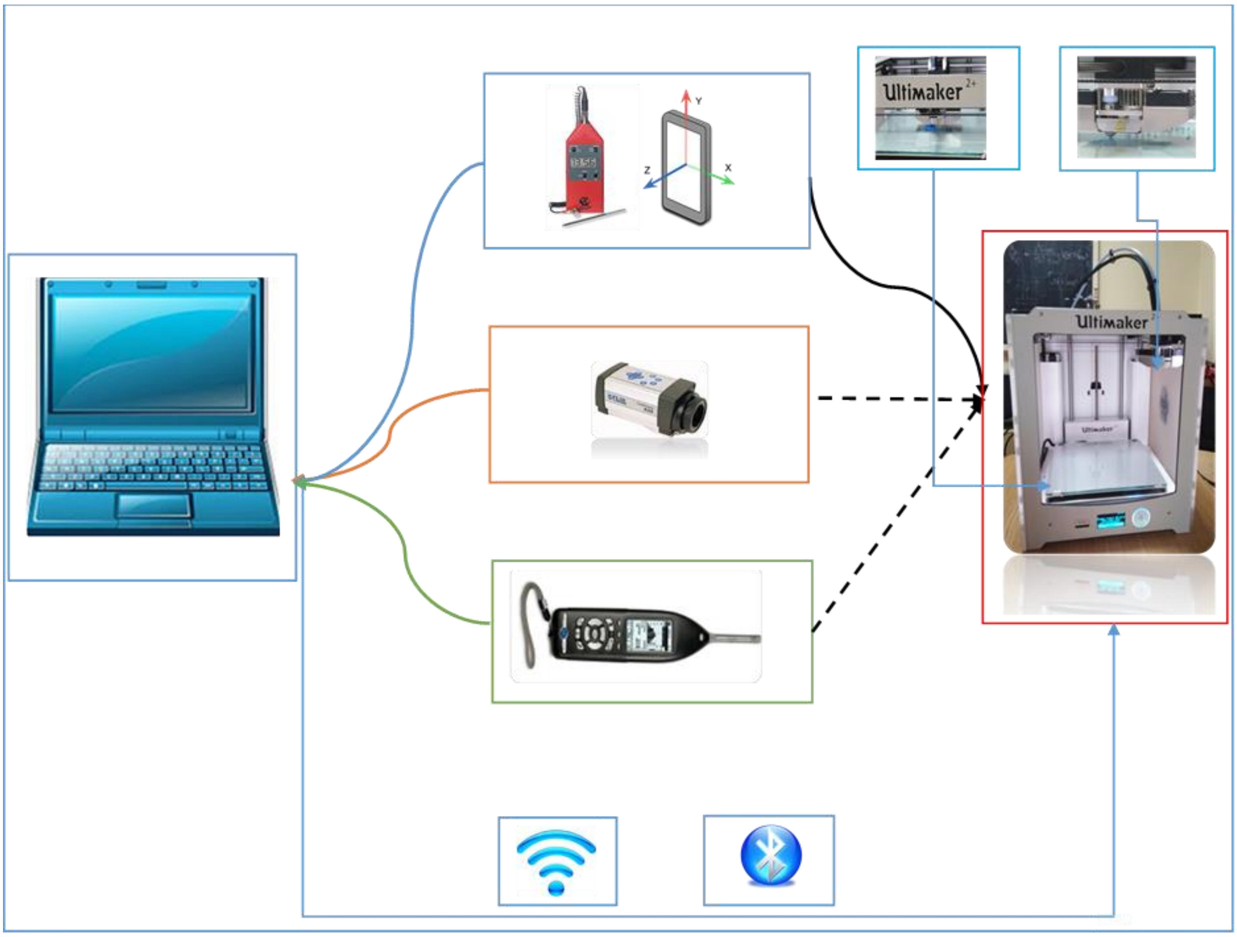


Fig. 90. Measured and logged sound signals using Larson Davis 831 Sonometer during the test 2

3.4.3. CBM of 3D Printing Process – Test 3

In the third test, the experimental part included the condition-based monitoring of the ***printer plate*** and the ***printer nozzle***, that are parts of the Ultimaker 2+. *Because of the fact that Ultimaker2+ 3D printer is a closed one, it cannot be monitored the motors of the positioning system and de feeding system.* Similar with Test 2, the main scope of Test 3 was to analyse same different methods of condition-based monitoring for achieving CBM, by measuring: by measuring: the **temperatures** (by thermal camera & IR thermography), the accelerations/**vibrations** (by vibration meters), and the **sound** (by sound meters). In the experiments, the same piece P1 (Fig. 43) was printed using the Ultimaker 2+ 3D printer, process that took place in about 2h and 45 minutes. It can be observed that the sae piece printed with the Ultimaker, using the same condition as he previous test, was realized in a shorter time. The material used in the experiments was PLA. The software for the 3D printing was Cura, were the G-code file was created, and imported in the 3D printer flash-drive. The setup of equipment, devices and software used in the experiments from test 1 are presented in the diagram from Fig. 91 and the real setup in the Fig. 92. It can be observed the positioning of the devices, the connection between these and the main methods of monitoring used in the real conditions for CBM.



DEVICES

- B – Ultimaker 2 + for *3D printing*
  - P – Glass Plate
  - N – Nozzle (printer head)
- T - FLIR A20M Infrared Camera for *thermography*
- S - Sonometer Model Larson Davis 831 for *sound monitoring*
- V – Huawei Pro P20smartphone and vibration meter Quest VI-100 (calibration) for *vibration / acceleration monitoring*

Communication thought USB cable (Contact)

SOFTWARE

- Cura 3D software for *3D printing*
- ThermaCam Researcher Pro 2.8 for *temperature analysis*
- Noise vibration works (version 2.4.1) for *sound analysis*
- VibSensor (mobile App) for *vibration/ acceleration analysis*
- L – laptop for data analysis and processing

Wireless/Bluetooth communication (without contact)

Fig. 91. The setup of the experimental Test 3. Schematic diagram

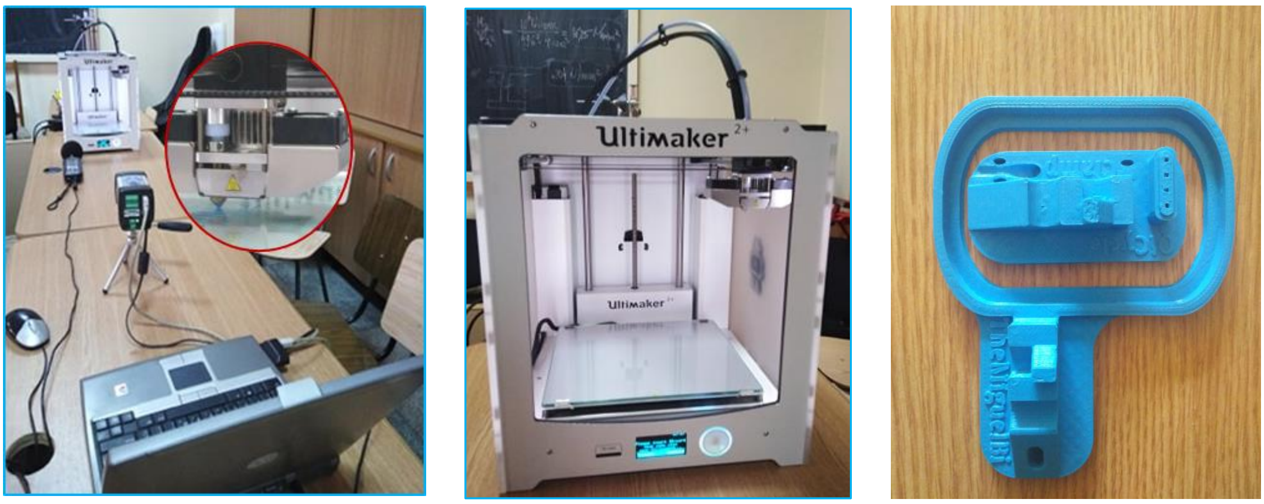


Fig. 92. The setup of the experimental Test 3. 3D printed piece – P1

In the Fig. 93-Fig. 100 are presented the temperature field distributions, in multiple phases of the 3D printing process using Ultimaker 2+ 3D printer, on the surface of the printing glass plate and the nozzle area. The pictures were chosen when the minimum and maximum temperature were encountered, on each spot from the areas of interest. There were chosen 2 points, one on the glass plate SP1, and the other one on the nozzle SP2.

Fig. 93. Nozzle temperature of 61.235°C, before starting the 3D printing process, at time 20:09 min

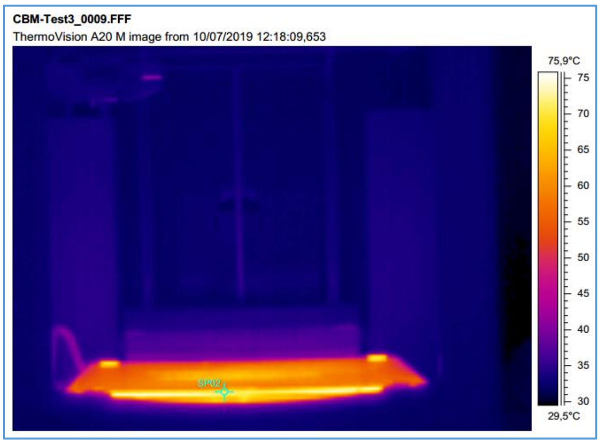


Fig. 94. Glass plate temperature of 73.181°C before starting the 3D printing process, at time 19:09 min

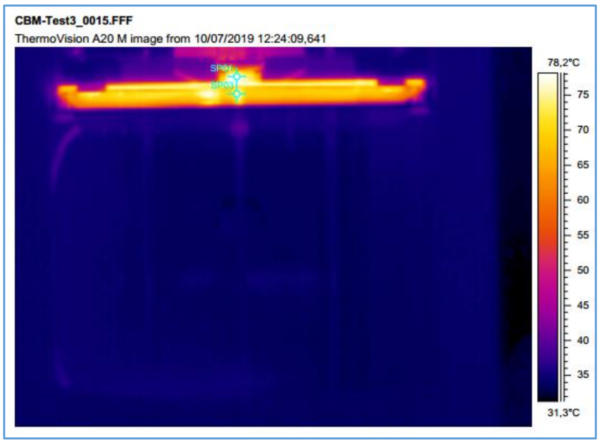


Fig. 95. Nozzle temperature of 77.370°C, during the 3D printing process at time 24:09 min

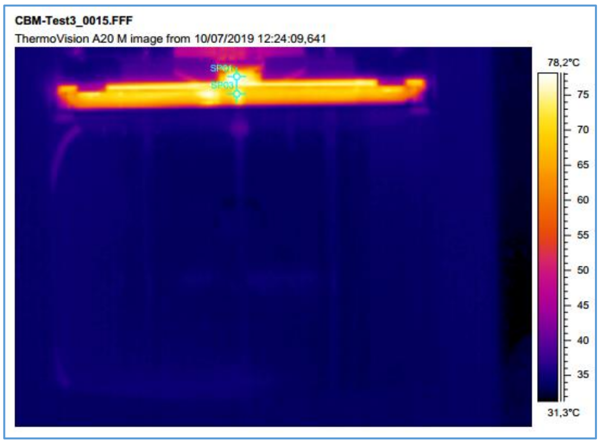


Fig. 96. Glass plate temperature of 76.032°C, during the 3D printing process, at time 24:09 min

Fig. 97. Nozzle temperature of 70.345°C, during the 3D printing process, at time 106:09min

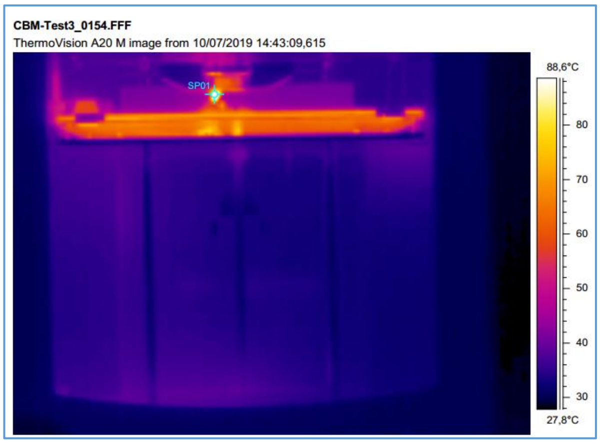


Fig. 98. Nozzle temperature of 100.242°C, during the 3D printing process, at time 164:09min

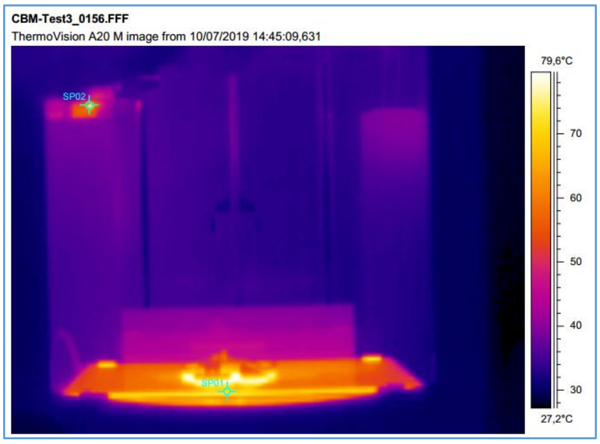


Fig. 99. Nozzle temperature of 59.321°C, during the cooling phase, at time 166:09 min

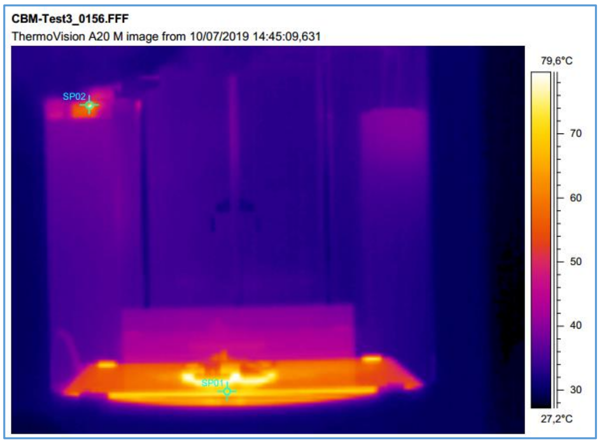


Fig. 100. Glass plate temperature of 69.282°C, during the cooling phase, at time166:09 min

The maximum temperatures reached on the nozzle during the 3D printing process using Ultimaker 2+ was 59.321 at time 166:09 min. The maximum temperature reached on the glass plate was 100.242°C at time 164:09min. Due to the fact that in test 3, the printing process was done by moving both the plate and the printer head, the maximum and minimum temperature during the process was hard to determine. Moreover, the thermography monitoring was achieved also during the cooling phase, hence after the 3D printing process stopped, in order to analyse the heat transfer.

During the printing process, it can be noticed that the temperature of the nozzle and the glass plate are have a very small variation. Because of the fact that the spot chose to represent the measurements for the nozzle is fixed, and because of the fact that in the real 3D printing process, the nozzle is moving along the plate for creating the 3D object, it can be noticed the variation of temperatures (Fig. 101). However, other monitoring solutions can be used for achieving CBM.

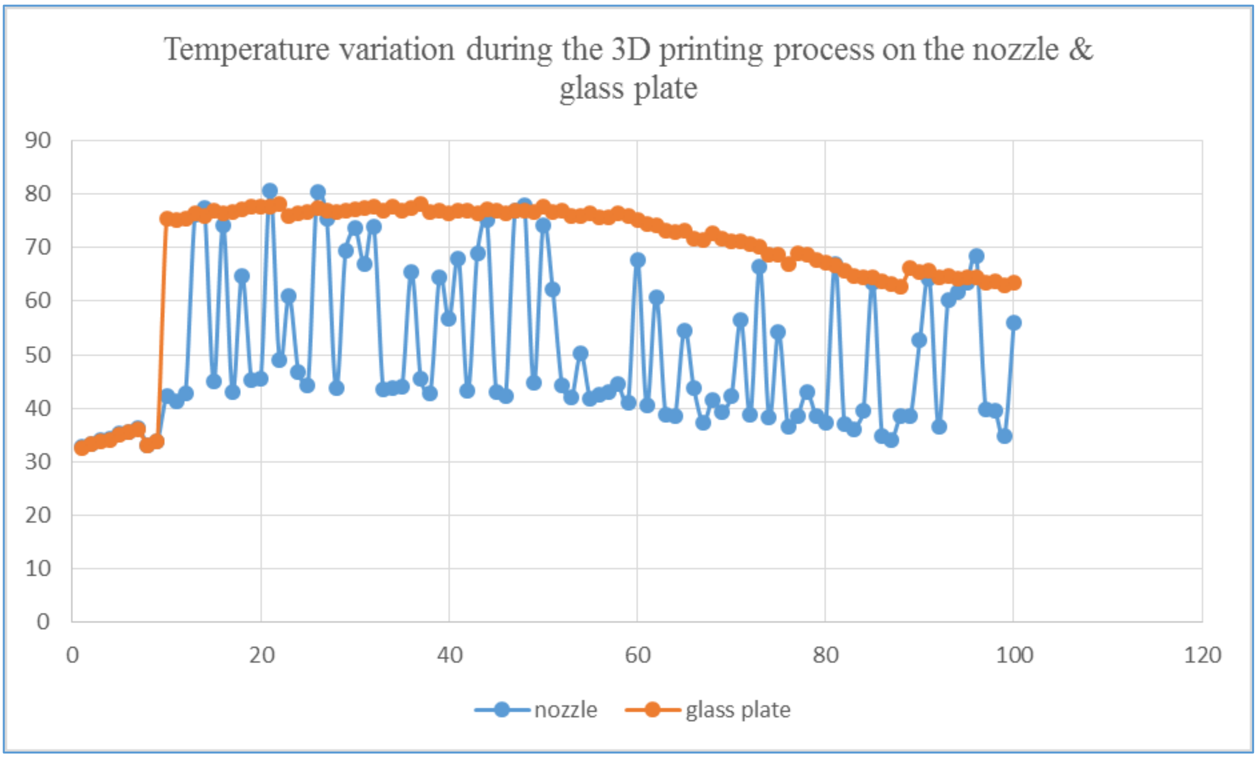


Fig. 101. Temperature variation during the 3D printing process on the nozzle & glass plate

The second part of Test 3 experiment was related to the vibration encountered during the 3D printing process using Ultimaker 2 + 3D printer. The measurements were achieved using a the same smart phone Huawei P20 as in test 2 (Fig. 88a) with accelerometer sensors, that measures along each of the main axes of the device. VibSensor was used for recording, analysing, storing, and processing the accelerometer and vibration data. In the XXX are presented the main vibration analysis parameters measured and logged using the Huawei P20 device and VibSensor mobile application in the test 3.

Start: 10 Jul 2019 (11:59:08.962 am)

Length: 252 min 21 sec

Points: 7,929 Gaps: 2 (15073 sec total)

Data rate: 100.0 Hz Units: m/s^2

Peak raw: X (4.72) Y (4.65) Z (14.63)

ISD: X (0.25) Y (0.34) Z (0.27)

Resonances:

X: 2.3 Hz (0.029), 0.2 Hz (0.018)

Y: 0.29 Hz (0.16), 2 Hz (0.017)

Z: 0.2 Hz (0.028), 1.9 Hz (0.02)

Fig. 102. Measured and logged vibration parameters using the Huawei P20 and VibSensor in Test 3

3.5. Probabilistic Bayesian networks model used for CBM

3.5.1. Bayesian Networks

Bayesian networks are graphical models consisting of nodes representing stochastic variables and directed links between the nodes, representing causal relationships. For a discrete model, each node has a discrete number of states, corresponding to the possible outcomes of the stochastic variable. If the stochastic variable is in fact continuous, it can be discretized such that each state represents an interval of values. To define the Bayesian network, the conditional probability distribution must be specified for each node conditioned on parent nodes (the nodes pointing towards a node). For a node with no parents, the marginal distribution is specified. The network can then be used for calculating the probability of each state for each of the nodes, and these probabilities can be updated, when any of the nodes are observed [92], [93].

3.5.2. Data Fusion

The data fusion approach in two stages. At the first, local data fusion stage, fault indicator values relating to each individual machine component are fused in order to assess the health of said specific component. The results of this local data fusion are given as inputs to the second, global data fusion stage, where the evidence acquired from the entire system is combined, refining the probabilities and therefore assessing the health condition of the whole system with improved reliability. Fig. 103 displays the scheme and the steps followed in order to conduct the Data Fusion Process.
The steps conducted throughout the proposed data fusion algorithm comprise of:

- Signal Processing and Feature Extraction;
- Local Data Fusion;
- Global Data Fusion.

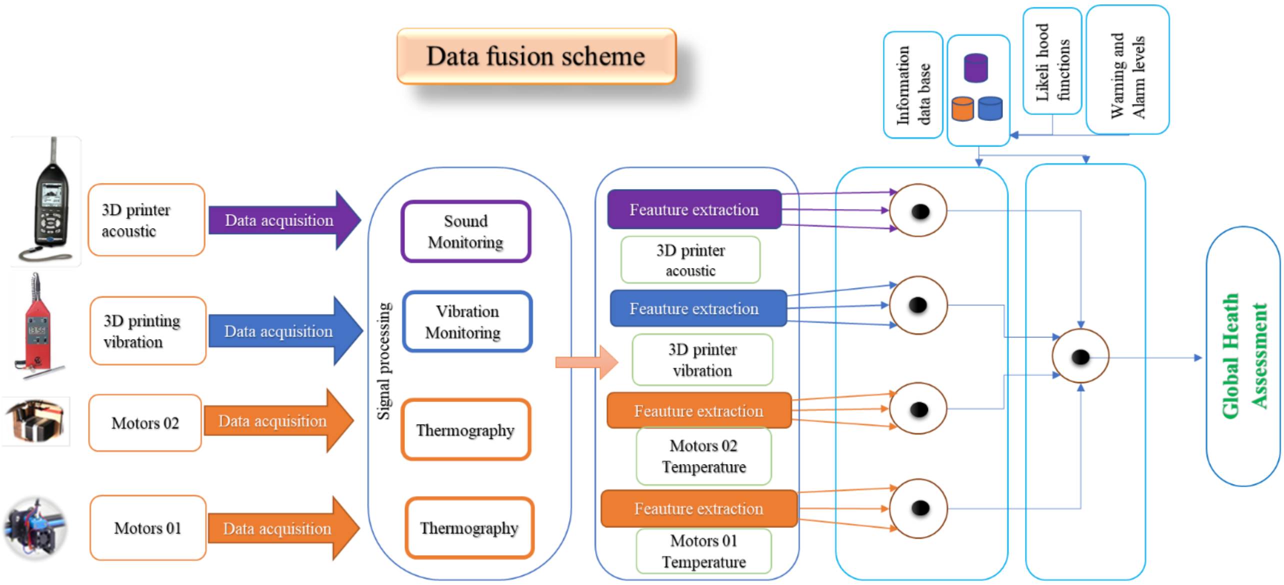


Fig. 103. Applied Bayesian network. Data fusion scheme.

3.5.2.1. Signal Processing and Feature Extraction

Depending on the nature of the system being monitored, different signals and signal processing approaches can be used for achieving condition monitoring and condition-based maintenance. When monitoring the smart industrial processes, typically process variables that should be monitored are temperature, vibration, sound etc. Once the signals have been processed, the following steps will consist in extracting the features or key indicators, that will allow the identification of the state of the system or device. The selection of relevant features or key indicators is very important in the condition monitoring, since a part of those tends to be specific to certain faults, whilst others are less relevant, or can react differently to many or all faults. This is an essential aspect, due to the fact that the condition monitoring accuracy depends on the features or key indicators sensitivity. Typical features extracted, depend mainly on the nature of the signal acquired. For temperature waveforms, typical features include: Maximum (Max) and Minimum (Min), Root Mean Square (RMS), Standard Deviation (STDEV), Crest Factor (CF), Skewness (Sk), Kurtosis (Kurt) and Signal Entropy. When considering temperature distribution, in addition to extracting the maximum values at particular time of system functioning, features such as the Temperature Spectrum Area and Temperature Spectrum Area Centroid may also be calculated. Furthermore, features can be formed as combinations of other extracted features or key indicators, for example the amplitude ratio between two different peaks, or the ratio between a peak value and the RMS value. When selecting or designing features or key indicators it is important to understand how a specific fault can influence the behaviour of a system. Once the features have been extracted, it is important to define a threshold level, from which it is known that the signal is presenting an abnormal behaviour. For the case of velocity vibration, the RMS values are referred in to the ISO standards, since they establish the warning and alarm levels of vibration according to the size (power) and foundation type of the machine [94]. For practical purposes, a warning threshold can be considered as the maximum feature or key indicator level, in which the machine operation is the just tolerable, on the other hand, an alarm threshold can be considered as the maximum level after which the machine operation is not permissible [92], [93].

3.5.2.2. Local Data Fusion

The data fusion process is split into two stages, the local data fusion and the global data fusion. Firstly, consider a machine with a total of M components, each component has N possible fault conditions and K health indicators. In this sense, considering that $i = 1, 2\ldots$, M the ith component will have a total of N_i possible fault conditions and Ki health indicators. The whole system will have a total of R possible faults, which comprise the faults of individual components and their different combinations. Each indicator will be represented as $y_{i,k}$, where it is read as the kth indicator of the itch machine component and each fault condition will be represented as $F_{i,n}$, where it is read as the nth fault of the itch machine component [92], [93].

For each ith machine component, there is a local data fusion process. Algorithm 1 (Local data fusion algorithm) describes the local data fusion process for the ith machine component [92], [93].

Algorithm 1. Local Data Fusion Algorithm

procedure Local Data Fusion $y_{i,1}, y_{i,2},\ldots, y_{i,K}, p(F_i^0)$
$p^-(F_i) \leftarrow p\ (FF_i^0)$
    for k = 1, K **do**
        If $y_{i,k} >$ warning$_{i,k}$ **then**
            $p\ (F_i|y_{i,k}) \leftarrow [p\ (y_{i,k}|F_i) \otimes p^-\ (F_i)]/[\sum^N_{n=1} p\ (y_{i,k}\ |F_{i,n})p^-(F_{i,n})]$
            $p^-(F_i) \leftarrow p\ (F_i|y_{i,k})$
            $k \leftarrow k + 1$
        else
        $k \leftarrow k + 1$
    $p\ (F_i|Y_i) \leftarrow p\ (F_i|y_{i,k})$
    return $p\ (F_i|Y_i)$

In Algorithm 1, $p\ (F_i^0)$ is a probability mass function that contains the initial values of probability that determine how likely it is for each fault condition of the machine component i to be present prior to the condition assessment. These initial probability values can be defined arbitrarily in most cases, but could also be obtained from other sources. For example, the initial probabilities might be calculated from reliability information from a fleet of similar machines, or assessed by an expert who has access to the operational history of the machine and/or experience with similar machines. $p(F_i^0)$ is a probability mass function, but can be represented as a vector whose elements constitute the probability values for each fault. In this way [92], [93]:

$$p(F_i^0) = [p(F^0_{i,1})\ \ p\ (F^0_{i,2})\ \ \cdots\ \ p\ (F^0_{i,Ni})]$$

Since the developed technique considers probability mass functions with discrete and defined values, in order to simplify the visualization of the implementation of the method, these functions will be subsequently represented as vectors. $p^-(F_i)$ is the a priori probability mass function for the machine component i (or the probability mass function before the data is fused), $p(F_i|y_{i\ k})$ is the a posteriori probability distribution for the machine component i (or the distribution of probabilities after fusing the data), $p(y_{ik}|F_i)$ is the likelihood function, which is a probability mass function that provides information about the likelihood that a fault condition is present in the machine component i, given that an indicator value (in this case $y_{i,k}$) has crossed its warning level. More details about the likelihood functions are provided in further sections. Finally, warning $_{i,k}$ is the predefined warning level for the kth indicator of the i_{th} machine component under analysis, and $\otimes$ is the element-wise product. Since there are a total of M machine components, a total of M local data fusion processes is carried out, providing a set of M posterior fault probability mass functions, which can be represented as follows [92], [93]:

$p(F_1|y_{1,1}, y_{1,2}, \dots y_{1,K1}) = p(F_1|Y_1) = [p(F_{1,1})\ \ p(F_{1,2})\ \dots\ p(F_1,N_1)]$
$p(F_2\ y2,1, y2,2, \cdots y2,K2) = p\ (F2\ Y2) = [p\ (F2,1)\ \ p\ (F2,2)\ \dots\ p\ (F2,N2)]$
……………
$p(F_M|y_{M,1}, y_{M,2}, \dots y_{M,KM}) = p(F_M|Y_M) = [p(F_{M,1})\ p(F_{M,2}) \dots p(F_M,_{NM})]$

If the Maximum A Posteriori (MAP) of these posterior fault probability mass functions is calculated, the index of such MAP will indicate the most likely fault to be present in each machine component. This process will be conducted later during the global data fusion. It is important to note that, depending on the machine component, a diff erent number of possible faults may be possible, thus the number of elements in the probability mass distributions could be diff erent.

3.5.2.3. Global Data Fusion

Before the global data fusion may begin, a number of data sets are required, specifically the initial global fault probability (iGFP) mass function and the posterior fault probability (PFP) mass functions (one per each machine component). The iGFP mass function, p (C0), is defined as [92], [93]:

$p\ (C^0) = [p\ (C_1{}^0)\ \ p(C_2{}^0)\ \ \dots\ \ p(C_R{}^0)]$
where C_r, r = 1, 2, 3, … , R, represent the diff erent fault conditions that can occur in the system and $p\ (C_1{}^0),\ \ p(C_2{}^0),\ \ \dots\ ,\ p(C_R{}^0)$ represent the initial probability that any of these faults is present before the Global Fusion stage takes place. These initial probability values can be obtained from the posterior fault probability mass functions (acquired after the local data fusion process), by determining marginal or joint probabilities depending on the nature of the fault condition (simple or combined), or by simply equally distributing the probability amongst all the global fault conditions. Conversely, the PFP mass functions are acquired after the local data fusion process is finalized.

To begin the global fusion process, the index of the Maximum a Posteriori (MAP) probability values from each of the PFP mass functions is extracted. This index is used in combination with the Global Likelihood Functions (GLF) of each component to conduct the global fusion process. The GLF is a set of probability mass functions (associated with a machine component) that provide information about the likelihood that a fault condition is present in the system (instead of specific machine components, see Section 3.4.2). The final result of the global fusion process indicates the probability of each specific fault condition being present in the system. Algorithm 2 (Global Data Fusion Algorithm) shows the steps taken when conducting the global fusion process [92], [93].

Algorithm 2. Global Data Fusion Algorithm

procedure Global Data Fusion $p(F_1|Y_1),\ p\ (F_2|Y_2), \dots, p\ (F_M\ |Y_M),\ p\ (C_0)$
Index function gives the index of the maximum argument
    $Idx_1 \leftarrow$ Index (argmax $(p\ (F_1|Y_1))$)
    $Idx_2 \leftarrow$ Index (argmax $(p\ (F_2|Y_2))$)
    …
    $Idx_M \leftarrow$ Index (argmax $(p\ (F_M|Y_M))$)
    $p^-(C) \leftarrow p\ (C^0)$
    for m = 1, M **do**
        $p\ (C|F_m) \leftarrow [GLF^m(Idx_m) \otimes p(C)]/[\sum^R_{r=1} GLF_m\ (Idx_m)_r\ p^-(C_r)]$
        $p^-(C) \leftarrow p(C|F_m)$
        $m \leftarrow m + 1$

p $(C|F) \leftarrow$ p $(C|F_m)$
return p $(C|F)$

In Algorithm 2, $p^{-}(C)$ represents the a priori global probability mass function, p $(C|F_m)$ represents the a posteriori probability mass function, GLFi (.) is the set of Global likelihood functions related to the ith component, C_r is the r^{th} value of the vector that represents the probability mass function C.

3.5.3. Construction of Likelihood Functions

The likelihood functions lie at the core of the Bayesian Inference algorithm. These functions contain the probabilistic information that is used in combination with the evidence gathered. For the case of the Data Fusion approach presented in this paper, there are two diff erent types of likelihood functions: those which are associated with each of the machine components, known as the Local Likelihood Functions, and those associated with the complete system, known as the Global Likelihood Functions [92], [93], [95].

3.5.3.1. Local Likelihood Functions

The local likelihood functions are associated with a specific machine component. These functions allow the different component features to be fused. Each feature or indicator has a likelihood function associated with it. Broadly speaking, the likelihood function is a probability mass distribution that describes the probability that a fault is present given that an indicator has crossed its threshold value. The structure of each likelihood functions may be given as [92], [93], [95]:

$$p(y_{i,k}|F_i) = [p(y_{i,k}|F_{i,1})\ p(y_{i,k}|F_{i,2})\ ...\ p(y_{i,k}|F_{i,Ni})]$$

where p $(y_{ik}|F_{i,1})$ represents the probability that the fault $F_{i,1}$ is present, given that the indicator y_{ik}, has exceeded its threshold. The probability values contained within the likelihood functions can be obtained through experimental tests in which the component condition is known, or from historical condition monitoring and maintenance data from multiple similar machines. Evidently, the more information that is gathered, the more reliable the final result will be.

3.5.3.2. Global Likelihood Functions

The Global Likelihood Functions (GLF) are associated with the whole system rather than its individual components. These Global Likelihood Functions provide a refinement of the diagnostics, since the Bayesian algorithm fuses all of the information acquired from each of the components, combining it in the second fusion stage. For some diagnostics situations, for example in the diagnostics of bearing looseness or excessive misalignment, two different faults can result in similar indicator values, potentially leading to false alarms or inaccurate diagnostics. The Global Data Fusion process is intended to reduce the influence of any potentially misleading or ambiguous information, thus providing the end user with a more reliable assessment of the condition of the system. In a similar fashion as when considering the Local Likelihood Functions, the GLF are constructed as a set of probability mass functions. However, in order to implement this technique, it should be represented as a matrix with the following structure [92], [93]:

$$GLF_i = \begin{bmatrix} p(F_{i,1}|C_1) & p(F_{i,2}|C_2) & \cdots & p(F_{i,1}|C_R) \\ p(F_{i,2}|C_1) & p(F_{i,2}|C_2) & \ddots & p(F_{i,2}|C_2) \\ \vdots & \vdots & & \vdots \\ p(F_{i,Ni}|C_1) & p(F_{i,Ni}|C_2) & \cdots & p(F_{i,Ni}|C_R) \end{bmatrix}$$

where GLF_i is the global likelihood function of the i_{th} machine component, and $p(F_{n,r}|C_i)$, where r=1, 2,…, R, represents the probability that the local fusion process will indicate machine component fault F_{in} , to be present, given that the system condition C_r is present. For the global data fusion process, only one row of the GLF is used. More specifically, when $GLF_i(n)$ is called in Algorithm 2, only the n_{th} row vector is considered for the calculations.

From a technical and economical point of view, it is easier to obtain the Likelihood Functions of one system component than from the whole system (composed of several components). In an ideal scenario the GLFs could be constructed using data obtained through experiments conducted under controlled laboratory conditions, with data recorded for each of the different types and combinations of faults. The costs of the tests required to obtain the Global Likelihood Functions and the improbability to be able to obtain data from the whole system in every possible fault condition motivate the establishment of alternatives to build the GLF.

There are various alternative approaches for constructing the GLF that may be envisaged. A pragmatic approach that may be quickly implemented is to build the functions on the basis of the opinion of an expert who understands the dynamic interactions between the components in the specific system (similar approaches have been applied previously by other authors [96]). Another potential approach for constructing GLFs may involve the use of models and numerical simulations of entire systems in order to simulate the interactions between components. Finally, historical condition monitoring and maintenance data from multiple similar systems may be used to generate the likelihood functions. In this case similar systems refers to systems comprised of similar components in a similar configuration. Again, it is evident that the reliability of a GLF constructed using such a method will depend on the amount of comparable data that is available.

3.5.4. Signal Processing and Feature Extraction

Depending on the source of the signal and its nature, different features were extracted. Generally speaking, two different types of feature were extracted: those which were based on temperature domain waveforms and those which were based on values extracted from the frequency domain. From the measured data, only temperature domain features were extracted, whilst for acceleration/vibration and sounds signals were analysed globally. In the table 10 are presented the monitoring methods and possible faults during 3D printer functioning.

Table 10. Monitoring methods and possible faults in during system functioning

	Motor 01	Motor 02	Nozzle
Thermography (Temperature)	*Not feeding with wire properly	*Non drive vertical *Non drive side horizontal	*Not fading wire properly *Wire melting abnormal
Vibration (Acceleration)	*Misalignment of 3D printing layers	*Non drive vertical *Non drive side horizontal *Drive side horizontal	*Not printing *Misalignment of 3D printing layers (output horizontal; output vertical)
Acoustic (Sound)	N-A	*Non drive vertical *Non drive side horizontal	N-A

Temperatures features were extracted from the IRT data. These features, applied in this case for measured temperatures, are typically used in statistics and could be considered as the common indicators used for achieving condition monitoring. Table 11 shows the temperature domain features used, where Ns represents the number of samples of the temperature, acquired during the 3D printing process, in an interval of 10 sec.

Table 11. Temperatures features/key indicators used for analysing the data

Feature / Key indicator	Equation
Minimum (Min)	$\boldsymbol{min(x_i)}$
Maximum (Max)	$\boldsymbol{max(x_i)}$
Mean/Average ($\bar{x}$)	$\boldsymbol{\frac{\sum_{i=1}^{Ns} {x_i}^2}{N_s}}$
Peak to peak (Pk2Pk)	$\boldsymbol{max\ x_i + min\ x_i}$
Standard Deviation (SD)	$\boldsymbol{\sqrt{\frac{\sum_{i=1}^{N_s} \lvert x_i - \bar{x} \rvert^2}{N_s}}}$
Root mean square (RMS)	$\boldsymbol{\sqrt{\frac{1}{N_s} \cdot \sum_{i=1}^{Ns} {x_i}^2}}$
Skewness (SK)	$\boldsymbol{\frac{\frac{1}{N_s} \cdot \sum_{i=1}^{N_s} (x_i - \bar{x})^3}{\left[\frac{1}{(N_s - 1)} \cdot \sum_{i=1}^{N_s} (x_i - \bar{x})^2\right]^{\frac{3}{2}}}}$
Kurtosis (Kurt)	$\boldsymbol{\frac{\frac{1}{N_s} \cdot \sum_{i=1}^{N_s} (x_i - \bar{x})^4}{\left[\frac{1}{N_s} \cdot \sum_{i=1}^{N_s} (x_i - \bar{x})^2\right]^2}}$

3.6. Results of Data Processing

3.6.1. Features / Key Indicators and Thresholds

After processing the data from the IRT and the proposed temperature domain features (Table 11), it was obtained the results, that are grouped on each tests from the experiments, and summarize in Table 12 and Table 13, as follows:

- ***Minimum (Min)*** and ***Maximum (Max)*** values. These values represent the maximum and the minimum temperature measured on the motors, during the 3D printing process. It can be noticed that the maximum temperature does not exceed 50ºC, that is the maximum operation temperature of the motors, and does not decrease below 20% more than the ambient temperature; the ***Maximum (Max)*** value of the measurements it can be considered a very important feature or key factor for achieving CBM, meanwhile the ***Minimum (Min)*** value is rather less important feature or key factor for CBM.
- ***Mean/Average ($\bar{x}$)*** is the number expressing the central or typical value in a set of data, in particular the mode, median, or (most commonly) the mean, which is calculated by dividing the sum of the values in the set by their number. The mean/average temperature is a rather less important key indicator for CBM ,but can be used in determine other important features or key indicators.
- ***Peak-to-peak (Pk2Pk)*** is the difference between the maximum positive and the maximum negative amplitudes of a signal distribution or waveform. In this case, the ***Pk2Pk*** can be considered a medium importance feature or key factor for CBM but gives important information related to the distribution.

- ***Standard deviation*** (***SD*** or ***σ***) is a measure that is used to quantify the amount of variation or dispersion of a set of data values. A low standard deviation indicates that the data points tend to be close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the data points are spread out over a wider range of values. Standard deviation may serve as a measure of *uncertainty;* hence standard deviation of the temperature measured gives the precision of the measurements. Analysing the measurements, if can be observed that SD value is low, that indicates that the temperature measured values are clustered closely around the mean. It can be concluded that SD is a very important key indicator for CBM because is leading to understand the nature of the temperature distributions.
- ***Root Mean Square (RMS)*** is also known as the quadratic mean and is a particular case of the generalized mean with exponent 2. RMS can also be defined for a continuously varying function in terms of an integral of the squares of the instantaneous values during the temperature distribution in the analysed points/spots. In CBM, the root mean square error of temperature is a measure of the imperfection of the fit of the estimator to the data, and can be considered a very important feature or key indicator.

Table 12. IRT data analysis and processing for test 1 in Motor 1 and 2

Point/Spot	SP01	SP02	SP03	SP04	SP05	SP06
Min [ºC]	29.81	27.90	27.94	28.93	30.58	28.59
Max [ºC]	46.07	44.26	44.44	44.47	45.49	44.11
Mean ($\bar{x}$) [ºC]	38.06	36.52	36.05	37.23	38.60	37.08
Pk2Pk[ºC]	75.87	72.17	72.38	73.40	76.07	72.70
SD	6.24	6.07	6.22	5.82	5.44	5.84
RMS	22.26	21.37	21.12	21.76	22.51	21.67
Sk	-0.14	-0.26	-0.10	-0.33	-0.31	-0.32
Kurt	-1.82	-1.75	-1.81	-1.72	-1.71	-1.72

Table 13. IRT data analysis and processing for test 2 in Motor 1 and 2

Point/Spot	SP01	SP02	SP03	SP04	SP05	SP06
Min [ºC]	32.52	32.58	32.69	34.84	34.54	34.56
MaxPk [ºC]	46.11	46.25	46.25	46.31	44.83	45.35
Mean ($\bar{x}$) [ºC]	41.33	42.13	41.78	42.60	41.77	42.22
Pk2Pk [ºC]	78.63	78.83	78.94	81.14	79.37	79.91
SD	3.66	2.71	3.23	1.76	1.60	1.66
RMS	39.90	40.66	40.34	40.99	40.18	40.63
SK	-1.03	-1.19	-1.32	-1.11	-1.32	-1.46
Kurt	-0.12	1.40	0.89	3.76	4.45	4.96

- ***Skewness*** measures basically if the data are symmetric from the mean. If the skewness is closed to 0 than the distribution of the data is symmetrical. If the tail of the distribution is pulled over the right side of the mean than the skewness is positive. Otherwise, if the skewness is negative, then the tail of the distribution is pulled in the left side of the mean. Both for test 1 and test 2, using the same points/spots positioned on the motor M1 and M2 of the Creality 3D printer we can consider that the skewness of the temperature distribution has a negative value that means that the tail of the distribution is pulled over the left side of the mean. If the skewness is less than -1 or greater than 1, the distribution is highly skewed. If values of the skewness are between -1 and -0.5 or between 0.5 and 1, then the distribution is moderately skewed. If skewness is between -0.5 and 0.5, the distribution is approximately symmetric. As can be observed in the previous tables, there are differences between test 1 and 2 skewness values, because of the fact that the measurement in the test 2, begun in the same time with the process, instead in the test 1 the measurement begun after 20 min after the starting of the process, and the values of the skewness are quite different.

- ***Kurtosis*** is a measurement of how pointy the distribution is compared with a normal distribution. If the kurtosis has a positive value than the distribution of data can be considered pointy, otherwise having negative values, the data distribution is flat. In the same way as the skewness, for both test 1 and test 2, using the same points/spots positioned on the motor M1 and M2 of the Creality 3D printer we can consider that the kurtosis of the temperature distribution has a negative value that means that the tail of the distribution is pulled over the left side of the mean.

Setting the warning threshold levels is maybe one of the most important and difficult tasks in the design of CBM of the systems. The improper definition of the threshold values for alarming levels can lead to an unsuccessful diagnostic of the systems and abnormal values can lead to warnings. The most suitable way is to choose a probabilistic approach for setting the threshold levels, based on Probability Density Functions (PDF) theory, that can be useful for determine statistical limits of alarming. The calculated statistical limits allow to distinguish between abnormal or typical behaviours of the systems. Often when constructing PDFs of features or key indicators, a Gaussian distribution is assumed, however this assumption cannot be generally applied. Instead the PDFs can be directly estimated from the values of the features themselves through the use of a non-parametric approach, for this study being selected the Kernel Density Estimation (KDE). In order to estimate the shape of a function f (temperature, vibration/acceleration, sound) it should be determined the density estimator, that can be expressed by the following equation:

$$KDE(x) = \frac{1}{N_s}\sum_{i=1}^{N_s} K_h(x - x_i) = \frac{1}{N_s \cdot h}\sum_{i=1}^{N_s} K\left(\frac{x - x_i}{h}\right)$$

where K is the kernel - a non-negative function - and $h > 0$ is a smoothing parameter called the bandwidth. A kernel with subscript h is called the scaled kernel and defined as $K_h(x) = 1/h\ K(x/h)$.

3.6.2. Three Model Applied Bayesian Network for CBM

Applying statistical methods and probabilistic approach for setting the threshold levels of functioning, based on Probability Density Functions (PDF) theory for determining the CBM for an AM/3D printing process using the experimental setup from the presented tests, it can be designed a three modes Bayesian network. As shown in Fig. 104, it can be assumed that faults of the devices component can be optimally detected by a hybrid of three diagnostic agents or fault detection methods. The probability of detection of each diagnostic agent is defined within a Confidence Matrix. Once the individual diagnosis of each diagnostic agent is estimated and placed in a Diagnosis Matrix, the total probability theorem can be used to incorporate all probabilistic fault detection results into one final response of the alarming system.

Bayesian network design with 3 inputs (M1 & M2 & Nozzle) is connected to 3 neurons or diagnostic agents (Thermography, Vibration Monitoring and Sound Monitoring). Each neurons are connected to individual diagnosis and are combined all probabilities of Functioning or Non-functioning components. For example, if temperature of M1 has a high level, the 3d printer cannot function. And if the vibration of nozzle is very high, the 3D printer gives bad result for, and the 3D piece is not printed properly.

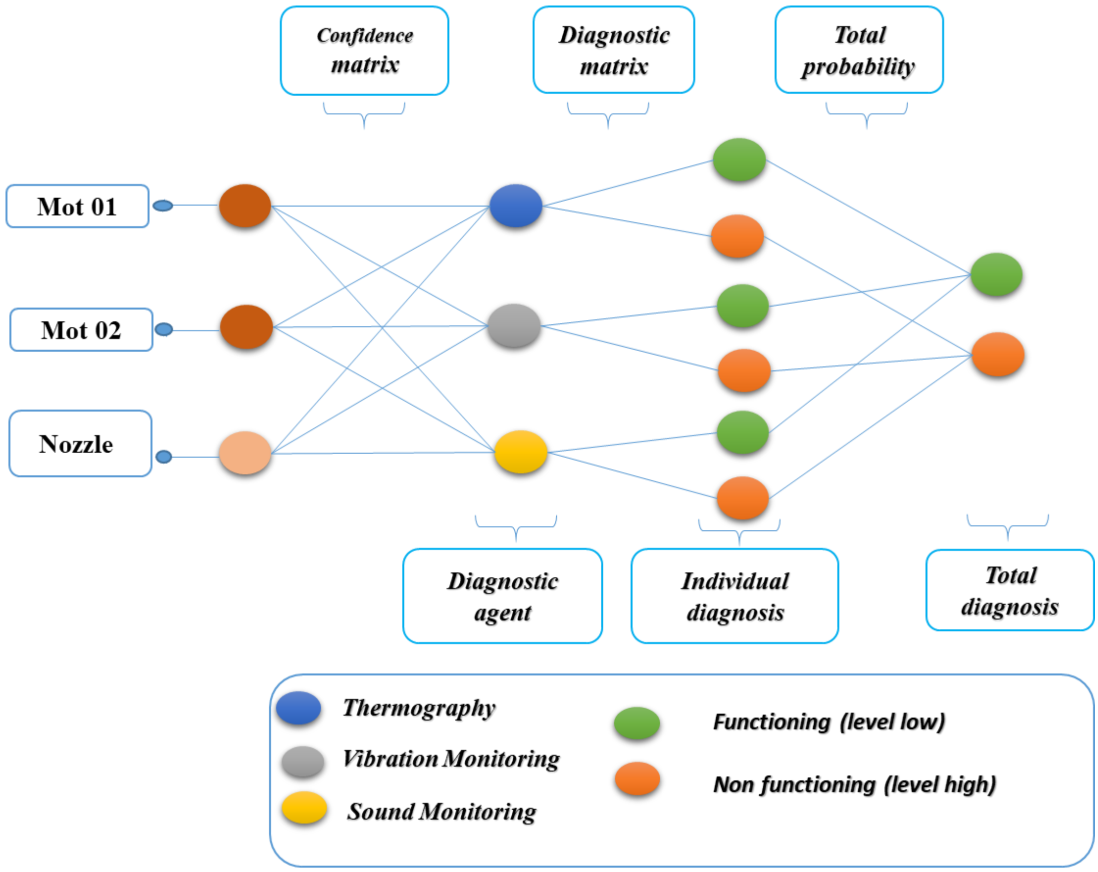


Fig. 104. Three model Bayesian network applied for achieving CBM

Conclusion

Chapter 3 of the Master thesis focused on the experimental and elaboration of the Condition-Based Maintenance for the Optimization of Smart Manufacturing Processes (SMP) using Infrared Thermography. Furthermore, other two CBM methods were applied in the experiments, by means of Sound and Vibration monitoring. The chapter include some considerations regarding the Smart Manufacturing Processes (SMP), especially focused on Additive Manufacturing/3D printing process. It was summarized information related to the process, materials with focus on the sensors, control, platforms and models for smart manufacturing processes in general. Additional new methods applied in SMP as artificial intelligence (AI), and specific to maintenance, machine Learning (ML), Cyber-Physical Systems (CPS) were described. Also, types of 3D printing, 3D Printing Materials, as plastics and metals, software for 3D printing were studied and presented, in order to choose properly and to define the experimental setup from the experiments. The experimental setup and used devices were presented (IRT - thermal camera, Sound monitoring by sonometer Larson Davis 831 and vibration monitoring using Quest VI-100 and mobile solution as smartphone and specific mobile applications. Moreover, the 3D printers, Creality CR-10S PRO 3D Printer and Ultimaker 2+ 3D Printer were presented, with their features and specifications. Afterwards, the experimental setup, tests and results were described and the resulting data were analysed and processed.

After the resulting data analysis and processing, a probabilistic model, based on statistical method using features/key indicators and their thresholds values, and a three model Bayesian network was applied for the elaboration for the CBM applied to SMP, specifically to AM/3D printing.

Final Conclusion and Remarks

The condition-based maintenance for the optimization of smart manufacturing process is absolutely critical for the proper functioning of the complex systems and devices.

- The thesis addresses condition-based maintenance optimization of the additive manufacturing process, using three types of monitoring: Infrared thermography (IRT), Vibration monitoring (VM) and Sound Monitoring (SM);
- Multiple software for different data acquisition, analysis and processing were studied and used: ThermaCAM® Researcher™ from Flir for IRT, Noise & Vibration Works (version 2.4.1) for noise and vibration analysis, VibSensor for vibration mobile recording, Cura printing software for 3D printing (using Ultimaker 2+ 3D Printer) and Simplify 3D (using Creality CR-10S Pro 3D printer);
- The measured data served to the development of a probabilistic model using Bayesian Networks, for a condition-based maintenance model in case of the AM process. This technique and approach can represent a successful integration of a large number of data monitoring sets, with complex modelling and analysis capabilities, that can lead, in the end, at an optimisation of the AM process;
- Summarizing, from the results obtained, it can be concluded that Bayesian probabilistic networks (BNs) can clearly contribute to the improvement of the CBM strategies, specifically when the data obtained from monitoring has non-linear behaviour and the classical mathematical models cannot be applied.

In conclusion, the thesis addresses complex fundamental and experimental researches with wide application in Industrial Engineering field, and specifically in Condition-Based Maintenance. The proposed model, reproduced at larger scale, can be applied in industry, not only on CNC machines, as the 3D printer can be considered, but also to robotic assembly lines, 3D coordinate measurement systems, portal cranes, etc. The measurement of vibration, sound and temperature can be done continuously, and the monitored values are integrated into a self-diagnosis monitoring system, such those encountered to the modern cars, and in the unfortunate event the machine receive a defective or abnormal data value, alarming systems are triggered and visuals appear and are signalled on board.

Future Research Directions

During the experiments and experience in conducting research in CBM, the following research direction have been identified and can be highlighted:

- The possibility of applying Machine Learning/Deep Learning techniques and algorithms for CBM of manufacturing processes;
- The use of artificial neural networks (ANN) for the analysis of non-linear datasets from condition monitoring and to simulate interconnected techniques of monitoring used for specific CBM of manufacturing processes;
- Correlating different methods of condition monitoring for elaborating alarming systems using sensors - IoT and IIoT in the framework of integrated Industry 4.0 concept.

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