

UIC RAIL SYSTEM DEPARTMENT Artificial intelligence Case of the railway sector State of play and perspectives

March 2021



ISBN 978-2-7461-3065-4

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Contents

1.	What is artificial intelligence?			3
	1.1.	Machi	ne Learning (ML)	4
	1.2.	Natura	Il Language Processing (NLP)	7
	1.3.	Roboti	CS	7
	1.4.	AI fron	n the user's point of view	8
2.	State of play of the European railway sector and perspectives			9
	2.1.	Europe	ean policy context	9
	2.2.	How AI technologies are currently being deployed within the railway sector -perspectives		
		2.2.1.	Image recognition in the fight against terrorism	10
		2.2.2.	Chatbots and virtual assistants for passengers	10
		2.2.3.	Sales prediction through ML	11
		2.2.4.	Robotics in railway stations	11
		2.2.5.	Robotics in trains	11
		2.2.6.	Robotics in warehouses	11
	2.3.	Predic	tive maintenance	12
		2.3.1.	Definition and advantages of predictive maintenance	12
		2.3.2.	Predictive maintenance on rolling stock	12
		2.3.3.	Predictive maintenance on infrastructure	12
		2.3.4.	Other operational decision supports	14
3.	Key success factors and the role of the UIC			15
	3.1.	.1. Railway experts from UIC members will be indispensable at all steps		
	3.2.	2. Interpretability and decision-making		
	3.3. Leading change		g change	15
		3.3.1.	Establishing a sense of urgency	16
		3.3.2.	Forming a powerful guiding coalition	16
		3.3.3.	Creating a vision	16
		3.3.4.	Communicating the vision	17
		3.3.5.	Empowering others to act on the vision	17
		3.3.6.	Planning for and creating short-term vision	17
		3.3.7.	Consolidating improvements and producing still more change	17
		3.3.8.	Institutionalising new approaches	17
4.	Next	t steps .		18
References				19

Key words

Artificial Intelligence (AI) - Machine Learning (ML) - Natural Language Processing (NLP) - Robotics - Data - Face recognition - Chatbot - Sales prediction - Predictive maintenance - Railways - UIC - Deep Learning

Executive summary

This article describes the state of play and the perspectives for the implementation of AI in the European railway sector.

To do so, it explains what Artificial Intelligence (AI) is, focusing on Machine Learning, Natural Language Processing, and Robotics.

It then considers the European policy context of the railway sector in relation to AI (Sustainable and smart mobility strategy, strategy on AI and data), and the cost leadership strategy of the railway companies in relation to increasing competition.

It describes how AI technologies are currently deployed in the railway sector and how they should be in the future. For example, it describes the possibilities of AI for face recognition in the fight against terrorism, chatbots and virtual assistants for passengers, sales prediction through Machine Learning, Robotics in railway stations, Robotics in train, Robotics in warehouses, and predictive maintenance on rolling stock and infrastructure.

It highlights the key success factors and the role of the UIC for the successful implementation of AI in the railway sector.

UIC (International Union of Railways)

UIC is the worldwide railway organisation, with 200 members (UIC, 2020a), representing 2,783 billion passenger.km, 8,991 tonne.km, 801,357 route.km, and 6.013 million rail staff (UIC, 2020b).

UIC gathers together the vast majority of European railway operators and operators from other continents, and can also rely on research institutes. In addition, UIC has developed synergies with around 100 leading institutions (World Bank, ISO, etc.). Finally, UIC is an admitted non-governmental organisation to the United Nations.

UIC has clarified its strategic focus areas: while continuing to globally promote railway as the most sustainable and carbon-free transport, **UIC reinforces its technical support to its members, notably through innovation projects**. A useful summary document called *'Technical Solutions for the Operational Railway'* has been published by UIC (UIC 2020c).

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1. What is artificial intelligence?

Artificial Intelligence (AI) is the source of the worst **fantasies**, and can create hopes or fears, sometimes justified, sometimes overestimated.

Fantasies, hopes or fears arise when the objective is to replace human beings and human experts (Wired, 2018) and examples include Eliza, the first chatbot, which posed as a psychotherapist in 1965; a Mercedes van fitted with two cameras and a bank of computers that drove itself 20 kilometres along a German highway at more than 55 mph in 1987; IBM's computer Deep Blue which defeated chess world champion Garry Kasparov in 1997; and AlphaGo, created by Google, which defeated a world champion player of the board game Go in 2016.

The mid-1980s saw what has come to be called the **Al winter**: confident projections did not work out, very few programmes replaced human experts, and many start-up companies aimed at replacing human experts failed.

However, **the race towards AI was relaunched** in 2004 with the Darpa Grand Challenge, a race for robot cars in the Mojave Desert that catalysed the autonomous-car industry (Wired, 2018).

There was another resurgence of AI during the 2010s: in 2010, we got Siri, and we could talk to our phones and in 2011, IBM's Watson played 'Jeopardy!' and beat human champions.

In 2012, researchers in deep learning stimulated new corporate interest in AI by showing that deep learning could make speech and image recognition much more accurate (Wired, 2018).

Today, a new Al wave is rising, based on massive computing and lots of data and with the involvement of major companies such as Google, Amazon, Facebook, Apple and Microsoft.

The term 'Artificial Intelligence' (AI) is a suitcase term and is not easy to define:

"There is nothing artificial about it," Ms Fei-Fei Li, a chief scientist at Google and a Stanford professor, once said. *"A.I. is made by humans, intended to behave by humans and, ultimately, to impact humans lives and human society."* (The New York Times, 2018).

Massive computing power, which only performs requested routine tasks and is controlled at every step by software programmers using a classical analytical approach, **is not AI. A classical algorithm**, however complicated, which does not deviate from the problem-solving method programmed by a software programmer, **is not capable of learning. It is not AI**.

"A large part of artificial intelligence today is based around automatic learning" (LeCun, 2018a).

To date, all applications of AI are examples of 'narrow AI'. By contrast, 'general AI', which refers to machines with common sense (Wikipedia, 2021a), capable of solving many different types of problems on their own like a human, does not yet exist (LeCun, 2020). Even more so, 'strong AI', which would be better than a human at many tasks, does not exist either.

At this stage, we understand that narrow AI does not rely on classical algorithms, controlled at every step by software programmers, which makes it difficult to interpret the results it provides. In addition, it does not yet possess human common sense. For these reasons, **authorisation to place AI on the market, particularly for safety cases, can be granted only if the human-machine system as a whole is considered**. We will come back to this at the end of the article.

In the rest of this article, we will describe narrow AI through three of its most important subtypes and its implications for business and for railways: Machine Learning, Natural Language Processing, and Robotics.

1.1. Machine Learning (ML)

Machine Learning is a subset of AI.

Machine Learning is "using example data or experience to refine how computers make predictions or perform a task" (Wired, 2018).

Different ML approaches exist:

- **Supervised learning:** the computer is taught what to do thanks to labelled example data. Thus, it is possible to train the software by giving it both an input example (e.g. photos) and the corresponding target label that it must predict.
- Unsupervised learning: the computer is taught without labelled examples, just from experience of data or the world: "You try to understand, based on observation, how things work". This is the case when the data is modelled "without having any explicit feedback about what you need to do with that data" (Jaakkola, 2020). This is trivial for human beings, but not for computers and software.
- Semi-supervised learning: a combination of both supervised and unsupervised learning methods.
- Reinforcement learning: typically for learning to act. For instance, when a robot reaches or pushes an object, it changes the state of its environment. The robot needs to learn to take this into account in order to act. Unlike supervised and unsupervised learning, reinforcement learning requires limited data (Venturebeat, 2020).

The typical Machine Learning (ML) process requires both data and algorithms.

A three-step process maximises the chances of learning success (Towards Data Science, 2018):

- Training: "A subset of real data is provided to the data scientist. The data includes a sufficient number of positive and negative examples to allow any potential algorithm to learn. The data scientist experiments with a number of algorithms before deciding on those which best fit the training data."
- Validation set: "The data scientist will run the chosen algorithms on the validation set and measure the error. The algorithm that produces the least error is considered the best. It is possible that even the best algorithm can overfit or underfit the data, producing a level of error which is unacceptable."
- **Testing:** "To obtain an accurate and reliable measure of error, a third set of data should be used, known as the test set. The algorithm is run on the test set and the error is calculated."

During this learning process, data scientists must **choose the best algorithm** from a considerable number of them.

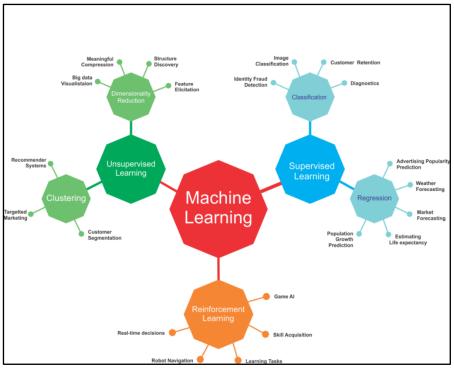


Figure 1: List of Machine Learning algorithms, (Skilllx, 2020)

The quality of the data chosen is also crucial.

"If not careful, bias can be introduced at any stage from defining and capturing the data set to running the analytics or AI/ML [machine learning] system" (Search Business Analytics, 2020).

Eight biases were identified: propagating the current state, training on the wrong thing, under-representing populations, faulty interpretation, cognitive biases, analytics bias, confirmation bias, and outlier bias (Search Business Analytics, 2020).

In order to avoid biases, it is necessary to start by recognising that data can be biased, both in terms of the data itself and the people who analyse or use it.

There are many adverse and ethical impacts of bias in data, ranging from making bad decisions to adversely affecting certain groups of people involved in the analysis.

One of the root causes of these biases is the way in which the problem is formulated into a machine learning problem, and the way in which data on the problem so formulated is collected. Close collaboration between data scientists and experts in the field is therefore crucial.

"There are two main ways of using Machine Learning in business: sensing and predicting" (Malone, 2020).

Sensing is useful with images. We can imagine use cases such as:

- business opportunities for fashion
- detection of skin cancers
- face recognition and recognition of retinas or fingerprints for commercial purposes or for combatting terrorism
- image analysis to help robots navigate their surroundings, recognise objects to be manipulated and avoid dangerous conditions

- image analysis for obstacle detection: self-driving cars, Automatic Train Operations (ATO)
- image analysis for fault detection: bridge, tunnels, sleeper, rails, etc.
- image analysis from satellite or drones for maintenance of buildings, tracks, bridges, tunnels, etc.

Sensing is also useful with **sounds and vibrations**, and there are potential use cases for the predictive maintenance of rolling stock, tracks and switches.

Thanks to prediction, we can also envisage use cases such as:

- medical diagnoses based on symptoms and lab tests
- weather forecasts
- financial fraud
- sales prediction, and its corollary, customer loyalty
- behaviour of equipment (and its predictive maintenance)

Concretely, in the case of predictive maintenance for example, we will use a two-step approach: one ML algorithm will sense and capture the state of the equipment; and then another ML algorithm will predict the future state of the equipment.

A technique called **Deep Learning** has made ML much more powerful. Traditional ML techniques employ various types of algorithms that learn to model functions and predict future actions from data. They provide numerical values from thousands of data points (Search Enterprise AI, 2020).

Deep Learning is a subset of ML. It is *"a machine learning technique in which data is filtered through self-adjusting networks of math loosely inspired by neurons in the brain"* (Wired, 2018). Indeed, it still involves the machine to learn from data, based on our understanding of neural networks. Nevertheless, it *"makes use of layers of information processing, each gradually learning more and more complex representations of data"* (Search Enterprise AI, 2020). As a result, Deep Learning requires much more data than traditional ML algorithms.

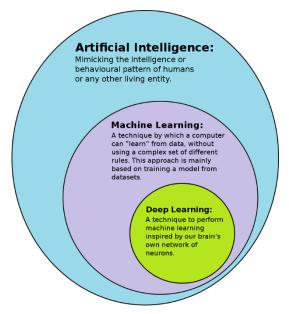


Figure 2: How Deep Learning is a subset of Machine Learning and how Machine Learning is a subset of Artificial Intelligence (Wikipedia, 2021b)

For image recognition, the same object can appear in many different positions. This makes it very difficult for a computer to recognise the image in all its possible forms. For this purpose, **convolutional neural network** algorithms are **used as a means of structuring a deep learning system**. With multiple detectors, that each recognises a specific part of the image, computers can better recognise the object. This also works for text recognition, speech understanding and translation, and is an integral part of many self-driving cars (Facebook Engineering, 2016).

The trade-off of these different techniques is their complexity. They effectively solve problems but remains rather opaque about how they actually solve them. **Interpretability** is therefore **an essential question**.

1.2. Natural Language Processing (NLP)

Natural Language Processing (NLP) is at the crossroads of linguistics, computer science and artificial intelligence. It deals with the interactions between computers and human language (text and speech). The result is a computer able to 'understand' the content of documents or speeches, including the contextual nuances of the language within them. Existing technology can accurately extract the information and insights contained in documents or in speeches, as well as categorise and organise the documents themselves.

Everyday existing examples are Google Assistant, Amazon's Alexa, Siri, Collins translators, Google Translate and chatbots. NLP can summarise texts, generate texts in natural language, and recognise and understand speech in natural language.

The five NLP business applications are (Emerj, 2019):

- Customer service: many companies transcribe and analyse recordings of customer calls. They also
 deploy chatbots and automated online assistants to provide immediate responses to simple needs and
 reduce the workload of customer service representatives.
- **Reputation monitoring:** companies can now scan the entire web for mentions of their brand and products and recognise when they need to take action.
- Placement of advertisements: NLP can help find the exact word and meaning sense to give to an advertisement, after checking many texts, especially in web forums.
- Market intelligence: 'What's going on with my competitors?'
- Regulatory compliance: for example, NLP can help pharmacovigilance for studies to be carried out after a drug has been placed on the market. Indeed, a lot of information on adverse drug events is located in socalled unstructured clinical narratives or patient reports on their health, either in electronic medical records or in web forums.

1.3. Robotics

"Now **robots put computation in motion**. They are programmable mechanical devices that take input from the world from through the sensors and impact the world through their actuators. The robots think about the input from the sensors, think about the task they must do, and then issue commands to their motors to move in the world. Robots come in many different shapes. Robots have humanoid shapes, but it is not necessarily the only way to think about robots." (Rus, 2020). A rubbish bin, an autonomous car, an autonomous train: anything could be a robot.

Of course, robots can use ML to recognise their surroundings or objects to be manipulated.

Nevertheless, the additional current challenges for Robotics today are:

Robots on wheels are easier to operate than legged robots, because legged robots need extraordinary perception of their surroundings.

- Robot mobility is much easier than manipulation: excellent sensors enable robots to have good situational awareness and to correctly measure distances to obstacles. Algorithms enable machines to map, locate and identify different types of objects around them.
- Manipulation: robots have very hard and rigid end effectors with limited capacities. The objective of Soft Robotics is to create soft-tissue machines, which have the same type of compliance as humans.

The different use cases of Robotics are:

- Industrial robots able to streamline picking and packing processes in warehouses (Wired, 2011). For example, in 2017 Amazon reported 45,000 robots working across 20 facilities.
- Robots facing people: robots as workers in the fast food industry (Fortune, 2016), robots delivering medication in hospitals (Panasonic, 2010), robots able to accompany ill people in hospitals in Japan (NSK, 2015), robots cleaning up airports (F.Robo Clean, 2013) or railway stations (France Bleu, 2017) (Le Petit Journal, 2020) in the presence of passengers, and robots providing passenger information (Easy Voyage, 2015).
- **Collaborative robots** specifically designed to work alongside human employees are on the rise. They are cheaper, built with human cooperation in mind, and therefore easier to programme.

Future challenges will be to create **robots that can better interact with each other and with people** in a human-centric environment, such as railway stations and warehouses. Future principles will be to enable human-robot teams to better cooperate, taking advantage of what machines can do better than people and what people can do better than machines.

1.4. Al from the user's point of view

We could measure AI by its ability to enhance the collective intelligence of a human-computer system. In other words, *"how can people and computers be connected so that, collectively, they act more intelligently than any person, group, or computer has ever done before?"* (Malone, 2020).

To this end, AI could concretely be a tool, an assistant, a peer, or even a manager of human beings:

- Used as a tool, computers perform the tasks you give them, but people monitor almost every step of the way.
- Used as an assistant, AI can work without your direct attention. AI can be more proactive, helping to formulate and solve problems (e.g. semi-autonomous cars, medical diagnoses, chatbots, etc.).
- Used as a peer, AI systems can do things automatically, only referring to humans for unusual things. In the
 case of prediction, integrating people and computers as peers in this way yields better results than either
 could achieve alone (Malone, 2020).
- Used as a manager of human beings, machines can help telephone representatives improve their interactions with customers on the phone by giving them feedback on the emotional quality of conversations. They help them improve their interpersonal skills.

In a nutshell, the human-computer system can improve over time: humans figure out how to better do the things that they are already doing; programmers improve their machines; and machines learn from their own experience thanks to various kinds of Machine Learning.

2. State of play of the European railway sector and perspectives

2.1. European policy context

It is true that the European railway sector is receiving more and more support:

- **The European Year of Rail 2021** is "shining a light on one of the most sustainable, innovative and safest transport modes we have!" (European Commission, 2020a).
- The 'Sustainable and smart mobility strategy' of the European Commission (European Commission, 2020b) stresses the need to double high-speed railway traffic by 2030 and railway freight traffic by 2050 and to promote collective travel. In addition, the European Commission (EC) insists upon the need to stimulate innovation and the use of data and AI for smarter mobility.
- This impetus is in line with the European strategy on AI and data (European Commission, 2020c), which aims to make Europe a leader in trustworthy AI and in the data economy. Thus, the European Commission will implement rules and a legal framework, notably for transport:
 - For high-risk cases, **AI systems** must be transparent, traceable and guarantee human oversight. Authorities must be able to test and certify the data used by algorithms. Unbiased data is necessary to train high-risk systems to perform properly and to ensure respect for fundamental rights, in particular non-discrimination.
 - The EC will establish a true European data space. First, the EC will put in place a regulatory framework for data governance (access and re-use between businesses, between businesses and government, and within administrations). Second, the EC will support the development of technological systems and the next generation of infrastructures, such as clouds. Finally, the EC will launch sector-specific actions to create European data spaces, for example in the fields of industrial manufacturing, the green deal, mobility or health.

European railway stakeholders will have to take this new European context into account and use it to their advantage.

Nevertheless, European Railway Undertakings (**RUs**), and consequently Infrastructure Managers (**IMs**), **face many challenges** which existed before the COVID-19 outbreak and have become even more important since:

- Strong competition between passenger RUs and long-distance buses and car-sharing
- Impending competition between passenger RUs
- Strong competition between freight RUs and trucks
- Strong competition between freight RUs

In 2018, RUs shared only 7.9% of the European inland passenger transport market (Eurostat, 2020a) and only 17.9% of the freight market (Eurostat, 2020b). In addition, there is constant pressure on prices: price is the main disadvantage when comparing freight trains with trucks (European Court of Auditors, 2016), and revenue per kilometre decreases for passengers (ARAFER, 2019).

In this context, the European railway sector must rely on a cost leadership strategy without jeopardizing the quality of service. Al must support this cost leadership strategy.

2.2. How AI technologies are currently being deployed within the railway sector -perspectives

In Europe, the EC established in 2016 the Shift2Rail Joint Undertaking, focused on railway research and innovations. It "aims to double the capacity of the European rail system and increase its reliability and service quality by 50%, all while halving life-cycle costs." (Shift2Rail JU, 2021a). The capabilities to be developed were "automated train operation; Mobility as a Service (MaaS); logistics on demand; more value from data; optimum energy use; service timed to the second; low cost railway solutions; guaranteed asset health and availability; intelligent trains; stations and smart city mobility; environment and social sustainability; rapid and reliable R&I delivery." (Shift2Rail JU, 2021b).

At this stage, forerunners have carried out innovative solutions. But AI has not yet been widely implemented in Europe.

2.2.1. Image recognition in the fight against terrorism

Terrorists attack trains. This was the subject of *"The 15:17 to Paris"*, a film directed by Clint Eastwood. Standard airport luggage scanning has been attempted in railway stations but has proved ineffective, except for specific operations such as the Eurostar service. This is why we must implement alternative solutions, capable of detecting abnormal passenger behaviour or dangerous situations in railway stations and on trains, in order to improve security for railway staff and passengers.

Face recognition is already being used in railway stations in China before boarding a train (Global Times 2017) and by Eurostar when passing through customs (RFI 2017). It can provide a huge amount of data to national authorities.

ML is particularly effective for image analysis. Provided that the existing national regulatory frameworks and the future European framework allow the storage of such data, accurate algorithms may help predict abnormal passenger behaviour. This should be carried out through co-operation between police, RUs and IMs.

2.2.2. Chatbots and virtual assistants for passengers

Chatbots are used for making reservations, booking passenger tickets and as virtual assistants.

Since 2017, it has been possible to use a chatbot for **SNCF reservations and tickets** through different channels (OUI.sncf, 2020a, 2020b): by text via the SNCF website and Messenger; and by voice via Google Assistant and Amazon Alexa. However, customers' experience could be much improved. French is the only language available, but French voices are not easily recognised, and it is not possible to fill out a claim form. The verdict of a French journalist (France Inter, 2019) via Alexa was also disappointing: no added value compared to the usual website, as well as privacy concerns.

A much better experience is provided by **Julie, the virtual assistant for Amtrak** (Amtrak, 2020). She helps customers to book reservations, plan vacations and navigate the website. She answers frequently asked questions and can give further information about the loyalty programme, stations and routes. She simultaneously writes and speaks her answers and questions, enhancing the experience for disabled persons or foreigners. Her voice is understandable.

But the key advantages of Natural Language Processing (NLP) could be used much more effectively:

- Speech recognition could be extended to include foreign languages.
- As stated by Emeritus Professor Frank Levy (Levy, 2020), NLP could help call centres extract the meaning of customer words captured by chatbots, and then avoid customer claims.

- The concept of knowledge graphs implemented by IBM Watson (Malone and Gil, 2020) could be leveraged thanks to a well-structured database based on conversations with customers through chatbots, allowing better understanding of their sentiments and enhancing their experience.
- A potential and desirable improvement could be the use of Google's Wavenet artificial voice (Forbes, 2017), which could give virtual assistants voices that are almost indistinguishable from those of a human being.

Based on these returns of experience, chatbots and virtual assistants for passengers should be more widely implemented, supporting both the cost leadership strategy (less work for call centres) and a differentiation strategy (better customer experience).

2.2.3. Sales prediction through ML

RUs are selling more and more electronic tickets, and now have a large amount of annotated data from their customers. However, it becomes easier to predict sales through supervised ML if *"you have some historical data to see how a customer appears, and what the consequences are later on"* (Jaakkola, 2020). Achieving this will require salespersons to annotate the data, data scientists to train, validate and test the algorithms (Towards Data Science, 2018), and managers to decide the appropriate actions to be implemented in relation to the predictions provided by the machines.

Sales prediction through supervised ML is a promising field for RUs.

2.2.4. Robotics in railway stations

If we consider passengers in **railway stations** as guests waiting for their trains and asking for information, then Robotics in hotels, airports or hospitals could be adapted to railway stations to improve service quality and cost efficiency.

- For example, Panasonic (Panasonic, 2010) has developed robots that can deliver medication in hospitals without bumping into people, and NSK (NSK, 2015) has created Lightbot, a guidance robot. Such robots could guide persons with reduced mobility or blind people from the platform to the train and avoid contact between them and station staff during the COVID-19 outbreak.
- Humanoid Pepper robots already provide information to customers in shops (Softbank, 2021). This concept was already tested in SNCF railway stations in 2016 (France 3, 2016) and could be extended to inform passengers in other railway stations.
- Vithanage, Harrison and DeSilva (2019) described automated cleaning robots in stations.

These are already in use in airports (F.Robo Clean, 2013). In the wake of the COVID-19 pandemic, robots may be even more useful for both improving cleaning in stations and avoiding contact between passengers and cleaning staff. The most recent example is St Pancras International station, Eurostar's terminus, which has deployed ultraviolet robots to fight against the spread of the new coronavirus (Le Petit Journal, 2020).

2.2.5. Robotics in trains

The same **cleaning robots could be used on trains**. A prototype was created in 2015 for aeroplanes (Germfalcon, 2015).

2.2.6. Robotics in warehouses

Rolling stock maintenance is based on the use of thousands of parts, stored in warehouses. The organisational processes should be streamlined following the templates of the latest robotized warehouses, for example Amazon (Mountz, 2011) or the British supermarket Ocado (The Verge, 2018).

2.3. Predictive maintenance

2.3.1. Definition and advantages of predictive maintenance

There are different types of maintenance (ISO, 2012):

- Breakdown maintenance: "performed after a machine has failed"
- Preventive maintenance: "performed according to a fixed schedule, or according to a prescribed criterion, that detects or prevents degradation of a functional structure, system or component, in order to sustain or extend its useful life"
- Condition-based maintenance is a preventive approach: "performed as governed by condition monitoring programmes"

Thanks to advanced statistical methods, such as Machine Learning, it is now possible to set up predictive maintenance, which can "dynamically define when a machine is okay or need to be maintained". Thus, "predictive maintenance predicts future breakdowns by giving you a probability, whereas conditionbased maintenance prevents additional breakdown cost by telling you something is wrong now" (Neurospace, 2019).

This is why, subject to considerable adaptation of maintenance activity planning, **predictive maintenance can improve availability, reliability, punctuality and safety, while supporting a cost leadership strategy**. In addition, it can improve **return of experience**, paving the way for **future innovations** in the field of maintenance.

It should be noted that predictive maintenance requires far more data, due to its statistical methods.

2.3.2. Predictive maintenance on rolling stock

Few research activities on AI and predictive maintenance of rolling stock are available today. For example, only five studies¹ on the subject were presented during the 2019 World Congress on Railway Research in Tokyo (WCRR, 2019).

Rolling stock maintenance has a considerable impact on train operations, availability, reliability, punctuality and costs. In addition, rolling stock manufacturers see maintenance as a new field of activity. This is why RUs and manufacturers consider rolling stock maintenance to be a competitive advantage, which hinders cooperation between the different stakeholders on this subject.

A large amount of existing data is collected by entities in charge of maintenance and rolling stock manufacturers, and the future European regulatory framework for data governance (European Commission, 2020c) will allow access to and re-use of data between businesses. As a result, the reconfigured context of this data, and therefore of AI, will push for increased cooperation between the different stakeholders in AI-based predictive maintenance of rolling stock.

In this context, and with the help of maintenance experts and data scientists, it would be useful to work on some initial use cases: detection system of wheel tread defects, anomaly recognition of train bearing temperature, etc.

2.3.3. Predictive maintenance on infrastructure

The punctuality and the safety of trains depend in particular on the availability and reliability of infrastructure (tracks, tunnels, bridges, embankments and cuttings, etc.), which makes **predictive maintenance on infrastructure an important issue**.

¹ 'Development of rolling stock under floor visual inspection system by image processing technique', 'A modular Computer Vision Based Solution for Condition-Based Maintenance of Passenger Rolling Stock', 'Decision Support Model for Rolling Stock Assignment and Predictive Maintenance Scheduling', 'Condition Based Maintenance applied on Railways Compressed Air Generators (rotary screw) for the application of Dynamic Maintenance Management System', and 'Utilizing Deep Learning to Manage Warning Signs of Air Conditioning Unit Malfunctions'.

The **context** is different to that for rolling stock and is **more favourable** to predictive maintenance based on AI. Firstly, there is no competition between the different IMs, which facilitates cooperation.

Secondly, the data required for AI is already collected by IMs on a huge scale.

Today, availability, reliability and safety depend mainly on periodic preventive maintenance tasks carried out on the basis of data collected through patrols and periodic manual inspections. Indeed, the stakes are high: for example, Konux (2020) states that *"switches are the most critical part of the rail infrastructure, causing approximately 20% of infrastructure-related delay minutes [of the trains] and costing* €12bn a year globally to *maintain and replace"*. In addition, safety issues cannot be solved properly today because of a lack of data. Let us keep in mind the last two accidents in Strasbourg and in Central China in March 2020, both due to unexpected landslides in cuttings (IRJ, 2020 and Xinhuanet, 2020).

Replacing patrols and periodic manual inspections with more frequent, automated and standardised inspections is a major objective. This could increase availability, reliability and safety. In addition, it could provide the repeatability and consistency of the big data required for AI.

Fortunately, **innovations are expected** and many have already been introduced:

- The ORBIS Programme implemented by Network Rail has already increased the amount of valuable information to workers (Network Rail Consulting, 2021).
- Replacing patrols and periodic manual inspections is a promising area of work, with examples including automated tunnel examinations (Network Rail, 2019), track machine vision systems (Japanese Railway, 2019), robotic inspections (Catapult Transport Systems, 2021), inspections of river bridge piers by amphibious snake robots (HiBot, 2020), and the inspection of pipes such as narrow aqueducts by smooth robots (HiBot, 2015).
- Mark Gaddes (Gaddes, 2019) explains that **Robotics** is necessary to automate inspection. Many existing activities are already robotized: robotic arms on maintenance vehicles detecting and repairing rail defects, robotic platforms with advanced sensing for confined spaces, etc.
- Felix (Loccioni, 2018) is "the first certified mobile robot for the automatic inspection of railway switches and crossings", is equipped with artificial vision, and is able to rapidly take measurements, transfer data, increase maintenance performance and reduce costs.
- Vithanage, Harrison and DeSilva (2019) wrote a review of research on Robotics and autonomous systems in railway maintenance, covering bridge inspection robots (fully automated operation or remote operation by distant user), and automatic tunnel inner wall deterioration monitoring systems.
- The Erevos project (Esmera, 2017) "will deliver a novel full-fledged solution for aerial monitoring of railways using drones for vegetation management and boundary structure inspection".
- Smart maintenance using data analytics has been implemented on Indian railways (Global Railway Review, 2020a).
- Infrabel focuses on digital data for the predictive maintenance of tracks and switches and crossings (Global Railway Review, 2020b).

Finally, predictive maintenance through ML is particularly well adapted to railway infrastructure.

According to LeCun (2018b), ML is particularly effective for image analysis. Thus, it could improve the detection of faults or damage on a switch, on a rail, in a tunnel or within a cutting. Using these newly available databases, together with collaborative work from both data scientists and infrastructure maintenance experts, precise algorithms could provide better guidance for any additional maintenance tasks aimed at avoiding disruptions or accidents.

In summary, **implementing ML vision systems and automated inspections will reduce the time** needed to carry out inspections, and most importantly **increase the availability and repeatability of data** (daily inspections instead of quarterly), **supporting the cost leadership strategies of IMs while improving the punctuality, safety, availability and reliability of the infrastructure**.

2.3.4. Other operational decision supports

Other operational decision supports could benefit from AI.

For example, **Machine Learning can facilitate several use cases**, including train path allocation, traffic management, the management of passenger flows through railway stations, abandoned luggage detection, and track occupation diagrams in marshalling yards and railway stations.

In **cybersecurity**, robots are capable of automating threat intelligence and prevention systems (Automation Anywhere, 2018).

3. Key success factors and the role of the UIC

3.1. Railway experts from UIC members will be indispensable at all steps

Their key roles will include helping to select accurate data to be collected, assisting data scientists and data engineers in transforming this into appropriate information, and providing the right tools for workers to analyse this information and subsequently act on it.

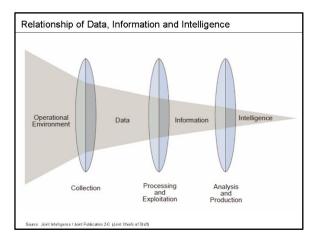


Figure 3: Relationship of Data, Information and Intelligence (US Defense, 2020)

3.2. Interpretability and decision-making

Al technologies solve problems but remain rather opaque (ML, Deep Learning, Convolutional neural networks, NLP, etc). Consequently, their **interpretability** is an **essential question**. However, there is currently no system on the market for interpreting the results provided by ML (Jaakkola, 2020).

Under these conditions, the role of experts will remain crucial for several years to come.

Medical imaging is nowadays able to diagnose skin cancer more reliably than a doctor. However, it took years of research to do so and the railway sector is not at that point yet. This is why **decisions**, particularly in the field of railway safety, **will still have to be made by humans**, even if Al is able to provide the decision-makers with valuable information and predictions.

Finally, the authorisation to place AI on the market, particularly for safety cases, will be granted only if the human-machine system as a whole is considered.

3.3. Leading change

It will take time and effort to achieve transformational change in AI in the railway sector.

"The most general lesson to be learned from the more successful cases is that the change process goes through a series of phases that, in total, usually require a considerable length of time. Skipping steps creates only the illusion of speed and never produces a satisfying result. A second very general lesson is that critical mistakes in any of the phases can have a devastating impact, slowing momentum and negating hard-won gains." (Kotter, 2014).

Applying John Kotter's eight-step process, in the right order, without shortcuts, could facilitate the implementation of AI in the railway sector: 1) establishing a sense of urgency; 2) forming a powerful guiding coalition; 3) creating a vision; 4) communicating the vision; 5) empowering others to act on the vision; 6) planning for and creating short-term vision; 7) consolidating improvements and producing still more change; 8) institutionalising new approaches.

UIC's role will be to help UIC members to implement this eight-step process.

3.3.1. Establishing a sense of urgency

With the help of experts from UIC members, UIC will schedule conferences, webinars and workshops to provide CEOs, C-level executives, project managers and the IT departments of UIC members with arguments in favour of AI, including market and competitive realities, political context, state of the art in terms of AI, best practices, potential use cases in railway sector and in other sectors, and potential grants.

Beyond the railway expertise of UIC and its members, UIC will need to acquire expertise in AI (data scientists and data engineers) sourced from outside the railway sector (suppliers or academia).

3.3.2. Forming a powerful guiding coalition

UIC will involve C-level executives, project managers, IT departments and experts from UIC members, as well as manufacturers and suppliers, through **collaborative projects**.

The first collaborative project will focus on AI for predictive maintenance on rolling stock and infrastructure. In this field, it will aim to analyse and define the required data to be collected and to monitor and choose the best AI algorithms for transforming data into appropriate information. To this end, it will carry out a comprehensive inventory of existing and potential AI use cases. It will assess the impact of each solution on regulatory context, telecommunication framework, life-cycle cost, asset management schemes, operational rules and safety models. It will benefit from contributions from other UIC projects, such as *RFID tagging for Track Components + Automated Video Railway Inspection System; Drone4Rail* on inspections of structures and infrastructures by drones; *Maximising the benefits of Big Data for Asset Management; Asset Management Whole System Decision Making; DYNMEASURE,* which aims to define the most appropriate framework for the various track-side and on-board measurement systems; and IRS 70712-1 on broken rail detection, which promotes the classification of specific rail defects through Deep Learning.

It will also benefit from UIC projects on Digital Railway Modelling, particularly for data labelling.

UIC will publish technical reports and implementation guides.

3.3.3. Creating a vision

CEOs of railway companies will have to develop strategies for realising that vision:

- McKinsey (2015) published 'An executive's guide to machine learning' that can be adapted to any aspect of AI: hiring AI experts to help C-level executives create the strategic vision; recruiting data scientists and data engineers; recruiting 'Translators' people able to bridge the disciplines of data, AI and decision making to provide actionable insights that generalist managers can execute; and implementing a data strategy with the help of IT departments, business units and technical experts to fill gaps in the data and break down silos. At this early stage, it is important to recruit on the one hand, data scientists capable of implementing the appropriate AI algorithms, building specialised models and maintaining clean subsets of training data, and on the other, data engineers capable of building and maintaining data pipelines, databases and processing systems (Tech Target, 2020).
- CEOs will have to encourage the combination of machines and people, enabling the adoption of the vision by front-line staff and managers. For example, robots could be considered as collaborative, starting to do 'the dull and dirty tasks' (Acorn, 2017). In addition, according to Tessa Lau (Malone and Lau, 2020), anthropomorphizing the robots could *"increase the chances of robot adoption"* in an environment where human-robot interactions are important (e.g. railway stations or warehouses).

- CEOs will rely on IT departments, which will play a central role when re-engineering the whole process of their organisation: for example, in rolling stock maintenance centres "the bots aren't intelligent; they don't make decisions for themselves. But their actions are all coordinated by a central computer." (The Verge, 2018).
- CEOs will have to anticipate any ethical concerns surrounding AI, including impact on employees, management and jobs, potential mistakes made by machines, bias in algorithms, and privacy. Indeed:
 - Al will drastically reduce repetitive tasks for both front-line employees and managers. In addition, it
 will dramatically change existing jobs and create new roles and responsibilities. Al will increase the
 availability and accuracy of information, letting employees and their managers identify the highest
 added-value tasks, including decision making on tasks to be performed. In 2016, the biggest strike
 in twenty years in the UK was over automation (Rail Technology Magazine, 2020). Therefore, CEOs
 must carefully negotiate any drastic change with trade unions, especially on how to upskill or reskill
 employees and managers.
 - Potential mistakes can be made by complex systems such as Deep Learning which remain a 'black box' (Nehme, 2018). In such cases, CEOs will ensure that people perform oversight of the machines.
 - Nehme (Nehme, 2018) states that *"Training data* [of ML algorithms] *can often be biased, skewed, incomplete or inaccurate"*. CEOs will have to implement strict processes for mitigating this shortcoming.
 - Chatbots and virtual assistants may collect private data from customers. Since 2018, the General Data Protection Regulation "imposes obligations onto organisations anywhere, so long as they target or collect data related to people in the EU", in order to protect privacy of European citizens (GDPR, 2020). CEOs must abide by this regulation.

Through its dissemination capacities and workshops, UIC will help its members (CEOs, C-level executives, project managers, IT departments, business units, experts, etc.) demystify AI, recruit data scientists, communicate this roadmap to other sectors and the European Commission, and break down silos. Thanks to its collaborative projects, UIC will publish implementation guides focusing on ethical concerns, safety and operational issues.

3.3.4. Communicating the vision

UIC will support all communication efforts from CEOs.

3.3.5. Empowering others to act on the vision

3.3.6. Planning for and creating short-term vision

UIC will provide use cases.

3.3.7. Consolidating improvements and producing still more change

UIC will publish guidelines and specifications concerning various technical solutions and their operational impacts, facilitating market uptake of AI innovations in the railway sector.

3.3.8. Institutionalising new approaches

For the last four steps, **UIC** will enhance awareness of early improvements and wins by **disseminating** them among UIC members in Europe and all around the world.

4. Next steps

Artificial Intelligence has not yet been widely implemented in the European railway sector.

The political context and the acceleration of innovations in the field of AI will create great opportunities for railway companies and will lead to tremendous changes.

UIC will help its members and the railway sector during this promising period.

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Published by: UIC - Rail System Department Director of publication: Christian Chavanel Cover and Iayout: Ludovic Wattignies Photo credit: Adobe Stock

ISBN 978-2-7461-3065-4 Copyright deposit: March 2021 www.uic.org

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