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# Future challenges in condition monitoring from an industrial perspective: the case of the Independent Carts Systems

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**Abstract** In this paper, the authors discuss about the future challenges of condition monitoring in an industrial context. One of the authors is Line Manager at Data Processing & Analytics for Equipment, Industry 4.0 & MES Products division of Tetra Pak Packaging Solutions S.p.A., a multinational company that approached condition monitoring and diagnostics fifteen years ago. So far, they have gained experience and have a clear idea of what the Industrial field expects in the coming years. In this paper, the analysis of a specific case study is an opportunity to suggest more general research themes on condition monitoring.

**Keywords** Future perspective · Condition monitoring · Diagnostics

## 1 Introduction

Industry 4.0 is a true Industrial Revolution, which, like the previous ones, takes several years to mature fully and complete. This is and will include successes and failures, risks, uncertainties and changes of direction, but which ultimately fulfils its design. Companies that take this path must necessarily have a long-term vision. It is not enough to have an adequate infrastructure in terms of IIoT (Industrial Internet of Things) complete with cloud, edge and data collection on the machine. Above all, it is necessary to have an effective

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analytics for diagnosis and prognosis, which cannot be separated from a fruitful and continuous collaboration with the academy, and, when possible, from the involvement of the designers of the automatic machine, in order to understand which points of interest to prioritize and identify the indicators to monitor and how to do it. This can be done starting from the available scientific literature [1,2], and from the simplest solutions. Artificial Intelligence, for example, is certainly a powerful and new opportunity [3,4], but on its own it does not solve the problem of analytics: it must instead be integrated with Domain Knowledge (i.e. the knowledge of the physical processes behind it) to be guided in the right direction in what is sometimes called a Hybrid Approach [5]. This approach, as we can see, requires a long-term breath, and a significant investment, which cannot have a short-term return on investment. If you want to fully ride the Fourth Industrial Revolution, it is a price to pay, in order to offer a reliable service and improve the management of the machines in the medium-long term.

## 2 Predictive maintenance: a case study

One of the opportunities, in terms of industrial business application in the field of Industry 4.0, is Predictive Maintenance service for automatic machines. In its industrial sense, Predictive Maintenance refers to maintenance operations previously carried out periodically (Preventive Maintenance) on the automatic machine, actively identifying an incipient component or functional failure, through the use of data collected by the machine, aggregated and processed through appropriate algorithms [6]. In the following, a recent mechatronic solution called the Independent Cart Systems (ICS) is taken as an example. It consists in modular linear motors, which have linear or curved shapes and can be connected to each other to get a closed-loop path. Several carts are placed on the motors by means of rolling bearings. The drive and electric parts, i.e. the coils that move the carts by a controlled magnetic field, are placed in the fixed part of the ICS (the frame) also called the rail. The carts contain permanent magnets and an antenna or other magnetic means the drive uses to check their position on the rail. Each cart is direct driven independently from the others and can have high dynamic performances (e.g. they can reach a speed of 4 m/s or even above), which surpass those given by common rotary servomotors in several applications.

From an industrial point of view, new technology like ICS is an opportunity and a challenge. It allows new design of drive-lines and kinematic chains, assuring more flexibility than rotary servomotors used so far, reducing the mechanical complexity of the machine. On the other side, the economic sustainability of new technology is provided only if the reliability of the system is always granted. Possible faults of ICS could be divided into electrical and mechanical faults. In this paper the focus is on the mechanical side only. Despite the tough design of both rails and carts, the bottle neck is the presence of rolling bearings between the cart and the rail. The number of bearings for

each cart depends on the specific cart used and can include bearings with different sizes [7]. In the next section, critical issues about condition monitoring are detailed.

### 3 Critical issues and future prospects

There are several aspects to consider and to solve when preparing and maintaining such a solution. The first difficulties are in terms of knowing what to monitor, how to do it (for example with digital tags or added sensors when the quantity to sample is not observable in the standard machine configuration), and which analytics to apply. This includes the sampling policy, sampling frequency, where and how to position a possible sensor, all of which is industrially sustainable, primarily in terms of costs and then also in terms of life and reliability.

Depending on the specific application, an ICS can include more than one hundred carts on the same rail. Each cart usually has three or more bearings to assure stability during the motion. As a consequence, the total number of bearings monitored can exceed three hundreds units; a huge number compared to the typical number of bearings monitored so far in an Industrial application (but still a lower number than an equivalent mechanical solution doing the same function, with the same flexibility and same total capacity). The diagnostics focus should move from the single machine to the fleets of components. The extension of the predictive policy to a series of mechanical systems requires a strong statistical-based condition monitoring to ensure good reliability as a whole. For example, L10-life is used for the bearing lifetime calculation [8] but it computes the reliability for a single bearing. In case of several bearings in series, the reliability of the whole system is equal to the product of the reliability of each component, so it is significantly reduced by the number of bearings available [9]. A condition monitoring system that has 1% of false alarm (over the entire life) on 2 bearings (e.g. electric motor) can be considered a good result, but if we extend this to fleets of 300+ bearings it is no longer acceptable. In the last decade, many scientific papers have been published on the application of complex statistical methods to machine diagnostics [10–12]. In particular, they focus on Bayesian inference that updates the probability of an event (or hypothesis) as more evidence or information becomes available [13]. These techniques must be extended to increase the robustness of fault prediction (or the computation of the Remaining Useful Life), considering the reliability of several bearings in series but also the variability of the working condition for each of them. Such characteristics can be relevant for other manufacturing sectors comprising fleets of vehicles, such as AGV (Automated Guided Vehicle) in automated warehouses or material handling conveyor systems.

Faults can occur on the rail as well, with different wear processes and expected vibration signals and highly dependent on the inertial loads of the carts and the end-effector that can be mounted on top (e.g. for pick-and-place oper-

ations). Since each cart is moved independently with different motion profile - providing that carts do not overtake each other - non-stationary and non-cyclic working conditions must be considered. **Currently**, condition monitoring of machines in non-stationary conditions is the most common application field in **journal publications** on machine diagnostics (examples in [14–16]). A lot of techniques have been successfully proposed in **the** literature [17], and the term *non-stationary* can refer to variable speed applications [18] or variable loads like in mining machines [19]. Indeed, all manufacturing processes that exhibit variable working conditions can benefit from results in **the** non-stationary diagnostics field.

The sensing of so many carts and the frame is challenging from several points of view. Possible choices could be, e.g. to sense the current of the statoric drives, using the available geometric transformation to port it to the cart reference frame, or add accelerometers directly on-board the cart for a better measure, but with added problems of energy supply, robustness and cost. In the medium term future, the issue of how to collect data from a moving object is being attacked with wireless sensors, that will become cheaper and easier to install, and possibly automatically finding available spectrum windows on **the premises**, i.e. on site. This will probably include also 5G solutions, with the necessary Data Security and Privacy aspects, maybe using Block Chain techniques when needed. Hopefully, the diagnostics will be more and more embedded in newly designed equipment, as said, but also in newly designed industrial systems, such as is already done in IO-Link digital sensors [20]. As well, actuators (e.g. servo motors) will include by design MEMS accelerometers, and other sensors, and transfer the digital information seamlessly to the drive, machine CPU and cloud. These solutions will require also a processing step of the data to avoid time and cost consuming data-transfer via the cloud. As a consequence, we foresee an increasing interest in the field of condition indicators. Finally, data fusion from different sources can minimize the use of external sensors. Indeed ICS are direct drive systems, thus the measured current, velocity, position, position error, and temperature have a lot of information on the behaviour of the load, including possible incipient wear or other health indicators. Although vibrations are probably the most used and informative data, we expect that diagnostics in the medium term future will **result** from different types of information. Regarding the available literature, the Instantaneous Angular Speed (IAS) **has proven** that it is possible to diagnose bearings failures **by** recording the speed of motor shaft at high frequency [21, 22]. The challenge will be to extend the IAS paradigm to the data available **from** embedded encoders, that are always present on servomotors to control the motion profile. According to the Scopus database, the number of papers on multi-sensor data fusion techniques have tripled in 2020 and some of them focus on bearing diagnostics [23–25]. With reference to the condition indicators, recent publications not only present new parameters but also the computational steps to determine the optimal threshold based on statistical inference [26–28]. Possible results can be relevant for the manufacturing fields

characterized by high value components with redundant sensors and/or in a hostile environment (e.g. off-shore wind farms).

Regarding signal processing, it is worth mentioning three key points. Despite the number of carts the frame is the same, i.e. it receives from, and transmits vibrations to, each **cart**, not only as a result of the dynamics of system but also as a consequence of the working processes (e.g. clutching of mechanical parts, cutting of packaging material, etc). Too many sources of "noise" can mask the occurrence of a fault in the early stage, new techniques of source separation will be needed, maybe focusing on instantaneous transfer path analysis (TPA) between a cart and the rail or maximizing the likelihood between the measured TPA and the computed one. Blind source separation techniques [29–31] aim to identify and isolate the contribution of specific components (e.g. gears or bearings) based on expected characteristics of their vibration data. TPA techniques [32,33] take into account the distance between the source and the measuring point, and the degradation of the signal **along** this path. Possible results will be relevant for all manufacturing industries with a cyclic and continuous productivity: these processes have a strong periodicity due to the hourly capacity of the machine, including colored mechanical noise (e.g. impacts due **to** cutting tools) and characteristic fault frequencies of the components.

Another key point is the intrinsic complexity of what is being monitored. It is not possible to be able to predict all the faults, related to all fault modes, of the component or function under observation. There are aspects of the system that are undetectable (unobservable in the Kalman canonical decomposition), from an identification point of view in terms of Control Theory. Other aspects of the system are uncertain, i.e. a proper measurement of them is not **guaranteed**, e.g. the contact forces between the rail and the bearings in opposite configuration due to the local effects of the magnetization field between carts and rail. As a consequence, the introduction of an uncertainty analysis in new condition monitoring algorithms should be encouraged. A research field that seems promising to mitigate uncertainties is Transfer Learning [34]. It is emerging as a technique to improve the performance of artificial intelligence models when the distribution of the data used to train the model is different from the distribution of the new data **to which the models are applied**. Although it was initially developed in Computer Science, it has been applied to the diagnosis of machines in recent publications [35–37].

The last key point is the issue of Artificial Intelligence (AI) as an enabler of condition monitoring if properly guided by a deep engineering and operational knowledge of the machines. The use of this technology is still in constant evolution and brings with it various challenges, for example in terms of deployment on the cloud rather than on-edge. A necessary consequence is also the way of updating the on-edge algorithms in effective terms, possibly closing the loop through federated learning techniques, which allow a lean deployment of AI solutions, which continuously learn and improve, without weighing down the system. An opportunity for algorithm deployment is also represented by dockers containers, which allow a more agile and dynamic management of

**Table 1** Main critical issues for ICS systems and future research perspective

Critical issue	Main Drawback	Research perspective
High number of carts	High number of components under test	Switch from single component diagnostics to component fleet diagnostics
Carts driven independently	Non-cyclic and non-stationary working conditions	Diagnostics in highly non-stationary conditions (loads and speed)
High number of sensors	High data transfer	Developing of new and reliable condition indicators
Cabling of the sensors	High costs of the sensors Several sensor on moving parts	Diagnostics by data fusion Developing of wireless sensors (including embedded post processing)
Synchronous events	Low Signal-to-Noise ratio or masking events	Developing of source separation techniques
Uncertainties	Unreliable condition monitoring system	Developing of uncertainty analysis in condition monitoring
Fleet of machines and growing amount of data	Not taking advantage of having a large fleet of <b>past</b> cases and data	Use of AI for condition monitoring

the on-premises solution (i.e. on site), without sacrificing robustness. Table 1 summarizes the main critical issues of ICS and future research **perspectives**. Possible solutions developed for the condition monitoring of ICS, can also be applied **in** other fields of application, namely any servo-driven (rotary or linear) set of loads, that are similar or identical, but driven independently (e.g. with **slightly** different profiles, or with different phase). The servo-driven sets of load, in order to have a convenient approach and economy of scale, **should** be with high **numbers** of modules, each with rolling elements in the mechatronic solution (in the load itself, or in the servo motor that drives the load).

## 4 Conclusion

A maxim attributed to Niels Bohr is: "Making predictions is always difficult, especially regarding the future". Predictive Maintenance is no exception: machines are complex systems that require years of maturation of the analytics with large amounts of data available. **In a** longer term vision it's possible to foresee Prescriptive Maintenance solutions, where the production operation is automatically, or semi-automatically driven by Condition Monitoring analytics results. This system must also be capable of Cognitive Decision Making through the ability to query through all data sources, seamlessly. This is the vision of what the manufacturing industry expects from research in the field of machine diagnostics for the future.

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