

Augmented reality and smart approach for remote maintenance

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Abstract: Industrial 4.0 systems exemplify identifiable and diagnosable systems, although specific failure and safety parameters necessitate visual identification. Hence, it is crucial to incorporate visual techniques in conjunction with traditional sensors or interconnected equipment. The objective of this work is to introduce a methodology for diagnostic and safety analysis that relies on Internet of Things, augmented reality, and data analysis. By merging computer-generated elements, such as visuals or sounds, with the physical world, augmented reality enhances the user's perception of reality.

In our previous work, smart glasses were designed for the purpose of augmented reality. These particular glasses were intentionally designed and created for the express purpose of aiding and supporting maintenance operators in their daily tasks and responsibilities within their respective work environments. The primary objective of these glasses is to furnish these operators with highly relevant and significant information pertaining to the specific equipment they are currently working on or targeting. By doing so, these glasses aim to enhance the efficiency, effectiveness, and overall performance of maintenance operators, ultimately leading to improved productivity and a more streamlined and optimized workflow. Through the employment of a database, the aforementioned glasses were capable of exhibiting the operators with assignments associated and preventive maintenance tasks. Nevertheless, it is important to acknowledge that the glasses lacked the ability to ascertain if the equipment in question was in a secure and functional condition. As an integral component of the ongoing project, a plentiful array of experiments has been executed and a notable volume of data has been amassed. This accumulation of data has expedited the commencement of a cognitive progression. The ultimate objective of this progression is to augment the proficiency of the smart glasses in detecting prospective hazards linked to the apparatus within the operator's visual range. Thereby promoting a more proactive approach to risk prevention.

Keywords: remote maintenance, augmented reality, smart diagnosis, decisional process.

1. INTRODUCTION

Machinery and systems serve as the foundational components of various industries, representing the initial stages of production. Regrettably, they are susceptible to malfunctions and irregularities that can lead to financial losses and human and environmental damages. Addressing these issues typically involves conventional maintenance methods, which demand a significant amount of time and effort to pinpoint and rectify errors.

Industry 4.0, Maintenance 4.0 and even Safety 4.0 is a broad field and is constantly evolving. Therefore, it is important to lead innovative technologies such as the IoT, cloud computing, machine learning, big data, and augmented reality, which are playing an increasingly important role (Elafri et al. 2022).

On the production line of the Audi A8, Google Glass were used. This work integrates the Google Glass into a routine maintenance schedule with ongoing chores. At the conclusion of the final examination, the calibration of the driver

assistance system test bench was chosen. In order to guarantee the steady quality of the test bench in the driver assistance system, employees in this application must carry out a few calibration procedures during their Monday morning shift. Periodically, all sensors and actuators are inspected (weekly, monthly, yearly) (Rauh et al. 2015)

Microsoft's approach to augmented reality, or "mixed reality," is the HoloLens. These holograms can be used to show information, mix in with the real world, or even create a virtual one thanks to their many sensors, sophisticated optics, and holographic processing that easily merges with its surroundings. Compared to two non-AR conditions, the HoloLens AR (Augmented Reality) condition produced better overall human performance on the assembly task (Hoover 2018).

Additionally, AR finds application in ensuring safety, particularly in the context of occupational safety. As mentioned in, (Tatić et Tešić 2017) the use of tags on machinery enables users to access instructions from a database, guiding them on the appropriate and safe actions to

take. AR is primarily employed for instructional purposes, with a primary objective of ensuring the safety of workers in their occupational roles. (Gualtieri, Revolti, et Dallasega 2023) Used Augmented Reality and Dynamic Digital Models to create a human-centered conceptual model. AR applications are typically built on previously saved data that is not updated dynamically in real time.

1.1 Maintenance, Internet Of Things and augmented reality

With the rapid advancement of technology in recent years, the Internet of Things (IoT) has emerged as a pivotal and indispensable means of enhancing maintenance efficiency in various industries. As a result, IoT has now assumed a paramount role in optimizing the maintenance processes of organizations, thereby leading to significant improvements in overall operational performance. By seamlessly connecting devices and systems, IoT enables real-time data acquisition and analysis, facilitating the timely identification of potential issues and the proactive implementation of maintenance measures to prevent any disruptions or downtime. A remote intervention can begin with an onsite operator who identifies failures and requests updates or new functionalities. The operator contacts the "after sale services" department, explaining the problem and providing initial diagnostics. This helps the assistant understand the issue and offer advice. For accurate diagnosis, the remote assistant can request a "Diagnosis Buffer." Further investigation and experimentation can be done in collaboration with the onsite operator to resolve the problem.

Certain software applications allow users to manage and control processes remotely. This functionality enables a remote assistant to access the system and perform maintenance tasks like updating, configuring, and modifying settings. This remote access enhances productivity and flexibility in handling maintenance activities. (AISSANI 2023)

Smart glasses are considered here as a final device like any sensor on production equipment in CIM pyramid see figure 1 (Anon s. d.)

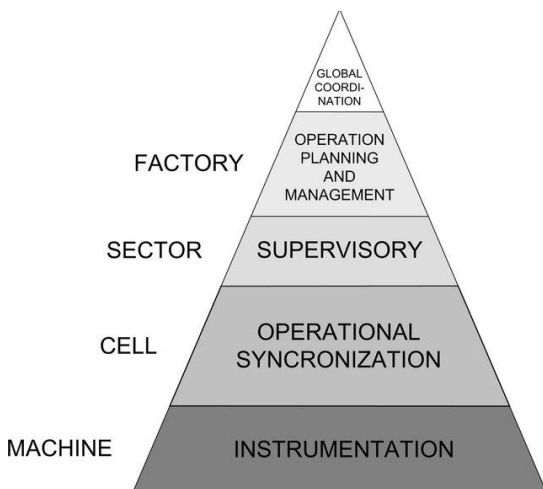


Figure 1 CIM Pyramid

1.2 Decisional process in remote Maintenance

The architecture of remote maintenance involves configuring two or more distinct systems or subsystems that operate independently and exchange data. One system acts as a data acquisition system, gathering structured data, while the other serves as a data processing system, receiving and processing this data. The transmitting system can send data autonomously or in response to requests from the receiving system.

The processed data outputs can be used by human operators or directed to a procurement system for coordinating further data acquisition. Effective communication between the systems requires standardized data structures to ensure compatibility.

Remote maintenance can be set up at a single production site or distributed across various sites, potentially coordinated from a central maintenance center. This flexible architecture can adapt to diverse operational scenarios (see figure 2 as example).

The internet connection for industrial sites differs from home or office connections, as it necessitates specific devices capable of connecting to technological equipment. These unique requirements for internet connectivity in industrial sites are often associated with industrial networks.

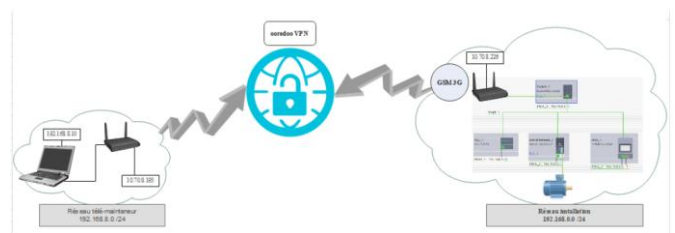


Figure 2 Network for remote maintenance

2. PROPOSED ARCHITECTURE

2.1 Equipment

In the proposed architecture an engine is the controlled equipment and a real time diagnosis is made using two principal equipment which are:

Infrared Thermography: When a mechanical part wears out prematurely, its temperature increases, leading to rapid heating and eventual failure. Most faults cause abnormal heating or cooling. The goal of thermographic inspection is to detect and pinpoint surface temperature variations. This is achieved using an infrared camera combined with image processing software, which captures an image of the inspected area. Each pixel's color in the image corresponds to the temperature at that specific point on the object.

Vibration Analysis: Complementing thermographic analysis, vibration analysis examines the structural vibrations of mechanical parts. Moving mechanical parts generate forces and deformations, causing surface displacement that is recorded in a spectrum. For easier analysis and calculation,

measurements are converted from the time domain to the spectral domain. Initial measurements are taken when the machine is new to establish a baseline vibration signature. Regular measurements are then compared to this original signature to detect faults. Increased vibration levels indicate potential issues. The operator uses a vibration analyzer, balancer, and data collector for vibration analysis and data processing.

Smart glasses for augmented reality: these glasses are equipped with a camera, processor, and display. They can collect images, process them, send the data to a remote device, and receive data to display

And then the remote processor which can process data, learn and make decision

2.2 general architecture

These devices are connected to a processing engine where data is collected, structured, and queried. This data can be used in the learning process to link each system state (a collection of data) to a maintenance decision (testing, repairing, replacing, etc.). When the system is described and the database is queried, this constructed knowledge is used to make decisions about which maintenance actions to take

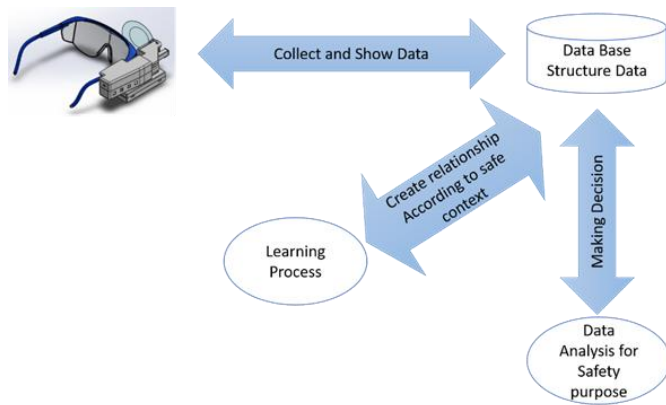


Figure 3, architecture of the proposed model

Vibration data is gathered by the analyzer and can be collected up to once per second from a programmable logic controller (PLC). This data is exported as waveforms and/or spectra, interpreted at intervals, and visualized as graphs. The data is also stored in tables (see Fig. 4), which include vibration measurements and expert assessments classified into three categories: "Tolerable," "Acceptable," and "Inadmissible." This classification serves as a learning decision node.

	v_vel	v_accel	h_vel	h_accel	a_vel	a_accel	Decision
3	1.472	0.011	3.077	0.055	0.779	0.007	Tolerable
4	1.241	0.008	2.752	0.045	0.606	0.004	Tolerable
5	1.043	0.006	2.600	0.042	0.741	0.01	Tolerable
6	1.154	0.007	2.595	0.038	0.703	0.008	Tolerable

Figure 4, Data file

2.3 Developing knowledge model

In this experiment, the collected data will be used to model a Bayesian network to represent the equipment's knowledge

history and automatically predict its state. We will use Agenarisk software for this purpose.

A Bayesian network consists of parent and child nodes connected by conditional probabilities, represented as P(A|B,C), where B and C are parent events with their elementary probabilities, and A is conditioned by the states of B and C. In our case, the variables include V_vel (vertical velocimetry), V_accel (vertical acceleration), h_vel (horizontal velocimetry), h_accel (horizontal acceleration), a_vel (axial velocimetry), and a_accel (axial acceleration). The decisional node, labeled "Decision," is filled by an expert according to the AFNOR E 90-300 standard. The model is illustrated in Fig. 5.

Once the model is created, a learning phase can begin. This involves learning the correct values of descriptive parameters from observations (such as samples or records) (Aissani et al. 2021). The learned values can then be used to make future predictions about members of the same population.

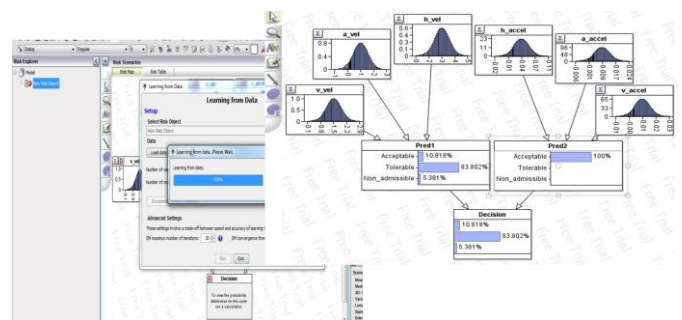


Figure 5, Bayesian Model

When the model is executed, the algorithm learns the posterior marginal distributions for the parameters based on the observations and the prior distribution. However, the prior model is complex to process, so an intermediate node should be defined to distribute this complexity: Pred1 and Pred2. These nodes use logical expressions that combine the states of three parent nodes in a specific order.

$$if(h_vel > 4 || a_vel > 4 || v_vel > 4, "Non_admissible", if((h_vel <= 4 & h_vel > 2) || (a_vel <= 4 & a_vel > 2) || (v_vel <= 4 & v_vel > 2), "Tolerable", "Acceptable"))$$

$$if(h_accel > 4 || a_accel > 4 || v_accel > 4, "Non_admissible", if((h_accel <= 4 & h_accel > 2) || (a_accel <= 4 & a_accel > 2) || (v_accel <= 4 & v_accel > 2), "Tolerable", "Acceptable"))$$

3. INFERENCE AND PROBABILITY PROPAGATION

The notable aspect of Bayesian Networks (BNs) is that once the initial probability values (priors) are assigned, a Bayesian inference engine (such as the trial version of AgenaRisk used here) can run the model and generate all the probability measures for the child or decision node. This tool also enables making inferences from the prior distribution by incorporating data to arrive at new, posterior beliefs in a rational manner, both top-down and bottom-up, allowing for

"what-if" analysis. While numerous analyses and scenarios could be explored, to keep this paper concise, only one scenario will be tested

a) Network analysis: Pred2 has Acceptable values as an evidence, its logic because no parent node can meet the conditions to access this value

$((h_accel > 4 || a_accel > 4 || v_accel > 4))$ because in our learning table that value doesn't exist. So in this case, decisional node meets Pred1 decision.

b) Scenario experimentation: What if acceleration vibration value exceeds the nominal value, this makes the system in "Non_admissible" situation "Fig. 6

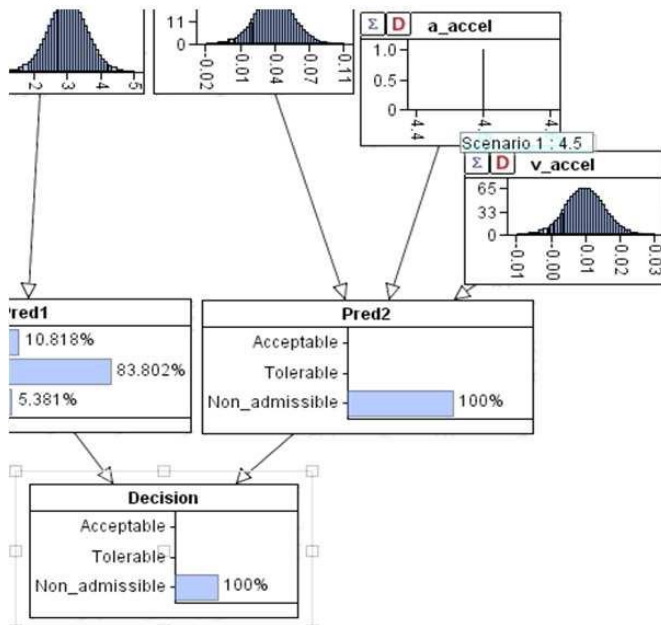


Figure 5, Probability table of Node Decision

c) Backpropagation: Now, we will analyze the conditions necessary to achieve an acceptable situation. The "Acceptable" observation is applied to the Decision node, and then backpropagation is performed on the parent nodes using inverted conditional probability. From "Fig. 6," we observe that the distributions for V_vel, a_vel, and h_vel have adjusted to be limited to the value of 2.0. The acceleration distribution remains unchanged because it already meets the acceptable conditions

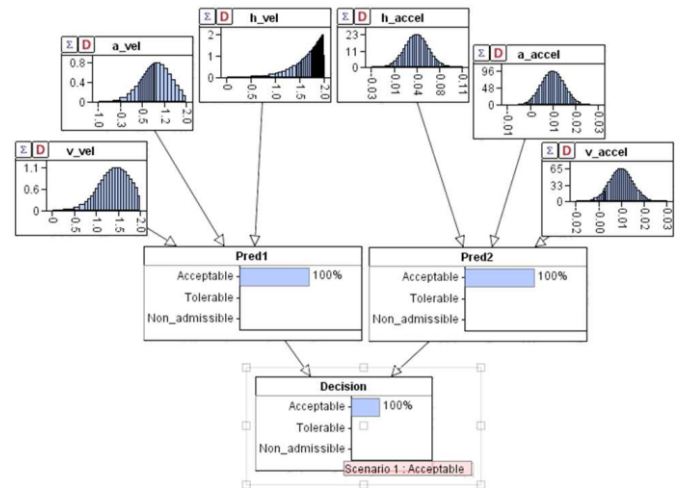


Figure 6, Decision equal "Acceptable"

From these experiments, we can conclude that a Bayesian network is effective for predictive maintenance. It can forecast the system state based on various inputs, and the resulting decision actions can be displayed on smart glasses for the operator to review and execute.

4. CONCLUSION

In highly automated production systems, it is crucial not only to maintain production efficiency but also to ensure minimal safety levels. However, traditional maintenance methods can be costly and time-consuming, leading the enterprise to invest in monitoring tools instead. The monitoring process and connected smart glass generates a large amount of system state data, which can be processed using machine learning to produce knowledge and predict system states. This allows for conditional maintenance, avoiding unnecessary tasks. Experiments in this paper demonstrate the use of Bayesian Networks for this purpose. Future work could explore other learning methods, particularly deep learning algorithms.

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