Industry 4.0 Concept in Railway Transportation

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Contributor: Zdenko Kljaić , Danijel Pavković , Mihael Cipek , Maja Trstenjak , Tomislav Josip Mlinarić , Mladen Nikšić

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railway transportation challenges emerging technologies sustainable transport

1. Introduction

The European Union's long-term goals are based on green energy transition. Thus, the European Commission has adopted a package of measures aimed at energy efficiency improvements, along with legally binding guidelines for meeting the objectives of the Paris Climate Agreement [1]. According to those guidelines, at least 32% of energy consumption in the European Union (EU) by 2030 must be from renewable sources. Member states, including the Republic of Croatia, need to ensure that at least 14% of fuel (energy) in the transport sector is secured from renewable sources, and the overall energy efficiency would need to be increased by 32.5% by 2030 [2]. Obviously, the strategy for the decarbonisation of the energy sector also causes significant changes in the transportation sector in terms of usable energy sources, which, in turn, is reflected upon the propulsion technologies currently in use, particularly in railway transport [3]. Specifically, 20% of the global consumption of fossil fuels is currently attributed to the transportation sector [4], which, in turn, makes it the second largest carbon dioxide (CO_2) emission source [5] contributing significantly to the alarming increase in atmospheric CO_2 concentrations [6] and associated greenhouse effects [7]. The contribution of railway transportation to the overall emissions of greenhouse gases (GHGs) varies depending on the country, with 4% of the overall GHG emissions share having been reported in [8]. The EU Strategic Program for Transport Research and Innovation developed the first long-term strategic approach to prepare for the envisaged transportation system transition in terms of research and innovation that combines innovative low-carbon technologies with connected and automated transport services and smart mobility [9], wherein a multitude of options is currently available for railway sector decarbonisation [10].

The need for a transition to more autonomous and connected transport has been identified as a necessary condition for achieving higher levels of efficiency and the decarbonisation of the transportation sector. According to the European Commission (EC), the goal is that by 2030, high-speed rail traffic will double across Europe, and this is planned both for urban and intercity collective travel [9][11]. For journeys of less than 500 km, carbon-neutral automated mobility for smaller groups of people or goods should be available [11]. Also, the EC document [12] states that: "… Digitalisation and robotisation in the field of the mobility of people and the transport of goods provide society with several potential benefits such as better accessibility and convenience for passengers, efficiency and productivity for logistics, improved traffic safety and reduced emissions. At the same time, there are concerns relating to safety, security, privacy, labour and the environment …". It therefore recommends that intensive research and development (R&D) of suitable solutions for intelligent transportation systems (ITSs) needs to be carried out. This need for additional R&D is especially emphasised in the fields of communication systems and sensor networks to minimise the risks of deploying these new technologies [13]. In particular, demands for the accelerated digitalisation of the transportation sector result in extremely large amounts of data, which mandate the utilisation of cloud computing. On the other hand, the implementation of long-term evolution (LTE) or fourth and fifth generation (4G/5G) mobile communication networks [14] and different remote (networked) sensor nodes [15], as well as robotics [16] and artificial intelligence (AI) in logistics [17], are seen as key factors for further advances in digitalised and automated railway transportation [18], including autonomous rail vehicles [19].

Steady progress in the development of sensor networks is visible in all domains, especially in the field of transport. Therefore, the effectiveness of communication equipment is particularly important due to requirements on transport volume and speed [20]. To this end, the Internet of Things (IoT) paradigm [21] or, more precisely, the advanced system of machine-to-machine communication (M2M) [22], together with different front-end intelligent sensors [23], allows for the transparent integration of large numbers of heterogeneous external systems [24]. Thus, it can facilitate the development of new digital services and novel possibilities for their application, especially when transport safety and security are concerned [25]. Also, the development of communication systems according to 5G functionalities opens new possibilities in the field of ITS and communications between traffic entities and their environments, and such internet of vehicles (IoV) paradigm [22] is especially important in the field of autonomous and cooperative vehicle management [26]. Reference [27] provides an overview of the possible technologies, protocols, and architectures of intelligent systems based on the concept of vehicle communication systems, with an emphasis on a wide variety of communication types such as vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I) and vice versa (I2V), vehicle-to-pedestrian (V2P) communication, and, generally speaking, any communication between a vehicle and a heterogenous communication node (V2X) [26]. Furthermore, future transport systems based on non-fossil vehicle propulsion technologies are also closely related to smart grid systems and 5G software-defined vehicle networks that have important roles in that field of research [28]. In particular, 5G communication networks offer distinct advantages in terms of connection speed and data transfer reliability (up to 20 times faster data rates for the same transmission quality) compared to the standard Global System for Mobile Communications-Railway (GSM-R) systems [29], and this low latency of 5G networks enables the implementation of various security functions over multiple heterogenous domains [30]. Thus, 5G communications have been suggested for the digitalisation of urban railways [31] and the telemetric monitoring and automation of railroad networks [32], along with sophisticated applications in the accurate positioning of railway traffic entities in real time [33]. The latter is significant in the context of railway traffic safety, especially when atmospheric and weather conditions at micro-locations are taken into account [34]. This primarily concerns railway traffic incidents related to weather conditions [35], but it may also refer to the feasibility of the scheduled transportation by rail under adverse weather conditions [36]. The application of smart remote sensor networks facilitating timely and structured information about atmospheric conditions may offer an additional advantage in the planning of railway transportation, as indicated in [36], which is of particular importance when considering increased weather condition volatility due to climate change [37].

2. Industry 4.0 Concept in Railway Transportation

Industry 4.0 is a concept applied to many different industries and enterprises to make them more intelligent, dynamic, and flexible to meet the challenges of the highly dynamic global market [38]. This is carried out by integrating information technology (IT) systems with different physical systems (such as existing conventional industries) to create the so-called interconnected fully digitalised cyber-physical system [38], whose implementation also introduces inherent new challenges [39]. The above cyber-physical system paradigm has ushered a new way of thinking about technical systems, processes, business models, products, and services, and naturally, the potential new customer pools opening due to the digitalised approach inherent to Industry 4.0 [40]. Industry 4.0 can be regarded as the industry's development stage after previous industry revolutions. **Figure 1** illustrates this on the example of logistics and transportation systems development. Advances in the transportation and logistics sectors have been closely linked to advances in other industries [41] and thus may also serve to increase both the competitiveness and sustainability levels of related enterprises [42].

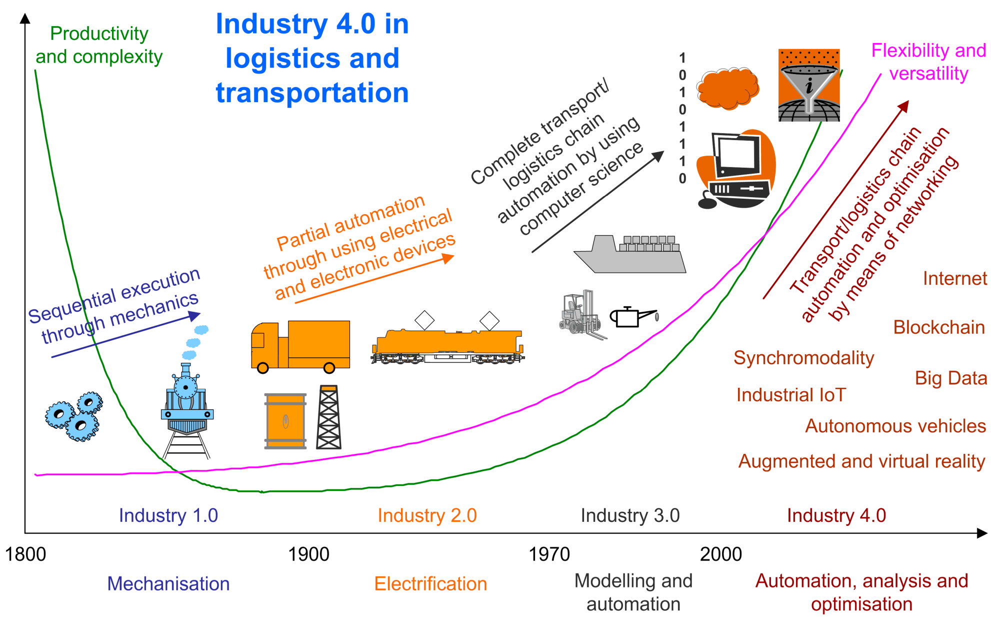

Figure 1. Industrial revolutions and their consequences to transportation and logistics.

A railway transportation system consists of many subsystems such as a railway track and related groundworks, signalling and safety systems, telecommunications, electric power stations as part of the electrification infrastructure including the overhead power lines, signalling and safety devices to secure road and pedestrian crossings, and other auxiliary systems. It is evident that the railway infrastructure is a complex and demanding system with high operational and maintenance costs. The Industry 4.0 concept and the related digital transformation can benefit many of these subsystems, especially with the improvement in energy efficiency, transportation safety, and security. These subsystems may include (i) autonomous and automated transportation,

(ii) multimodal and intermodal transport systems, (iii) the application of big data analytics and artificial intelligence for predictive maintenance, (iv) the supervision of critical infrastructure and resilience improvement measures, and (v) smart grid connection.

2.1. Autonomous Trains and Automated Railway Traffic

Due to the demand to reduce automobile traffic in highly urbanised areas, new innovative transportation technologies are introduced that can facilitate high levels of urban mobility with less traffic congestion and improved energy efficiency. The Autonomous Rail Rapid Transit (ARRT) vehicles that were proposed recently have the advantages of rapid implementation, adaptation of the driving mission en route, autonomous management, and possible integration, coexistence, and cooperation with other urban modes of transport (so-called intermodality). Some examples of such hybrid transportation systems include an autonomous personal transit (shuttle) system for public transport [43], shown in **Figure 2**, and a tram-like shuttle vehicle using virtual corridors defined for roadways [44], wherein these vehicles use built-in sensors to drive along the virtual route, with the additional benefit of being able to modify their driving missions in real time. These vehicles can undergo real-time route adaptation according to current traffic conditions, so the flexibility of road vehicles can be combined with the simultaneous regulation of such traffic in accordance with the rules of conventional railway traffic. These advantages make ARRT systems good candidates for future transportation in medium-sized cities [45].

Figure 2. Example of autonomous vehicle using the concept of virtual tracks and equipped with 5G remote sensing and communication platform.

Innovative autonomous transport systems can also be made compatible with the current metro railway infrastructure with the possibility of having significantly lower implementation costs if they are integrated into the existing traffic infrastructure [46]. With the introduction of IoT, artificial intelligence and Big Data analytics, and next generation 5G communications, the autonomous vehicle supervision and control combines sensors, communication, and control and navigation software [47]. Spatial and temporal information about traffic entities is crucial for the effective management of vehicles with increased autonomy, such as when multiple independent autonomous high-speed trains are driven on the same railway track with hard mutual distance constraints [48]. Alternative very close formations may be used for the purpose of implementing advanced train dynamics control features, such as the concept of seamless inter-changeability (trains coupling and uncoupling on the move), as presented in [49]. A Global Navigation Satellite System (GNSS) is typically used for geospatial positioning and vehicle speed estimation, such as for the predictive control of autonomous transportation systems [50]. Due to the GNSS limitations of positioning precision and signal availability, high-speed trains also require alternative positioning methods, such as the use of independent inertial measurement unit (IMU) sensor suites [51] or signals from 5G communication networks. The latter can indeed provide very accurate location information with much higher availability that GNSS [15], which can be used for the cooperative control of multiple trains, further augmented by train-to-train communications [52].

The Industry 4.0 concept can facilitate a more systematic utilisation of information flows, including Industrial IoT technologies for better interconnectedness of different traffic entities and big data analytics for the purpose of transportation optimisation. Thus, it represents a key enabling technology to facilitate automated rail traffic control and energy use optimisation and their integration in a straightforward fashion. This has been illustrated by examples in references [53][54], wherein the advanced information and communication technologies, data from remote sensor networks, and artificial intelligence have been successfully used to improve railway transportation safety and energy efficiency. Similarly, the utilisation of sensor suites on-board traffic entities coupled with massive data throughput inherent to 5G radio networks was identified in [43] as enabling technologies to increase the safety of autonomous transport. To that end, the authors of [41] discuss the concept of a “digital railroad” aimed to improve transportation safety by means of digital railway signalling systems, whereas the authors of [42] put forward arguments for the increased usage of emerging technologies, such as drones, smart sensors, robotics, blockchain, and artificial intelligence within the framework of Industry 4.0 for transport and logistics to improve their safety and energy efficiency. These aspects of Industry 4.0 in railway transport will also be discussed in the following subsections.

2.2. Multimodal Transportation

Railway transport can be divided into passenger transport and freight transport. There is a strong pressure on technological development and the integration of rail freight transport into the single European railway system (according to EU Directive 2012/34/EU). Also, with the process of globalisation and environmental requirements, the costs of transport services are a major factor in the overall business process, so they need to be optimised. Rail freight transport optimisation is primarily focused on energy efficiency and deeper integration with other transport and logistics sectors [55]. Due to these requirements, intermodal freight transport and multimodal transportation in general are developing rapidly [56]. Intermodal freight transport is the movement of goods stored within the same loading unit (i.e., a transport container) via successive modes of transport without handling the goods themselves when changing the mode of transport [57]. By integrating and coordinating the use of different modes of transport that are available in intermodal transport networks, intermodal freight transport provides an opportunity for the optimal use of physical infrastructure to ensure cost-effective and energy-efficient transport services [57]. **Figure 3** illustrates the difference between single-modal and multimodal transport chains. The number of necessary cargo-handling operations, connecting transport, and information exchange becomes increasingly complex in the case when multimodal transport is employed for the cargo to be moved from its origin to its destination [58]. Researchers can conclude that an information and communication infrastructure with a suitable database that supports the management of this type of transport is needed for efficient multimodal transport.

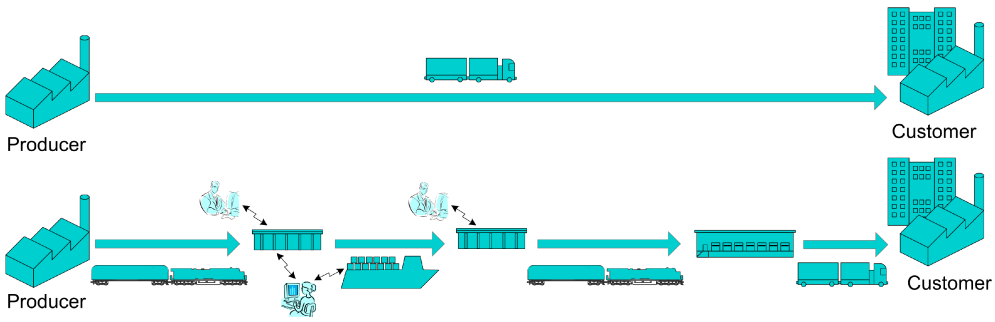

Figure 3. Comparison of single-modal and multimodal transport chains.

With the aid of information providers, so-called synchronous transport can be achieved by choosing modalities according to the latest logistical information, such as the transport requirements of goods and current traffic information [59]. It is therefore evident that the railway infrastructure needs to accelerate its digitalisation as a key pre-requirement for the subsequent improvement of rail transport cost-effectiveness [60] and energy efficiency [61] to increase its sustainability. There is a clear trend towards improving the energy, economic, and ecological (EEE) indicators in railway transport [62], as well as other transportation domains such as maritime ports [63], which are crucial when considering the intermodal transport of large volumes of goods and the sustainability of the overall transport sector [64]. Cutting-edge technical solutions, such as innovative containers and loading/unloading systems, may further help to achieve higher levels of technical interoperability, as well as to lower the overall transportation costs, such as when multimodal transport is considered compared to the case of railway transport alone [65]. This is also true when hazardous materials need to be transported [66], where risk assessment also plays a major role in transport planning and its subsequent implementation.

Optimising energy consumption and transportation time and cost in rail transport represents a multidimensional nonlinear problem with several technological traffic constraints, especially when increased degrees of autonomy are concerned, where a number of additional safety constraints also appear [19]. It was shown in [67] that a high level of synergy between facilities and equipment, management, business operations, and information systems is a key requirement for highly effective logistics and transportation processes, which may be sought by using optimisation tools. Consequently, these kinds of optimisation problems usually involve multiple objectives that need to be minimised, so optimisation methods that are suitable for multi-criteria optimisation problems need to be employed [68]. Dynamic programming (DP) was used in [56] to obtain an optimal combination of transport modes for a cargo container multimodal transport problem using rail, road, and waterborne transport and was subject to overall transport cost and duration. Since cargo transport routing is subject to optimisation in these kinds of applications, integer-valued states for routing description and mixed-integer linear programming (MILP) optimisation algorithms can also be used for that purpose [69].Geographic information system (GIS) software programs or stochastic programming [60] can be used to optimise the efficiency of multimodal transport, especially when considering passenger transport and ticket costs [70]. The optimisation of autonomous vehicles' traffic for multimodal transport is a relatively recent field of research [71], so experts from other areas such as mechatronics are often required [39] to carry out the analysis with sufficient levels of accuracy (see, e.g., [36]).

2.3. Predictive Maintenance

Big data is the most important term in today's digitalisation trend, and it denotes massive data sets [72] characterised by large volumes and different and complex structures, together with the requirement of complex analysis tools for the purpose of visualisation and the subsequent processing of data as input parameters for other systems. M2M data exchange, associated with smart sensors and IoT devices, and characterised by large data volumes, may be of particular interest when railway transport safety is concerned because of its utility in predictive maintenance in conjunction with proper classification and pattern recognition algorithms [73]. Predictive maintenance or condition-based maintenance recommends appropriate actions using a large set of collected data subjected to the processing and extraction of key features that are subsequently used for classification (normal operation, emerging fault, developed fault, and imminent failure) [74]. The classification result is subsequently used for timely maintenance decision making (**Figure 4**), thus reducing maintenance time and costs and avoiding unscheduled overhauls [74]. Sources of analysis data in railways can be wide and varied, such as (i) intelligent sensor networks on-board freight trains [75], (ii) optical sensors such as LIDAR (light detection and ranging) devices on-board trains, which are used for accident prevention [76], and (iii) cameras and other sensors aboard unmanned aerial vehicles (UAVs) used for infrastructure monitoring [77], just to name a few.

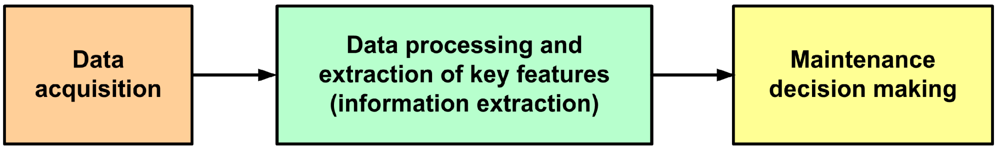

Figure 4. Principal representation of condition-based maintenance process.

Intelligent sensor networks on-board freight trains can be arranged depending on the type of transmission medium (wire, optics, or wireless) and type of data transmission, i.e., single-hop and multi-hop networks [75] (**Figure 5**). Naturally, wireless communication between sensor nodes and the data hub offers some distinct advantages over wire- or optics-based data links, particularly with respect to the lack of maintenance. In that respect, an electrical power supply for individual sensor nodes also plays a significant role, especially with freight wagons, which are typically unpowered, except for braking system pneumatics and the terminal signal light. Hence, such sensor nodes should either be equipped with a long-life battery or an energy harvesting system for on-board power supply [75]. One such case of autonomous sensors used for the online monitoring of the braking system pressure and mechanical vibrations by means of accelerometers, with a vibration energy harvesting system based on an inertial pendulum mounted on bogey suspension, was presented in [78]. The main conclusion in reference [78] was that the developed energy harvesting and ultracapacitor energy storage systems may need further miniaturisation and protection from environmental conditions before being deployable en masse. Other types of sensors that may be used for the online condition monitoring of railway vehicles include on-board inertial measurement units [79] and smart sensors within tunnels to facilitate an advanced risk assessment analysis [80]. Note that there are already commercially available on-board sensor systems that satisfy stringent requirements in terms of power autonomy (e.g., powered by means of solar panels) and high levels of robustness and ingress protection (IP class), thus allowing them to operate over a wide range of environmental conditions [81][82] that are characteristic for rail freight transport.

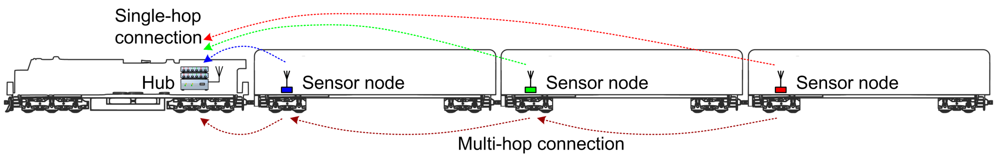

Figure 5. Example topologies of wireless sensor networks on-board a freight train.

Research in intelligent maintenance techniques in railways typically involves the utilisation of artificial intelligence, such as fuzzy logic and artificial neural networks (ANNs), and machine learning (ML) models in the form of support vector machines (SVMs) and support vector regression (SVR) models [73]. In that sense, the authors of [83] investigated a fuzzy logic-based thermography system for predictive maintenance in electric railway traction. Thermal cameras are used to collect thermal imaging data about rails and the catenary-pantograph system, and a fuzzy logic system utilising complex membership functions is used for image processing and related condition monitoring. Similar work related to track condition monitoring was carried out in [84], wherein the support vector machine (SVM) approach was used to model track geometry deterioration with a prediction accuracy over 70% reported in the paper. On the other hand, the authors of [85] utilised measurements from a ground-penetrating radar and compared the conventional frequency analysis (FFT) approach with the AI approach using long short-term memory (LSTM) neural networks and convolution neural networks (CNNs) for the prediction of hazardous conditions such as railway track fouling and deformation, with both AI methods performing remarkably well. Another example of CNN utilisation for predictive maintenance would be the analysis of features of vibration signals for the purpose of early fault detection, as shown in [74]. **Figure 6** illustrates the ability of the CNN used in [74] to extract and classify key features of different types of early mechanical faults of rotational equipment with respect to normal operating conditions. The distribution of test samples extracted from input signals and the output layer for the CNN are obtained by means of an appropriate visualisation software tool, which represents the results in a two-dimensional space of non-dimensional variables [74]. The results show good potential for predictive maintenance in railways when vibration measurements are readily available using on-board accelerometers, whose deployment was presented in [78].

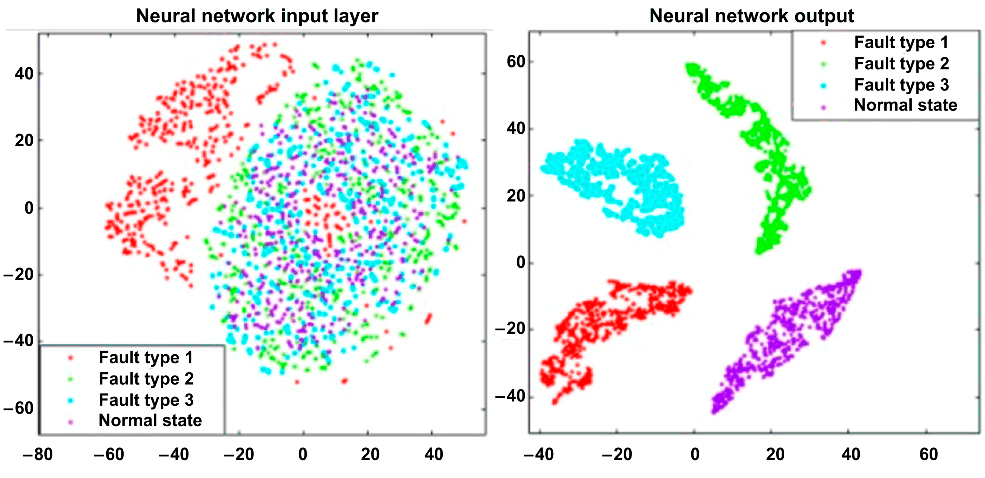

Figure 6. An example of early fault detection results obtained by means of CNN.

With the introduction of battery-based and hybrid propulsion in railway vehicles, specific aspects of battery energy storage system maintenance also need to be considered, which can be carried out within a multi-criteria optimisation framework [86]. Moreover, the three-dimensional (3D) reference architecture model from Industry 4.0 can be adapted to describe intelligent high-speed railways in terms of their (i) intelligent features, (ii) system levels, and (iii) life cycles, wherein intelligent features encompass different aspects of the railway vehicle and infrastructure maintenance [87].

2.4. Resilience Improvement Measures and Inspection of Critical Infrastructure

Railways, along with other transport networks, water and gas distribution networks, and electrical power grids fall into the category of critical infrastructure networks that are essential for the functioning of society and the economy [88]. The increased transport demand and the related increase in the railway network congestion results in an increased complexity in their operation. Increased transport demand and increased complexity of transport services cause disruptions within the controlled set of transport services. With climate change-related events affecting the railway infrastructure, such as damaging the tracks due to heat-related buckling, or flash floods and other extreme weather events affecting the infrastructure (**Figure 7**; see also [35]), there is a clear need for measures aimed at increasing railway systems' resilience to external events [89], including both anticipated and unforeseen ones [90].

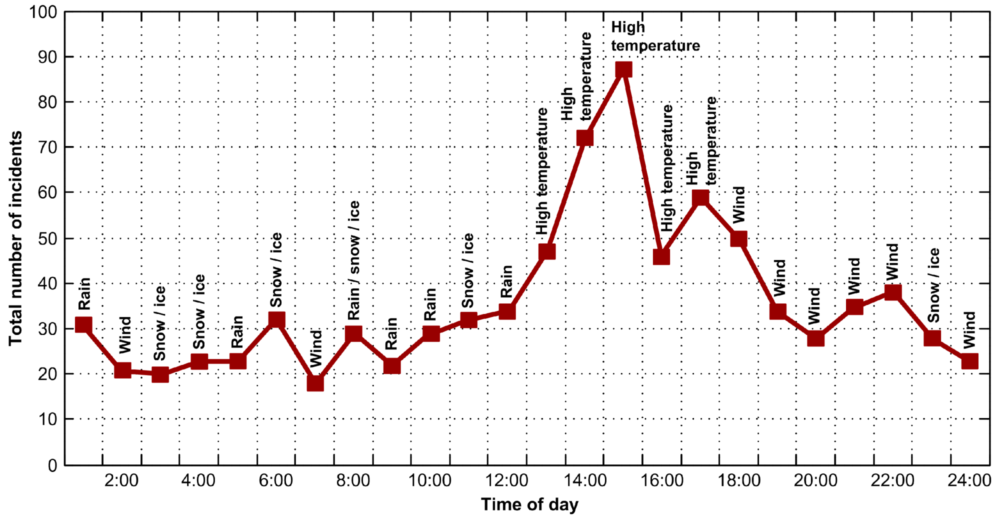

Figure 7. Total number of hourly railway incidents during a single day by most common types of causal events per hour of day (1995–2005).

According to [88], there are four characteristic approaches to estimate railway systems' resilience from the available literature:

- Topological approaches that use network and graph theory to perform assessments by removing links from the network in a stochastic manner (thus emulating stochastic disturbances) or according to a predefined strategy (thus emulating deterministic disturbances) using a well-defined mathematical theory;
- Simulation approaches, which model traffic flows within the system using software tools and can overcome the main disadvantage of the topological approach, i.e., the exponential growth of the problem with the number of combinations;
- Optimisation approaches, which can handle combinatorically complex scenarios in a systematic manner without the need to analyse every possible combination of events (which would be needed if the topological or simulation approach is used);
- Data-driven approaches, which do not require explicit traffic network modelling and can provide good a posteriori insights about network resilience using historical data.

Research on railway traffic network resilience focuses on different aspects of railway network operation and a wide variety of research methodologies, as indicated above.

For example, the topological approach used in [91] to model the railway transportation system in Paris, France was able to identify which railway system components have a major effect on the overall system's functioning, which may be crucial for emergency planning and train routing. Obviously, this kind of approach may also be used to model and analyse other kinds of traffic networks, with the concept of friability (loss of resilience) introduced in [92] to evaluate the effect of removing traffic hubs from the network due to traffic interruption. Object-enhanced time Petri net models were used in [93][94] to model and analyse the behaviours of railway transportation networks subject to traffic disturbances. As such, this approach offers a good basis for the development of future software tools at the strategic and operational levels of traffic management and control and for resilience assessment [93] practically throughout all the phases of railway traffic system conception [94]. Machine learning methods [95] and Bayesian network models [96] have also been used in traffic network resilience and vulnerability assessment studies. On the low-end side, resilience improvement measures may include advanced strategies for train platooning and dynamic interval optimisation to minimise departure delay times and, consequently, to dynamically adapt the train departure timetables [97]. The timetable design is obviously a trade-off between the opposing requirements of stability and feasibility, and robustness and resilience, wherein the former requirements are typically met by using deterministic traffic models, whereas the latter require a stochastic-oriented modelling approach [98]. Other methodologies that are typically used in the resilience assessment of low-level and small-scale problems may include the use of dedicated traffic simulation suites, such as the Simulation of Urban Mobility (SUMO) [99] and the hardware-in-the-loop (HIL) approach, to validate the simulation results [100].

Naturally, special attention needs to be paid to cybersecurity challenges associated with the utilisation of IoT-based technologies and the overall cyber-physical system complexity, cloud services and interconnected infrastructure, and remote access security measures to prevent or alleviate the hazard of cyber threats and to ensure the availability and continuity of railway services [101]. A possible example is radio unavailability in tunnels and logistics facilities, and the presence of local radio interference or intentional jamming that prevents wireless communication between moving or stationary traffic subjects. The latter problem may be solved by using spread-spectrum (channel hopping) communications, wherein channel selection may be based on the game theory approach [102]. These aspects may be of particular importance when high-speed railway signalling equipment is concerned [103], as well as in the case of the transport of hazardous materials, whose routing needs to be carefully planned and executed to minimise the transportation risks [104].

Another crucial aspect of railway transportation system resilience is the comprehensive inspection, surveillance, and supervision of critical railway infrastructure, such as tracks [83][85]; overhead power supply lines [83]; power stations, communication, and signalling equipment [105]; and tunnels [68], bridges, and viaducts [106]. To that end, reference [107] illustrates how the use of numerous inexpensive narrow-band remote sensors can improve railway transportation safety in the presence of varying wheel-to-rail traction conditions due to the variability of atmospheric conditions. To automate the surveillance and inspection processes, novel image acquisition methods using LIDAR-based photogrammetry are commonly used [77] along with high-definition (HD) video cameras [106] and thermal imaging using forward-looking infrared (FLIR) cameras (**Figure 8**a). These are increasingly being mounted on UAV-based platforms to scan the terrain, buildings, and other parts of railway infrastructure [108], as illustrated in **Figure 8**b.

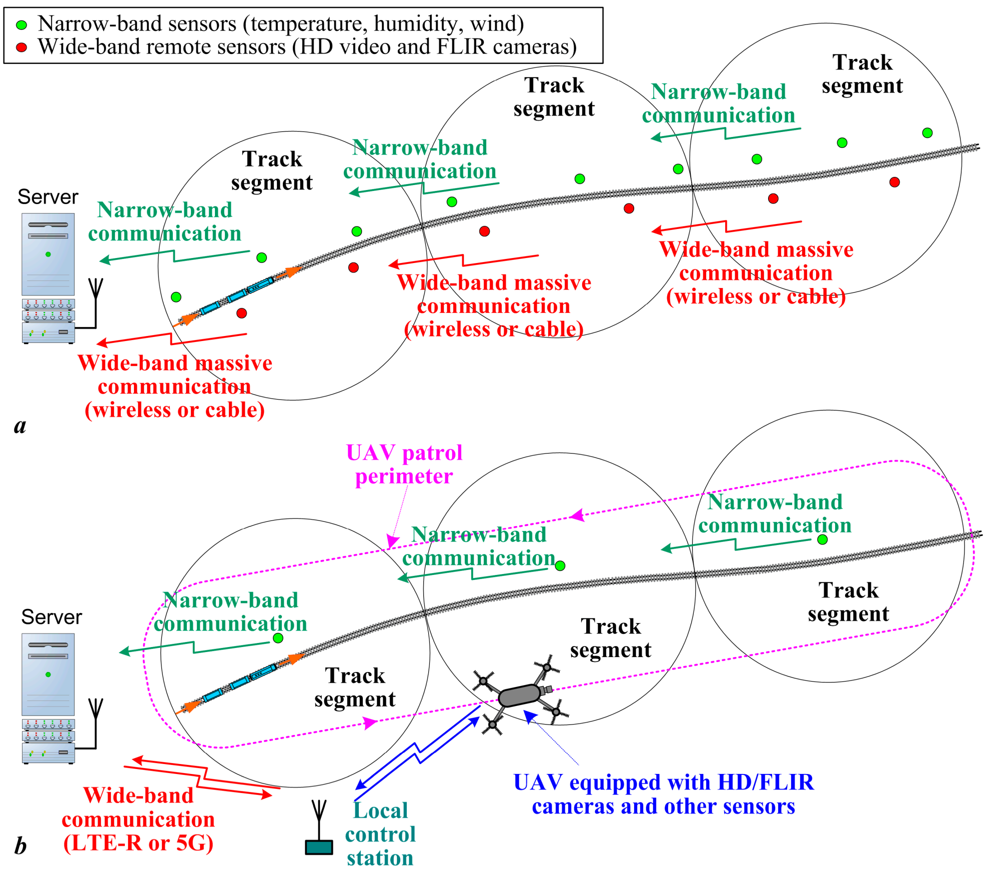

Figure 8. Illustration of narrow-band and wide-bandwidth remote sensor networks for railway infrastructure surveillance (**a**) and possibilities of reducing the number of sensors when using UAV-based surveillance platforms (**b**).

The main advantage of UAVs compared to conventional means of surveillance is that one UAV can carry high-performance sensors and cover a very geographically large area using mobile data connection for data transmission, while a conventional surveillance system requires much more expensive information, communication, and energy infrastructure, a larger number of sensors to cover the entire area that should be monitored [109] (cf. **Figure 8**a,b), and possible different transmission systems for high and low data rate sensors. However, when UAVs are used for surveillance, especially during long missions, there is a certain risk of collision with the surrounding terrain or other aircraft, as indicated in [110]. Reference [110] analyses different collision risk sources and possible outcomes and recommends the utilisation of an emergency parachute for a UAV in order to mitigate the risk of propulsion failure and the loss of UAV control. To extend the aerial coverage of the railway infrastructure, hybrid propulsion technologies may be considered for the surveillance UAVs, such as the internal combustion engine-generator set coupled with the auxiliary battery energy storage system. It was shown in [111] that such a propulsion system has at least double the energy density (and therefore endurance) of a conventional battery-based UAV propulsion while still retaining high control of the flexibility that is inherent to electric propulsion. Such hybrid propulsion-based UAVs for long-duration flight missions are already available commercially [112][113][114], so their more widespread use in critical infrastructure inspection and surveillance can be expected in the future.

Deep learning methods are frequently used in machine vision applications for critical infrastructure resilience analysis and protection, with ANNs typically being used for that purpose [115]. Among different neural network types, CNNs are normally used for feature extraction in object detection, e.g., to recognise patterns such as edges, shapes, colours, and textures in UAV-recorded HD pictures [116]. In the case of LIDAR use, the classification of features of the so-called “point cloud” has been performed by using the so-called random forest algorithm, which appears to be well suited for the problem of the classification of large 3D data point clouds [117]. Other methodologies used for feature detection during an HD picture analysis may include the Hypercomplex Fourier Transform (HPT) model [109] and a particular type of CNNs, the so-called Region-based Convolution Neural Networks (R-CNNs) [118].

2.5. Smart Grid Paradigm in Railway Transport

The concept of a smart grid (SG) does not have a single unambiguous definition. According to [119], “it combines a set of technologies and end-user solutions and addresses a wide range of policy drivers” in order to integrate the actions of all users connected into the electricity network (electrical grid), from electrical power sources to consumers, and the entities that can perform both tasks (so-called “prosumers”), so that continuous, efficient, economic, and sustainable energy balance can be maintained within the grid [120]. The smart grid paradigm encompasses a wide range of hardware, software, and communication system solutions (**Figure 9**), thus enabling the following advanced functionalities within the electricity grid [119]:

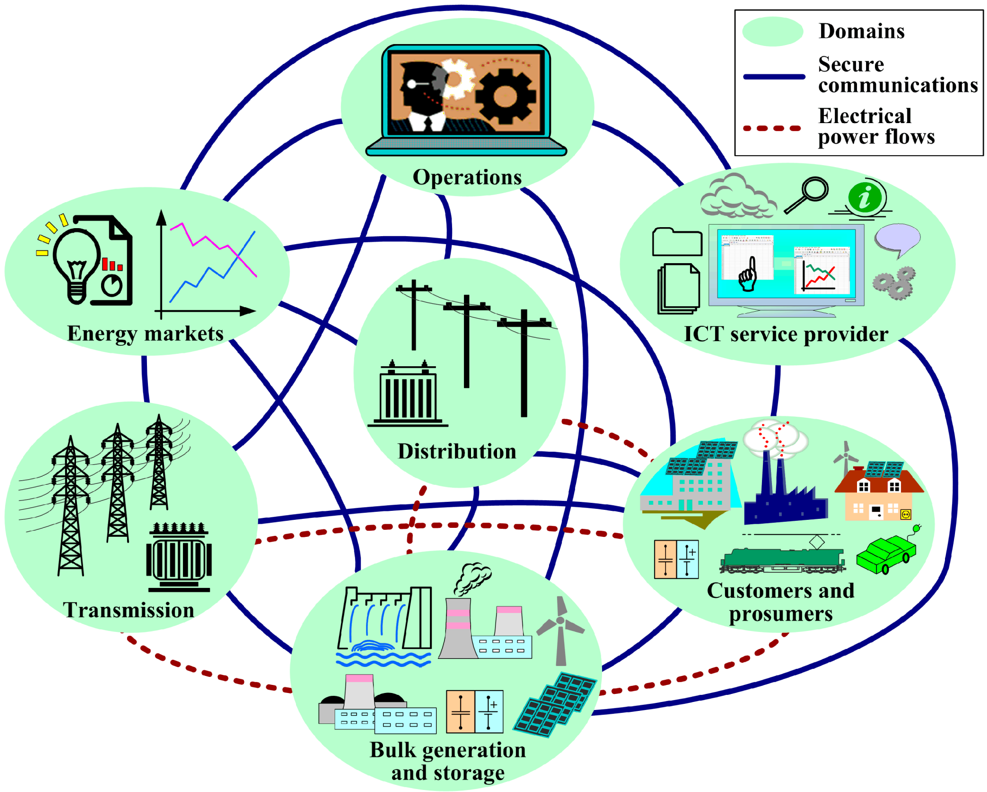

Figure 9. Conceptual model of smart grid.

- Demand response and demand-side management, which is accomplished through the utilisation of smart metering and smart consumers, local or distributed generation (DG), electrical energy storage (ESS), and, generally, any distributed energy resources (DERs) coupled with providing timely information about energy prices [121];

- Renewable energy sources (RES), along with distributed generation, residential micro-generation, and energy storage (the so-called microgrid concept), which have the potential to improve the energy sector's environmental impact [122], and are thus accommodated within the SG paradigm, which also provides means of resource aggregation [123];

- Improved reliability and security of the power supply through an improved resilience to deterministic and stochastic disturbances such as adverse weather conditions and cyber threats [124], and through measures such as predictive maintenance, fault isolation techniques, and an enhancement of the power transfer capabilities [119];

- The optimisation and efficient operation of assets and opening access to markets by means of intelligent distribution system nodes [121], wherein efficient asset management is carried out based on the timely response to highly dynamic demand using enhanced power transmission paths and an aggregated power supply [119];

- Maintaining the power quality, which is key for the correct operation of sensitive equipment [119].

To be able to provide the above functionalities within the SG paradigm, the following technologies need to be massively deployed within the electrical grid [119]:

- Information and communication technologies, which enable two-way communication to ensure the interoperability of automation and control and to ensure connectivity between heterogeneous communication nodes connected to different energy sources and loads [125], with the possibility of using the existing electrical network for narrow-band and broad-band communications (operating network, business network, and consumer network) (appropriate hardware and software for secure communications are needed for energy trading and demand-side response [126] and for the seamless integration of intermittent renewable energy sources into the electricity grid [122]);
- Sensing, control, and automation technologies, such as intelligent electronic devices for protective relaying, smart metering, fault recording, and any other sensing, control, automation and ICT systems for rapid diagnosis and event management [126], and advanced power flow control [123];
- Power electronics and energy storage technologies at different scales (power and energy ratings), including high-voltage direct current (HVDC), flexible alternating current transmission systems (FACTSs), and various back-to-back power converter topologies, which can facilitate the straightforward integration of renewable energy sources and electrical energy storage systems into the electricity grid [127].

A smart grid architecture model (SGAM) [128] is used to describe the complex interplay between the individual parts of a smart grid system [121] and can be divided into five individual layers (business, function, information, communication, and component), as shown in **Figure 10**. Naturally, the information flow within the model depends on reliable ICT resources to timely coordinate the interactions between the aforementioned layers. According to the standard presented in [128], these layers are further divided into different domains and zones, wherein domains cover the complete energy conversion sequence, whereas zones are divided to facilitate different hierarchical levels of the energy management system (see **Figure 10**). As discussed in [129], the SGAM concept is also applicable to the development of advanced energy management control systems in smart railways. A novel Internet of Energy (IoE) concept is proposed as a way of integrating different energy technologies into smart power systems using advanced ICT-based tools that were already developed within the Industrial IoT concept [130].

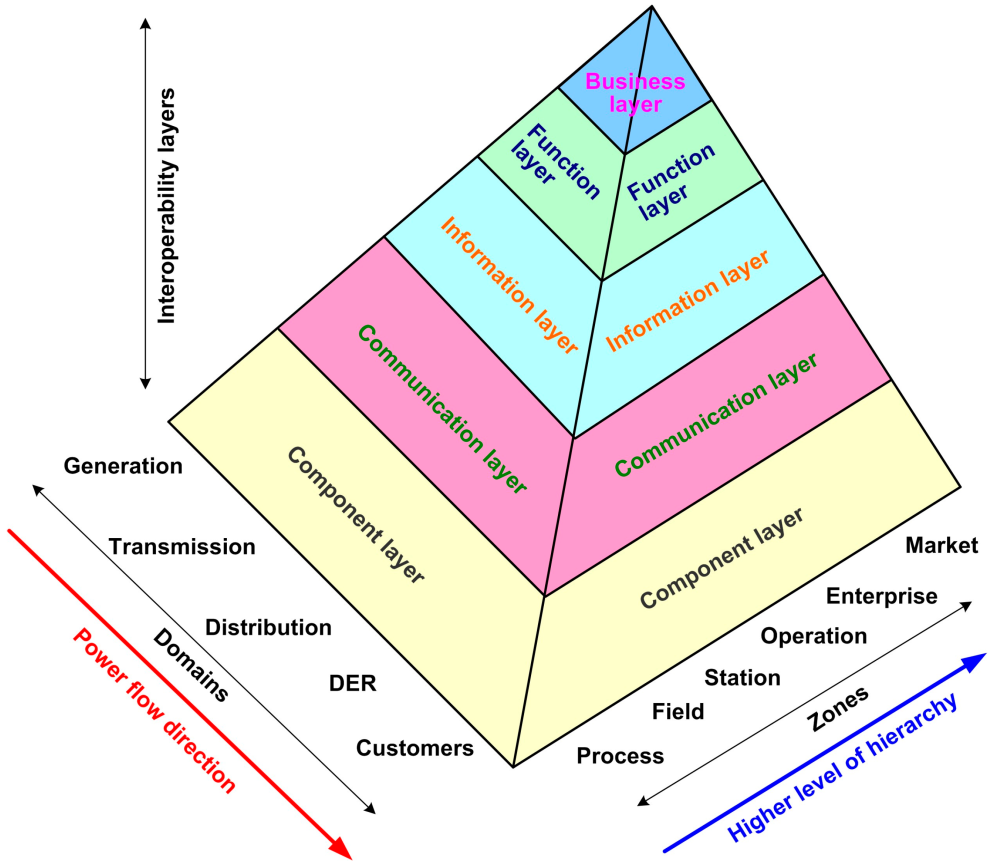

Figure 10. Conceptual representation of smart grid architecture model (SGAM).

Although smart grid technologies are market mature and have proven their benefits through successful implementation and use, such as increased reliability, energy availability, and energy efficiency using advanced ICT systems [131], there is currently relatively little effort in the research and development of smart grids for railway projects. The specific issues of railway transportation safety, security, and availability make the influx of such new technologies much more challenging. In that respect, a particular emphasis needs to be paid to reliable and secure broad-band communications to facilitate the integration of distributed power sources, energy storage systems, and smart energy management systems into the railway power system [132]. As illustrated in **Figure 11**, electrified railway power systems are connected to the main power grid, which provides the bulk power supply for the railway traction, wherein the electrical system operators (ESO) are tasked with balancing the power generation and demand, and the electricity market operators (EMOs) manage energy trading, either via contractual agreements or on energy markets [132]. The railway system operator (RSO) is tasked with controlling the railway traffic to ensure safe and reliable traffic flow, and it is also responsible for controlling the railway power system. In a smart grid for railways scenario, the RSO would also operate the distributed energy resources within the railway power system, that is, the energy storages and distributed generation assets, as shown in **Figure 11**.

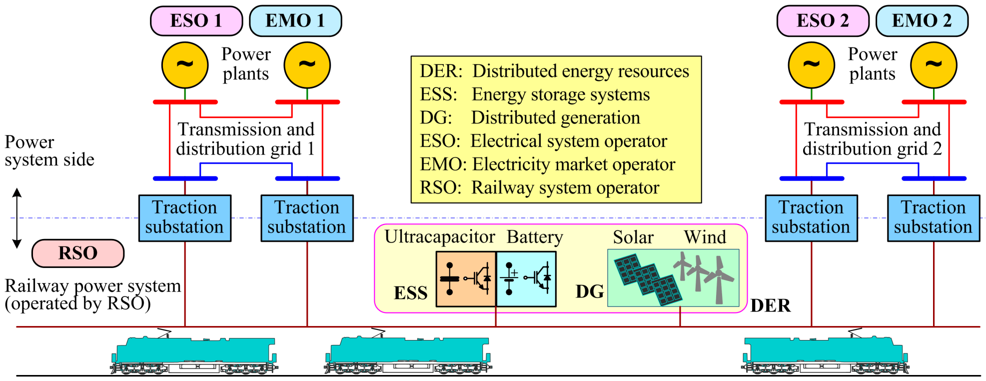

Figure 11. Railway power system interconnection with power distribution, transmission grid, and local distributed energy resources.

To facilitate the. effective control of a railway smart grid, the railway power system obviously needs to incorporate many advanced electrical power subsystems alongside DERs and ESS for local power balancing [132]. The effective power flow control between the railway power grid and the main power grid requires the non-reversible sub-stations (SSTs) to be augmented by power subsystems that are capable of real-time energy balancing, such as reversible sub-stations (RSSTs) and intelligent sub-stations (ISST), as shown in **Figure 12**. Such resources, along with the local ESS, can effectively handle reverse power flows from electric trains equipped with dynamic on-board energy management (DOEM) systems used for kinetic energy recuperation [129]. Since such a railway energy management system (REM-S) interacts with the main power grid and energy markets, its operation needs to be optimised [129] on a daily basis (day-ahead optimisation), which can take into account the daily train schedules, and on a short time scale (with schedules that are 15 min ahead being typical), which needs to fulfil the day-ahead power profile while taking into account the excesses and restrictions of local power production by coordinating between sub-stations and DERs. Real-time operators subsequently fulfil the commanded 15 min power profiles while also taking into consideration the real-time information and power flows from the local power network [129].

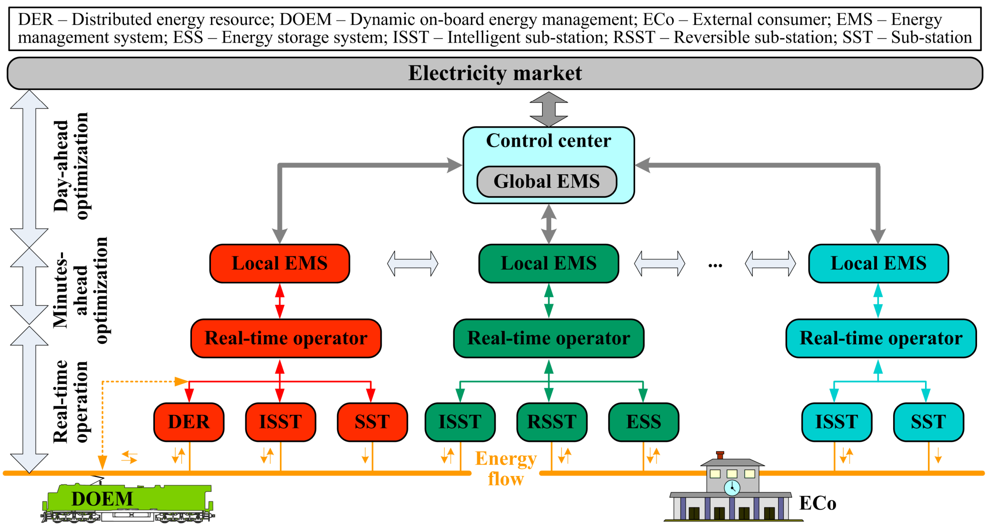

Figure 12. Concept of smart grid-based railway energy management system.

Obviously, the type of distributed energy resources (DG and ESS) and the means of their control would play crucial roles both in the day-ahead optimisation and local power flow control based on short time scale schedules. To this end, reference [133] considers a railway-to-grid smart energy management system based on advanced power converter topologies with electrical energy storages for a DC railway network, which can effectively re-route the energy between the power grid and the railway electrical network and increase their flexibility. Different power converter topologies for the integration of PV energy sources into the railway power grid are assessed in [134], whereas the authors of [135] discuss the use of energy storage systems on-board railway trains and propose a two-level hierarchical energy management system using AI in the form of a fuzzy logic system. It reports between 22.3% and 28.7% of improvement in energy efficiency with on-board ESS. The integration of a regenerative braking energy recuperation system with energy storage and PV systems into the railway power grid was analysed in [136]. Power flow optimisation has been performed by means of MILP and has shown the potential to reduce the cost of operation by about 30% compared to the conventional railway grid scenario.

The expected evolution of the information integration of the modern railway traffic management system and energy management towards the future smart railway, which is characterised by a wide use of wireless communication networks, independent power sources, and wide data processing capabilities of individual transport entities and infrastructure, opens up space for new research and areas that are not covered by this work. Examples of those are traffic regulations, technological problems of timetable management, the issues of maintaining new technological systems that are not directly included in the railway system, and technological systems that have direct consequences on the safety of railway traffic.

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