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Institution of Railway Signal Engineers

Applications of data driven technologies in railway systems and signal engineering

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Railway systems are a complex system of many subsystems which need to be integrated and operated properly to ensure the safety of train operations. Railway signalling is one such critical sub-system which is at the heart of train operations ensuring safety and optimum utilisation of line capacity.

Technological adaptation in this critical engineering discipline is evolving over time. There used to be a lag of about two decades in applying any new technology in railway signalling, given the complex nature of the safety and certification of products and systems involved.

The recent advancements in data driven technologies like Artificial Intelligence (AI), Machine Learning (ML), Big Data, Internet of Things (IoT) and data analytics are being implemented at a faster pace than ever. This paper will provide an overview of how these technologies are currently being applied and how they will be in future, with examples of rail industry use cases. The paper also discusses what can and cannot be done with modern technologies in railway systems and signalling.

Railway systems engineering – overview

A railway is a complex system of subsystems including rolling stock (trains), signalling, traction power (electrification), telecoms, track. All these subsystems need to be properly integrated to achieve safety and optimum utilisation of line capacity. These subsystems are broadly classified into mobile, fixed, and organisational elements. As modern technologies are being applied these systems are becoming more and more data driven.

Over the last two centuries railway signal engineering has undergone massive technological developments which can be compared with the four industrial revolutions. The initial signalling systems were based completely on mechanical interlocking with mechanical signals, levers, wires, and rods. The next development was electro-mechanical interlocking in which certain functions are controlled by electrical means and others by mechanical systems. Pure electrical systems followed which used large number of hard-wired electromagnetic relays to implement the principles of signalling to ensure safety. The next development was the Electronic Interlocking (EI) (also known as Solid State Interlocking (SSI) or Computer Based Interlocking (CBI) systems which use a combination of hardware equipment and software elements programmed to achieve safety logic. Over the last few decades modern signalling technologies like Communications-Based Train Control (CBTC) and the European Train Control System (ETCS) have become widely used on metro railways and main lines globally.

A simplified architecture of an ETCS and its subsystems is shown in Figure 1. There is a huge amount of safety critical data produced which can be used for getting better insights and enabling better decision making for all stakeholders.

Modern technology trends

The recent rapid increase in computing power allied to almost unlimited data storage and the availability of high bandwidth broadband connectivity, together with the variety of low-cost sensors (IoT) augmented by algorithms able to process these large volumes of data and artificial intelligence to compete with humans in making decisions, illustrates the trends in modern technology.

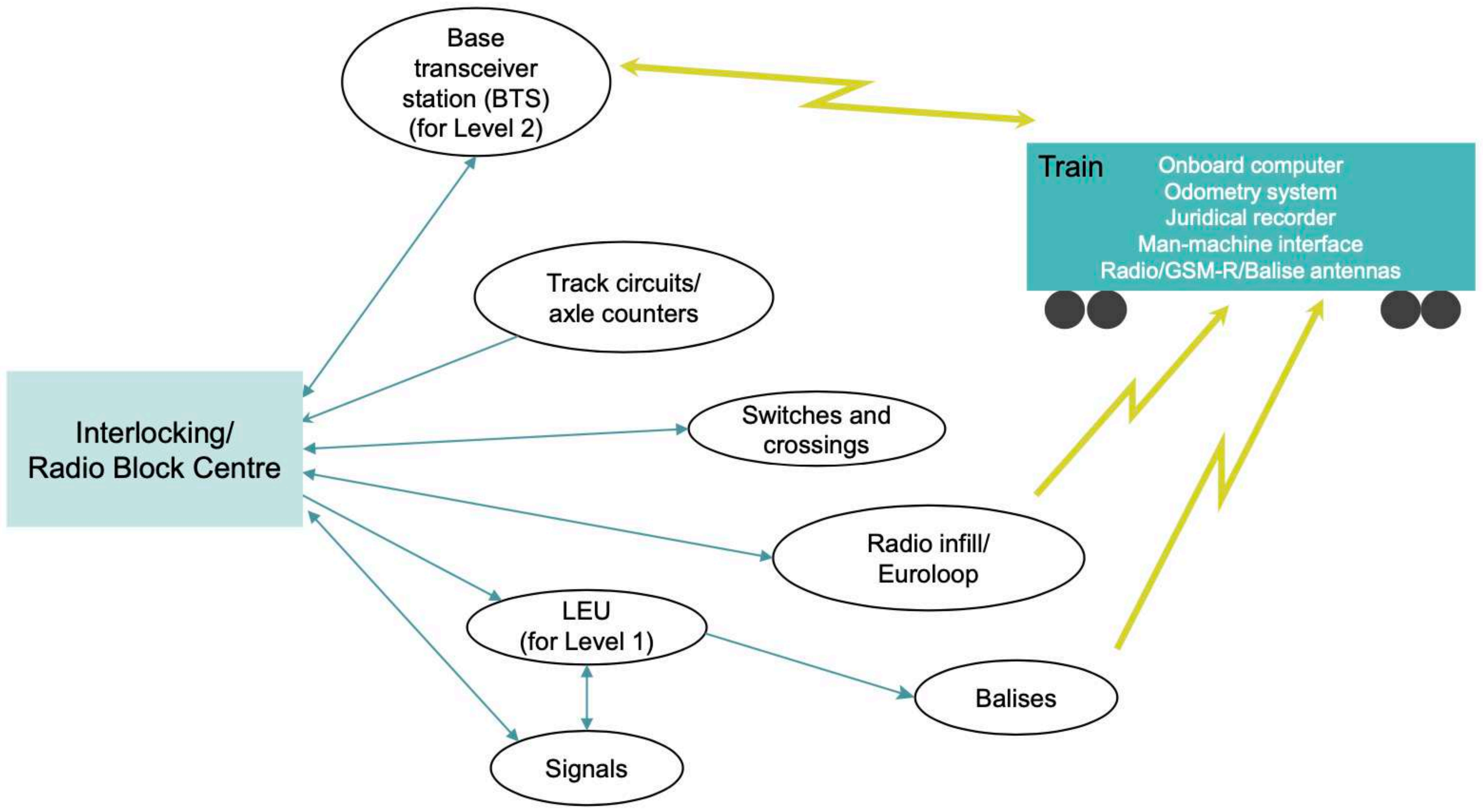
Data driven technologies can assist operators solve new challenges using the potential of big data. This can result in reduced disruption even as demand increases. Furthermore, predictive maintenance based on real-time information about the status of elements of the railway which has been processed by advanced analytics saves time and resources and further reduces the risk of disruption, thereby assisting the delivery of higher capacity at reduced cost and improved safety.

As trains are fitted with increasing numbers of sensors, they become, in effect, in-service inspection vehicles with subsequent big data analytics able to create location correlated information supporting predictive maintenance, whilst at the same time improving operational information with accurate train location data. Accurate information about current train position and condition supports scheduling and optimisation of operations.

On the trackside, sensors with wireless connectivity can facilitate continuous monitoring of equipment and local weather conditions, again supporting predictive maintenance and enabling prompt response to realtime environmental hazards.

Finally, Augmented Reality (A/R) and Virtual Reality (V/R) can improve the training and familiarisation of both technical and operating staff.

Figure 1 – ERTMS architecture and data flow.



Big Data – strategic driver of change in rail signalling:

Modern signalling and communications technologies are able to capture and store increasing volumes of valuable operations and maintenance related data. The magnitude of this data can however be overwhelming to system users. This is driving an increasing interest in the application of 'Big Data' tools, fully integrated within signalling/ train control system designs, to provide more efficient and effective system alarm management and system analytics, tailored specifically to the user needs. [1]

But how useful is data, especially big data? Modern airlines measure up to 165 000 parameters through their embedded sensors but it is reported that only roughly 2 per cent (3000 parameters) are actually used for predictive maintenance. Gartner's statistics suggests there were around 25 billion IoT devices at the end of 2021.

Data is fundamental to achieve the vision of the digital railway and analytics is critical to make sense of big data. The benefits driven approach requires domain expertise. The convergence between analytics capability and benefits of applying analytics in the rail domain is shown in Figure 2.

Traditionally, the approach to railway maintenance relies on the knowledge of designers and maintainers and their competency. It uses Failure Mode Effects Criticality Analysis (FMECA) and Reliability, Availability, Maintainability and Safety (RAMS) analysis. This approach is able to identify the train's abnormal behaviours based on known thresholds of relevant variables. The data is sampled and compared with thresholds and used for alarms to appropriate stakeholders.

The modern approach is based on asset digitalisation, huge volumes of data and uses big data platforms to create data lakes containing structured, semi-structured and unstructured data. AI, ML, and predictive analytics are used to analyse the data and insights are drawn, and abnormal behaviours are predicted which helps reduce performance issues.

Data is collected and analysed using big data, text analytics techniques. Information is extracted by the data set and used to feed risk models. The Safety Management System (SMS) is modelled using enterprise architecture with a dashboard including the list of the controlled and uncontrolled risks. The combination of big data analytics, risk models and enterprise architecture to map the SMS allows organisations to monitor their risks in real time. A vision of the rail industry making use of big data is explained in [2] where data is shared and analysed in real time and used for operational safety management.

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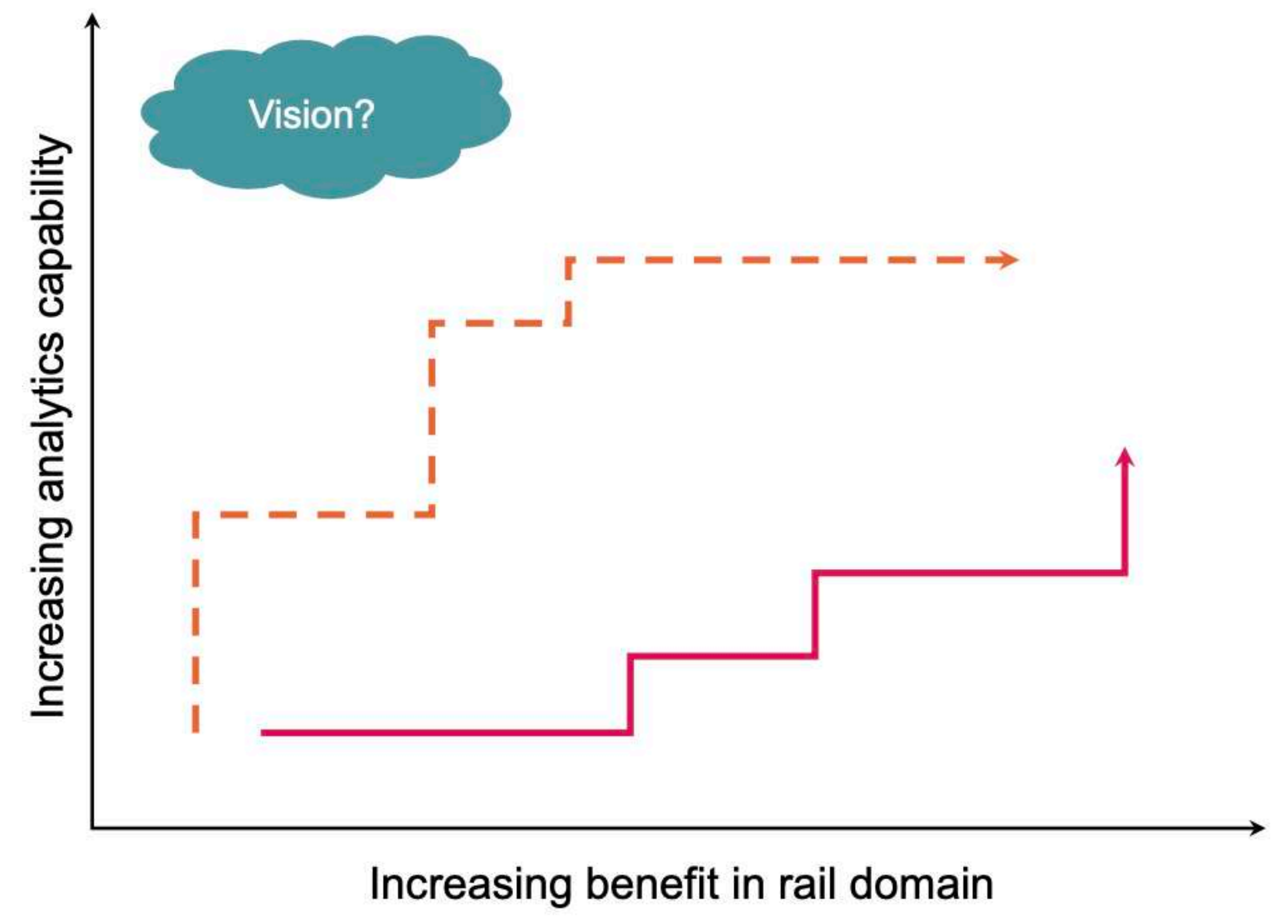
Figure 2 – Convergence between analytics capability and benefits in the rail domain.



Industrial IoT (IIoT) and railways

The opportunities created by IIoT and enabling communication technologies are being exploited by the railway industry to define a 'Internet of Smart Trains' paradigm. These modern technologies help in reducing the whole life cycle cost. Timely decision making is improved with new services like integrated security, asset management and predictive maintenance. Information Communication Technologies (ICT) such as cloud computing and big data enable the adoption of IIoT to integrate thousands of components from rolling stock to the station in the railway environment. The Internet of Smart Train paradigm holds the promise that rail systems can leapfrog in interoperability, safety, and cyber-security issues while rapidly modernising.

Use of IIoT enables real-time monitoring of asset health by a wide array of sensors, connected within an integrated environment and feeding the predictive maintenance decision-making process. The applications of AI, ML and big data analytics further enhance the improvements in rail domain. The areas of IIoT applications in the 'Internet of Smart Trains' paradigm is shown in Figure 3.

Examples of the services IIoT supports include moving from reactive to predictive maintenance and improved train control systems, both of which support better energy efficiency.

These main benefits from using IIoT in the rail domain are just the tip of the iceberg and there is a huge potential for application to other areas that could offer further benefits which have probably not yet even been identified. The enabling technologies for IIoT, massive data aggregation, correlation and analysis using highly sophisticated algorithms have the potential to change operations, maintenance, yield management and even passenger services in the future. The IIoT is set to revolutionise train operations, enabling improved customer service and competitiveness of trains. The enabling technologies for the IIoT for railways are shown in Figure 4.

Artificial intelligence, machine learning and deep learning applications in railways

Some of the areas of application of AI within the railway include Automatic Train Operation (ATO) to control speed profiles and therefore enhance delay prediction with the consequent ability to reduce delay. Ultimately this can lead to enhanced scheduling systems better optimised to the infrastructure available. Other benefits include predictive maintenance with the possibility of digital twins in support and thus improved asset management. Finally, there are the business opportunities such as automated fare collection and video analytics.

With AI for CBTC onboard ATO, AI doesn't have direct control of the train traction or brake but is limited to only 'advise' the higher SIL (Safety Integrity Level) functions about how to drive the train efficiently. AI considers efficiency related parameters such as passenger comfort, lower energy consumption, lower travel time, and makes decisions. AI can make mistakes sometimes and hence should not be allowed to have final authority in safety critical functions.

The areas where AI can be applied for non-vital SIL0 functions for CBTC onboard ATO are shown in Figure 5.

Use case – track monitoring – Convolutional Neural Network (CNN) application:

In the Netherlands, a manually labelled image dataset collected from approximately 700km of rail network is being used. Multi-class classification of squat defects (rail surface defects caused by metal fatigue) is done using a CNN-based ML algorithm. Rail head squats require extensive corrective maintenance and costs millions of Euros, and they also result in speed restrictions on the network. Assessment of the visual growth of a defect and its severity is done using an image dataset. A failure risk model is developed with the combination of image data for squat defect classification and analysis of crack growth from the data collected from ultrasonic measurements. [5]

The problem with self-learning systems based on deep neural networks is that without special measures we will not know what the machine has learnt and why it makes certain decisions. This problem is known as 'transparency' – the extent to which an AI system discloses the processes or parameters that relate to its functioning and decision-making. The machine may make an incorrect decision leading to an accident. An alternative approach which fulfils the accumulation of data and system validation by means of trial and error on the premise of the transparency problem is perhaps not practical in the railway signalling domain. Then the question is "To what extent should we permit AI/ML to learn/relearn or upgrade themselves?".

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Figure 3 – Areas of IIoT application on the railway. *[3] CC BY 4.0 licence.*

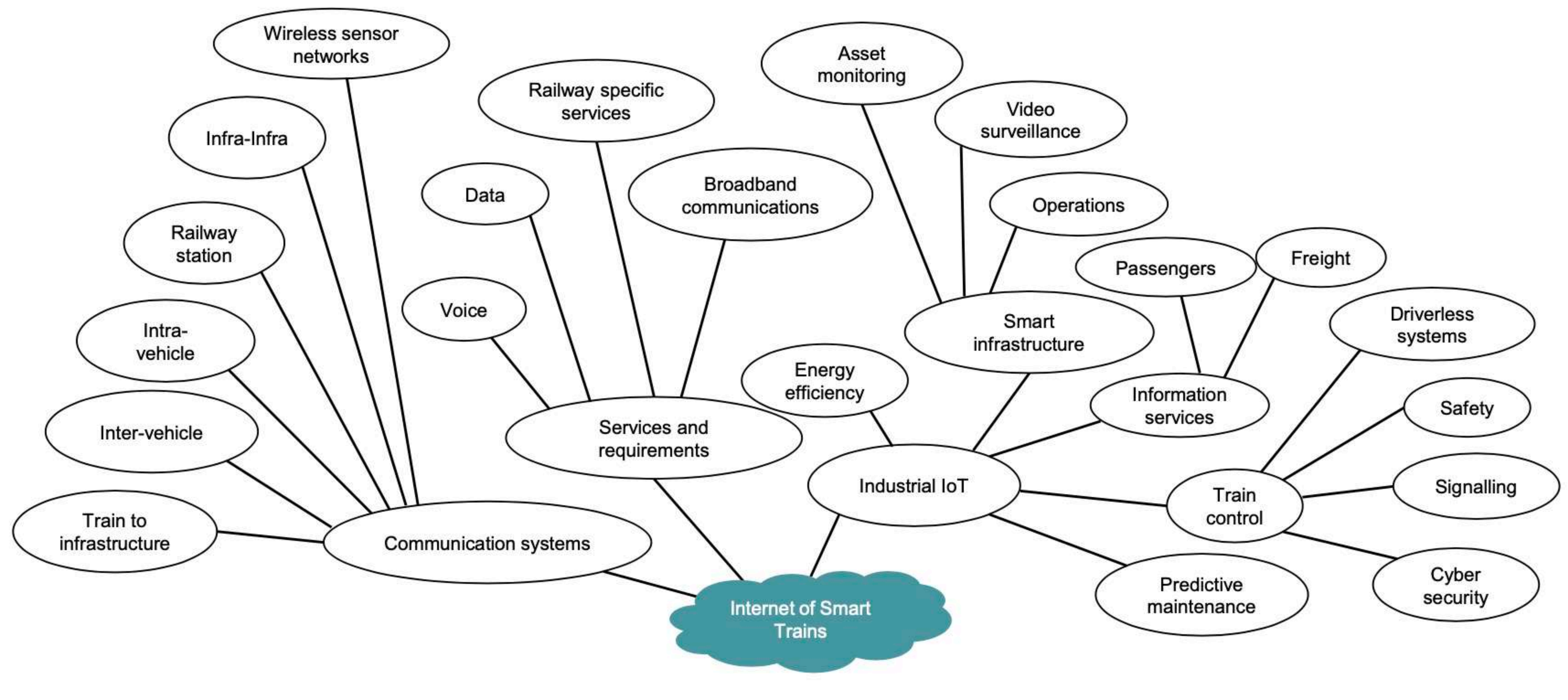

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Figure 4 – IIoT enabling technologies in the railway domain. *[3] CC BY 4.0 licence.*

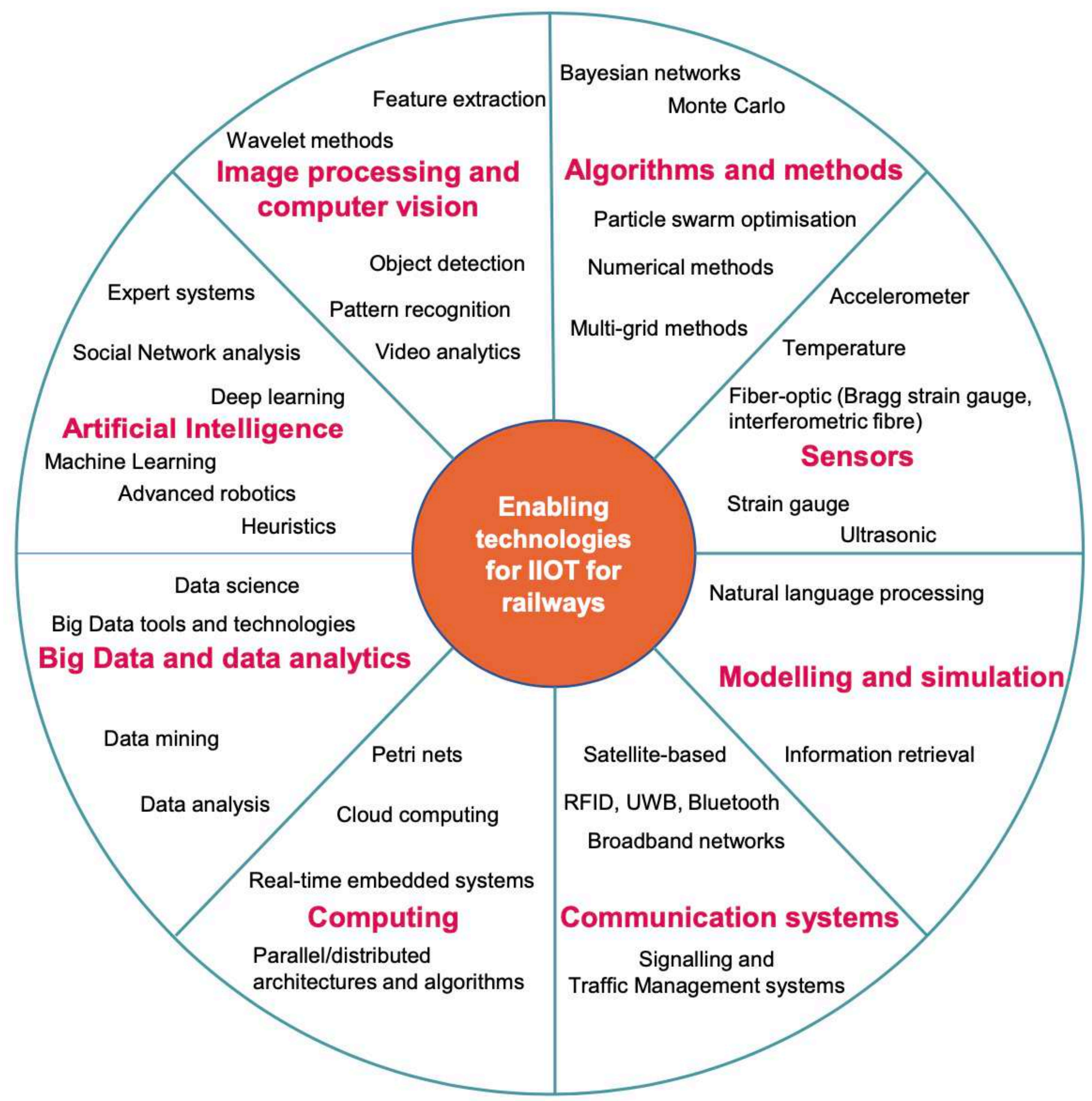


Figure 5 – Areas of AI applications for onboard train control equipment. [4]

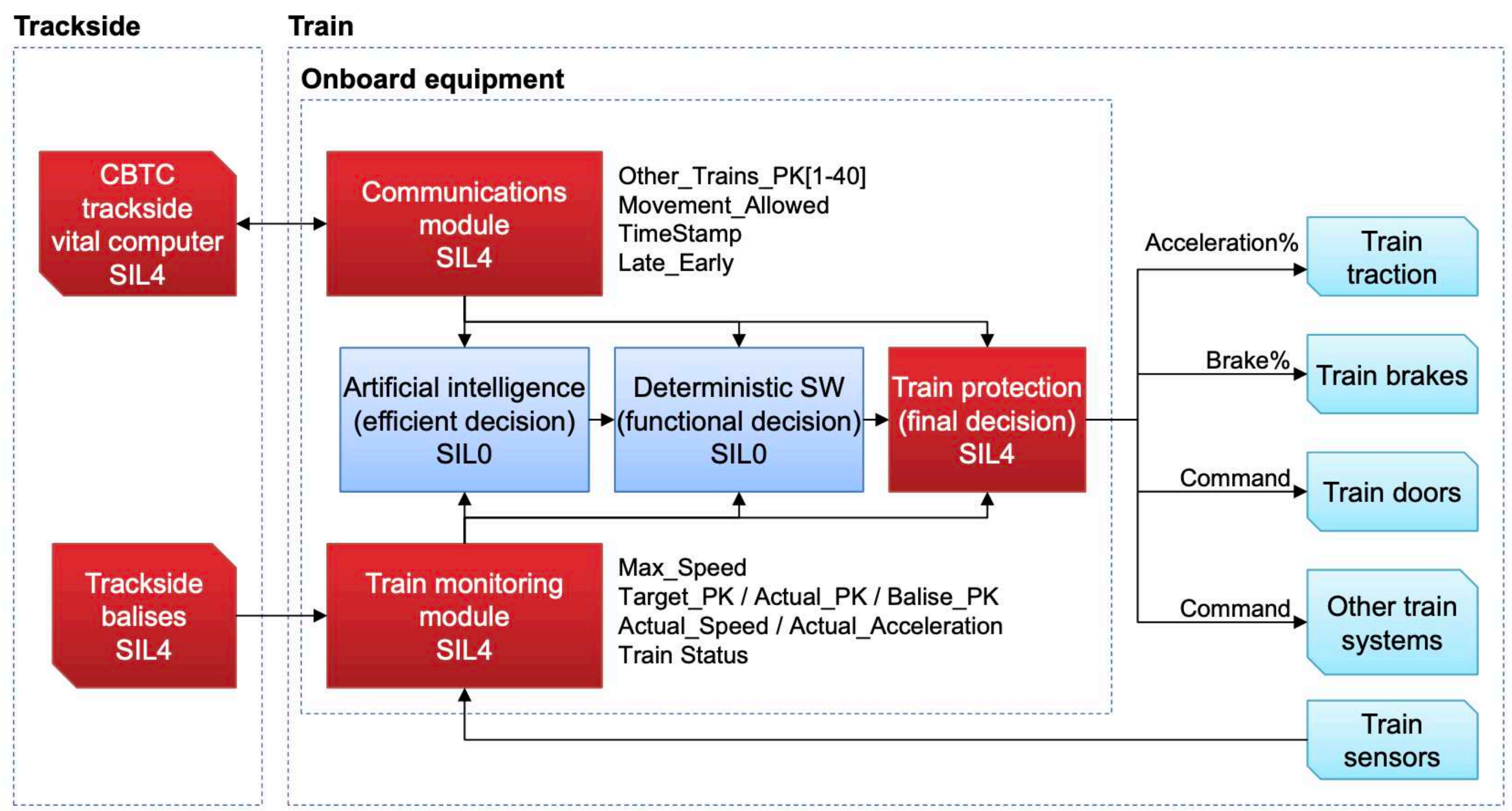
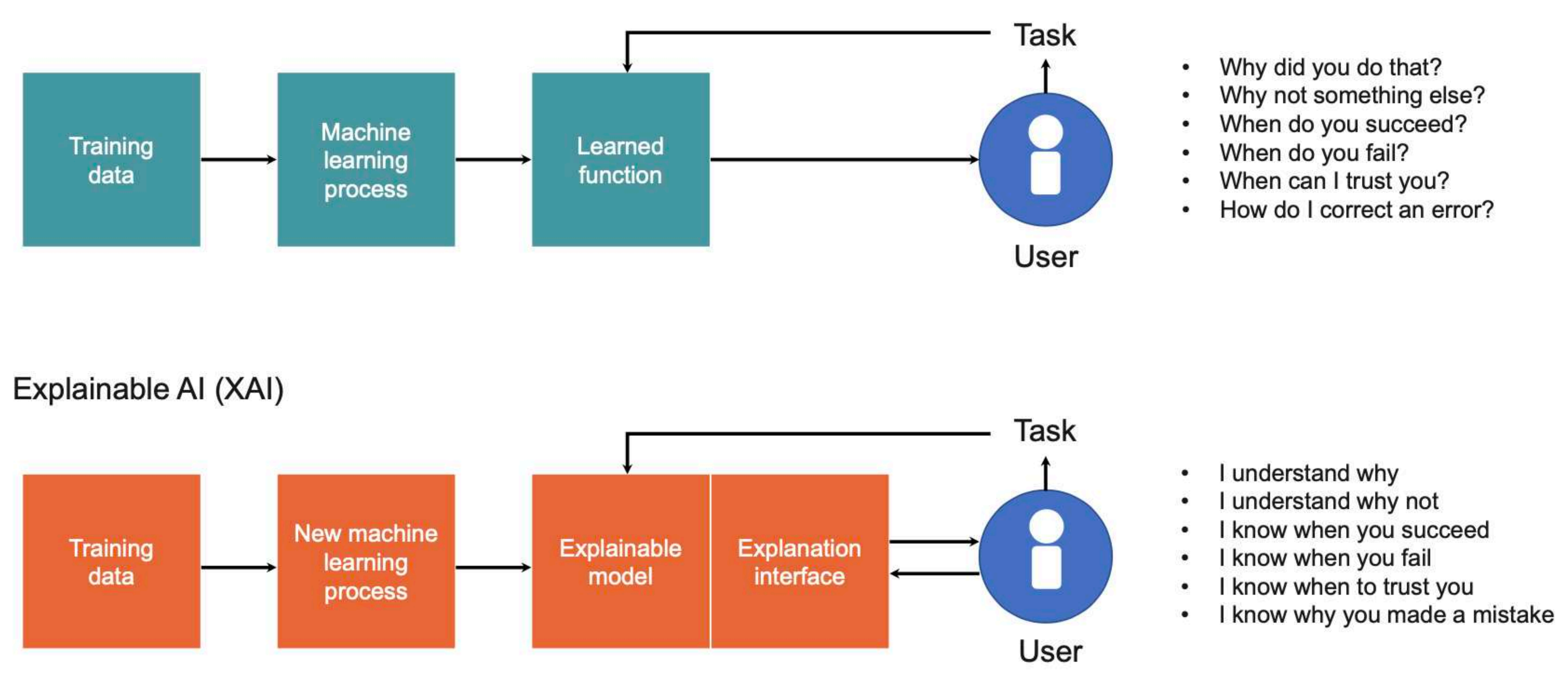


Figure 6 – Explainable AI.



Some of the challenges with ML algorithms include the need to ensure the ML model is not vulnerable to carefully crafted perturbations (adversarial robustness). It also needs to be recognised that ML systems will not give a defined output (deterministic) but a likely (probabilistic) output. It is important to ensure the training data and the test data do not have the same distribution of likely events because that would violate the independence of testing from design. It is also important that the algorithms behaviour is explainable and can be subject to post incident analysis. Typical errors should be identified and protected.

Whereas the commercial applications of AI mainly focus on analysis, one of the main concerns with the application of AI to autonomous systems is whether safety is ensured. Demonstrating the safety of autonomy and AI is not a mature discipline.

Other challenges that confront the application of AI to safety-related systems include the completeness of the safety requirements, a robust definition of exceptional circumstances, and the means of verification and the evidence provided to support the verification.

Explainable AI (XAI)

The current and desired state of AI/ML techniques for safety critical domains like railway systems and signalling is shown in Figure 6. The ongoing research in XAI hopefully will answer these pending questions and developments in other areas like 'autonomous vehicles/self-driving' cars will support this research.

To deliver a digital railway it is important that signal engineers in both the design and maintenance fields work with data scientists to develop effective and relevant algorithms that generate useful information about the health of the railway and its correct operation. This requires system thinking at every level. Partaking in Continuous Professional Development (CPD) and keeping up to date with the latest technology is essential. Finally, signal engineers and system engineers must adjust and understand how to use AI safely and efficiently, including by means of collaboration between industry and academia.

Conclusions and future work

Big Data, AI, ML, and other emerging technologies have huge potential in railways due to need for real time analytics and huge amounts of information processed every day. Domain expertise is vital to be able to effectively validate analytics hypotheses to generate useful outcomes. The question is no longer 'if' AI will be used in critical railway software, but 'when' and 'how' [4]. Recognition of the 'Human in the loop' is critical and it remains with applications of these technologies. Digital Railway, big data, AI/ML provides massive synergies to overcome the situation of 80 per cent of accidents caused by 'Human Error'. More has to be done to address the issues related to data quality, explainability and trustworthiness of ML algorithms. Industry-academia collaboration is key in applying the disruptive technologies to solve current and future problems in rail domain.

The following questions [6] remain to be answered if we are to successfully certify ML based railway signalling safety critical systems:

- What techniques are proposed to directly certify ML based safety-critical systems? (How to certify machine learning based safety-critical systems).
- What general techniques can be used to certify ML systems (such as robustness, explainability, verification)?
- What are the weaknesses or limitations of applying the state-of-the-art techniques to certify ML based systems?

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About the author

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Passionate about railway signalling since 1995, Veera has passed IRSE examination Modules A and 7. He also completed a six-month certification course in Artificial Intelligence/Machine Learning from the International Institute of Information Technology, Hyderabad and a two-year Advanced Management Programme in Business Analytics from the Indian School of Business, also in Hyderabad.

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