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Methodologies for the Assessment of Industrial and Energy Assets, Based on Data Analysis and BI

PhD INDUSTRIAL AND MANAGEMENT ENGINEERING

PhD Student: Rossana Coccia

Coordinator: Giulio Di Gravio

Supervisor: Alessandro Corsini

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Abstract

In July 2020, post pandemic onset, Europe launched the Next Generation EU (NGEU) program. The amount of resources deployed to revitalize Europe has reached 750 billion. The NGEU initiative directs significant resources to Italy. These funds can enable our country to boost investment and increase employment. The missions of Italian Recovery and Resilience Plan (PNRR) include digitization, innovation and sustainable mobility (rail network investments, etc.). In this context, this doctorate thesis discusses the importance of infrastructure for society with a special focus on energy, railway and motorway infrastructure. The central theme of sustainability, defined by the World Commission on Environment and Development (WCDE) as "development that meets the needs of the present generation without compromising the ability of future generations to meet their needs'', is also highlighted. Through their activities and relationships, organizations contribute positively or negatively to the goal of sustainable development. Sustainability becomes an integrated part of corporate culture. First research in this thesis describes how Artificial Intelligence techniques can play a supporting role for both maintenance operators in tunnel monitoring and those responsible for safety in operation. Relevant information can be extracted from large volumes of data from sensor equipment in an efficient, fast, dynamic and adaptive manner and made immediately usable by those operating machinery and services to support rapid decisions. Performing sensor-based analysis in motorway tunnels represents a major technological breakthrough that would simplify tunnel management activities and thus the detection of possible deterioration, while keeping risk within tolerance limits. The idea involves the creation of an algorithm for detecting faults, acquiring real-time data from tunnel subsystem sensors and using it to help identify the tunnel's state of service. Artificial intelligence models were trained over a six-month period with a granularity of one-hour time series measured on a road tunnel forming part of the Italian motorway systems. The verification was carried out with

reference to a series of failures recorded by the sensors. The second research argument is relates to the transfer capacities of high-voltage overhead lines (HV OHL), which are often limited by the critical temperature of the power line, which depends on the magnitude of the current transferred and the environmental conditions, i.e. ambient temperature, wind, etc. In order to use existing power lines more effectively (with a view to progressive decarbonization) and more safely with respect to critical power line temperatures, this work proposes a Dynamic Thermal Rating (DTR) approach using IoT sensors installed on a number of HV OHL located in different geographical locations in Italy. The objective is to estimate the temperature and ampacity of the OHL conductor, using a data-driven thermo-mechanical model with a bayesian probabilistic approach, in order to improve the confidence interval of the results. This work shows that it might be possible to estimate a spatio-temporal temperature distribution for each OHL and an increase in the threshold values of the effective current to optimize the OHL ampacity. The proposed model was validated using the Monte Carlo method. Finally, in this thesis is presented study on KPIs as indispensable allies of top management in the asset control phase. They are often overwhelmed by the availability of a huge amount of Key Performance Indicators (KPIs). Most managers struggle In understanding and identifying the few vital management metrics and instead collect and report a vast amount of everything that is easy to measure. As a result, they end up drowning in data, thirsty for information. This condition does not allow good systems management. The aim of this research is help the Asset Management System (AMS) of a railway infrastructure manager using business intelligence (BI) to equip itself with a KPI management system in line with the AM presented by the normative ISO 55000 - 55001 - 55002 and UIC (International Union of Railways) guideline, for the specific case of a railway infrastructure. This work starts from the study of these regulations, continues with the exploration, definition and use of KPIs. Subsequently KPIs of a generic infrastructure are identified and analyzed , especially for the specific case of a railway infrastructure manager. These KPIs are fitted in the internal elements of the AM frameworks (ISO-UIC) for systematization. Moreover, an analysis of the KPIs now used in the company is made, compared with the KPIs that an infrastructure manager should have. Starting from here a gap analysis is done for the optimization of AMS.

Abstract

Nel luglio 2020, dopo l'inizio della pandemia, l'Europa ha lanciato il programma Next Generation EU (NGEU). L'ammontare delle risorse messe in campo per rivitalizzare l'Europa ha raggiunto i 750 miliardi. L'iniziativa NGEU destina all'Italia risorse significative. Questi fondi possono consentire al nostro Paese di rilanciare gli investimenti ed aumentare l'occupazione. Le missioni del Piano Italiano di Ripresa e Resilienza (PNRR) comprendono la digitalizzazione, l'innovazione e la mobilità sostenibile (investimenti nella rete ferroviaria, ecc.). In questo contesto, la tesi di dottorato discute l'importanza delle infrastrutture per la nostra società, con particolare attenzione a quelle energetiche, ferroviarie e autostradali. Viene inoltre evidenziato il tema centrale dello sviluppo sostenibile, definito dalla Commissione Mondiale per l'Ambiente e lo Sviluppo (WCDE) come "uno sviluppo che soddisfi i bisogni della generazione attuale senza compromettere la capacità delle generazioni future di soddisfarne i propri". Attraverso le loro attività e relazioni, le organizzazioni contribuiscono positivamente o negativamente all'obiettivo dello sviluppo sostenibile. La sostenibilità diventa parte integrante nella cultura aziendale. Il primo tema di ricerca in questa tesi descrive come le tecniche di intelligenza artificiale possano svolgere un ruolo di supporto sia per gli operatori della manutenzione nel monitoraggio delle gallerie sia per i responsabili della sicurezza in esercizio. Grazie all'installazione di sensori IoT, è possibile ricavare enormi volumi di dati e fare sintesi di nuova conoscenza in modo efficiente, veloce,

dinamico e adattivo rendendola immediatamente utilizzabili da chi opera su macchinari e servizi a supporto delle decisioni da prendere. Le analisi sensor-based nelle gallerie autostradali rappresentano un'importante svolta tecnologica che semplificherebbe le attività di gestione delle gallerie e quindi l'individuazione di eventuali deterioramenti, mantenendo il rischio entro i limiti di tolleranza. Il lavoro di ricerca prevede la creazione di un algoritmo di rilevamento dei guasti con acquisizione in tempo reale dei dati provenienti dai sensori di galleria, al fine di aiutare ad identificare il livello di servizio della galleria in analisi. I modelli di intelligenza artificiale sono stati addestrati per un periodo di sei mesi con granularità delle serie temporali di un'ora. La galleria campione fa parte del sistema autostradale Italiano. La verifica è stata effettuata con riferimento a una serie di guasti registrati dai sensori stessi. Il secondo lavoro di ricerca riguarda le capacità di trasferimento di energia elettrica delle linee aeree ad alta tensione (HV OHL), essa infatti è limitata dalla temperatura critica delle diverse linee elettriche, che dipende dall'entità della corrente trasferita e dalle condizioni ambientali, cioè temperatura ambiente, vento, ecc. Al fine di utilizzare le linee elettriche esistenti in modo più efficace (in un'ottica di progressiva decarbonizzazione) e più sicuro, questo secondo lavoro propone un approccio di Dynamic Thermal Rating (DTR) che utilizza sensori IoT installati su una serie di HV OHL situate in diverse località geografiche in Italia. L'obiettivo è stimare la temperatura e la potenza al limite termico del conduttore dell'OHL, utilizzando un modello termo-meccanico guidato dai dati con un approccio probabilistico bayesiano, al fine di migliorare l'intervallo di confidenza dei risultati. Questo lavoro dimostra che è possibile stimare una distribuzione spazio-temporale della temperatura per ogni OHL e un aumento dei valori di soglia della corrente effettiva per ottimizzare la potenza al limite termico dell'OHL. Il modello proposto è stato validato utilizzando il metodo Monte Carlo. Infine, in questa tesi viene presentato uno studio sui Key Performance Indicators (KPIs) come alleati indispensabili del top management nella fase di controllo degli asset. Questi ultimi sono spesso sopraffatti dalla disponibilità di un'enorme quantità di KPI. La maggior parte dei manager fatica a comprendere ed identificare le poche metriche gestionali essenziali, quindi raccoglie e riporta una vasta quantità di tutto ciò che è facile da misurare. Questa condizione non consente una buona gestione dei sistemi. L'obiettivo di questa ricerca è aiutare l'Asset Management System (AMS) di un gestore di infrastrutture ferroviarie a dotarsi di un sistema di gestione dei KPI in linea con le normative di Asset Management ISO 55000 - 55001 - 55002 e dalla linea guida UIC (Unione Internazionale delle Ferrovie). Questo lavoro parte dallo studio di queste normative, prosegue con l'esplorazione, la definizione e l'utilizzo dei KPI. Successivamente vengono identificati e analizzati i KPI di un'infrastruttura generica, ed in particolare per il caso specifico di un gestore infrastruttura ferroviaria. Questi KPI vengono agganciati agli elementi core del framework di AM (ISO-UIC). Inoltre, viene effettuata un'analisi dei KPI attualmente utilizzati in azienda, confrontandoli con i KPI che un gestore dell'infrastruttura dovrebbe avere. A partire da qui viene effettuata una gap analysis per l'ottimizzazione dell'AMS.

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Nomenclature

Acronyms

BI	Business Intelligence
KPI	Key Performance Indicator
HS	High Speed Rail
AI	Artificial Intelligence
ERP	Enterprise Resource Planning
IRAM	Italian Risk Analysis Method
VAD	Expected Damage Value
ALARP	As Low As Reasonably Practicable
EDA	Exploratory Data Analysis
HV	Hight Voltage
OHL	Overhead Lines
DTLR	Dynamic Thermal Line Rating
RES	Renewable Energy Source
IoT	Internet of Thing
DTR	Dynamic Thermal Rating
EHV	Extra-Hight Voltage
AM	Asset Management
BS	British Standard
UIC	International Union of Railways
ESG	Environmental Social Governance
SME	Medium-Sized Enterprises
DGP	Gross Domestic Product (PIL)
HS	High Speed
NGEU	Next Generation EU

1 Introduction

1.1 Importance of transport and energy infrastructures

The infrastructures are considerate critical component for people lifestyle, smooth working of economy, national security and welfare of our entire society. For this reason, infrastructure has been front and center in the executive and legislative areas of our government. When it is spoken about infrastructure, most people automatically think of roads and bridges, these are the things most visible to and most frequently noticed by average citizens. However, infrastructure also includes dams, rail and other transportation lines (for people and freight); electric, gas and water utilities; schools; sewer lines; tunnels; waterways; airports; energy distribution lines; wind-turbine farms; and so much more.

As states and societies continue to struggle with the pandemic, an essential element of the post-Covid recovery will be the capacity to revive both public and private investments in infrastructure, thereby boosting growth and employment. Covid-19 pandemic came at a time in history when it was already evident and shared the need to adapt the current economic model towards greater environmental and social sustainability. In December 2019, the president of the European Commission, Ursula von der Leyen, presented the European Green Deal which aims to make Europe the first climate-neutral continent by 2050. In July 2020 of the Next Generation EU (NGEU) program was launched. NGEU marks a momentous change for the EU. The amount of resources put in place to boost investment and reform amounts to EUR 750 billion, more than half of which, 390 billion, are grants. The allocated resources to the Recovery and Resilience Facility (RRF) the largest component of the program, are raised through the issuance of bonds of the EU. NGEU initiative channels considerable resources to countries such as Italy which, although characterized by levels of per capita income levels in line with the EU average, have recently suffered from low economic growth and high unemployment. The allocation mechanism between member states reflects not only structural variables such as population, but also contingent variables such as the loss of gross domestic product related to the pandemic. NGEU funds can enable our country to boost investment and increase employment, also to resume the process of convergence towards the richer countries of the EU. In Figure 1 , it is presented the allocation of recovery and resilience facility grants.

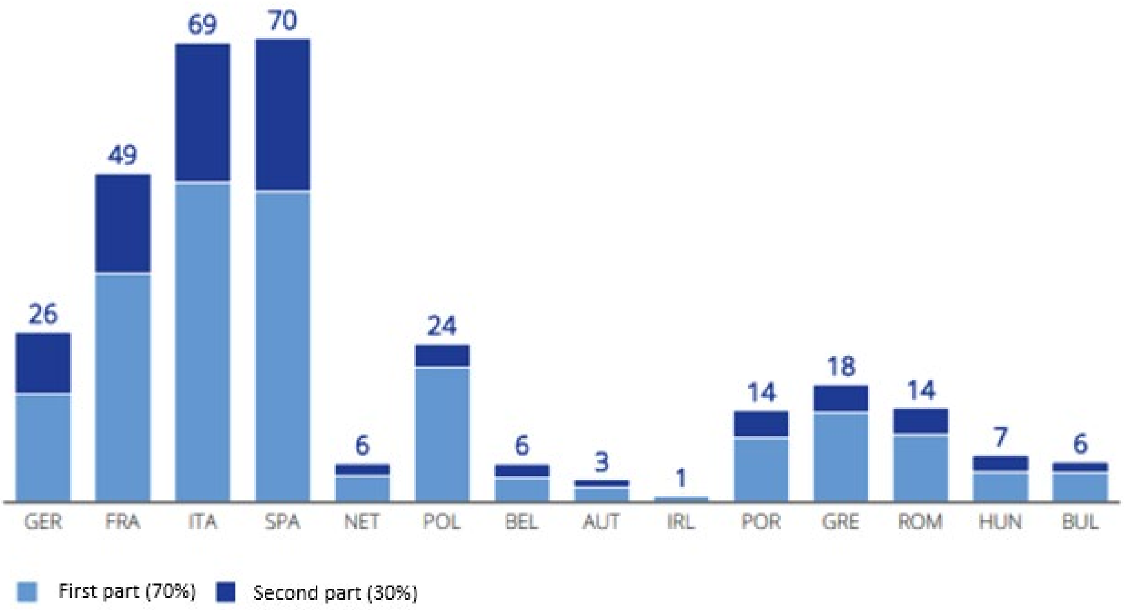


Figure 1. Allocation of Recovery and Resilience Facility Grants (non-repayable grants) - RRF (EUR billion). Source: PNRR

Infrastructure investment will answer to the new social and environmental needs, starting from health and poverty reduction, as well as climate change and the digitalization drive. Under the Recovery and Resilience Facility (RRF) promoted by the European Union, Italy will receive 191 billion euro in which infrastructure investments will play a fundamental role. The effort to revitalize Italy outlined in this plan revolves around three strategic axes shared at the European level: digitalization, innovation, ecological transition and social inclusion. The digitization and innovation of processes, products and services represent a determining factor in the country's transformation and must characterize every reform policy of the plan. Italy has accumulated a considerable delay in this field, both in the skills of citizens, and in the adoption of digital technologies in the production system and in public services. Recovering this deficit and promote investment in digital technologies, infrastructures and processes, is essential to improve Italian and European competitiveness; foster the emergence of strategies for diversifying production; and improve adaptability to market changes. The ecological transition, as indicated by the UN Agenda 2030 and the new European targets for the 2030, underpins the new Italian and European development model. Intervening to reduce emissions polluting emissions, prevent and combat land degradation, minimize the impact of productive activities on the environment is necessary to improve the quality of life and environmental safety, as well as to leave a greener country and a more sustainable economy to future generations. The ecological transition can also be an important factor in increasing the competitiveness of our system production, stimulate the start-up of new, high value-added entrepreneurial activities and encourage the creation of stable employment. The third strategic axis is social inclusion. Ensuring full social inclusion is fundamental to improve territorial cohesion, help the economy grow and overcome deep inequalities often accentuated by the pandemic. The three main priorities are gender equality, protecting and empowerment of young people and overcoming territorial gaps. Women's empowerment and combating gender discrimination, the enhancement of young people's skills, capacities and employment prospects of young people, territorial rebalancing and the development of the 'Mezzogiorno' are not single interventions, but pursued as cross-cutting objectives in all components of the PNRR. In Figure 2, it is presented the allocation of RRF resources to strategic axes (percentage of total RRF).

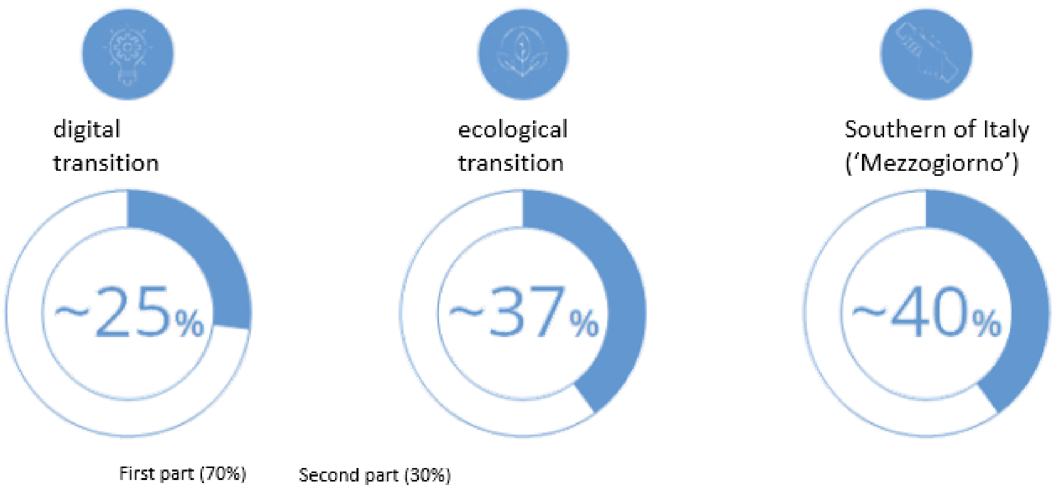


Figure 2. Allocation of RRF resources to strategic axes (percentage of total RRF). Source: PNRR

1.1.1 Motorway networks

Road infrastructure represents a key necessity of social and economic development of any country. The road infrastructure includes all types of roads in a very given space, as well as numerous structures and serve to move passengers and product. It includes all road classes, facilities, structures, assemblage and markings, electrical systems, so on required to supply for safe, untroubled and economical traffic (Masarova. J & Ivanova. E, 2013) [1]. Road transport covers transporting passengers and carrying product regardless the destination, the relatively high speed and without time restrictions. Road transport and its infrastructure alter to hold individuals furthermore as materials, raw materials, semi-finished and finished product meant available. Tunnels are important part of transport infrastructure. Using tunnels for transportation allows having efficient underground, redirecting traffic congestion from town centers, decreasing landscape damage due to major roads passing through open spaces, and more. Service level is an important parameter for flowing traffic. Road or rail tunnel maintenance should be thought of from the life cycle value perspective. Freeway tunnel systems embody traffic infrastructure, ventilation networks, electrical wiring networks and many others. Among these elements should be in a very useful state to achieve a suitable service level of the tunnel. With the appearance of recent technologies, it's currently potential to observe and track the condition and practicality of those things. Long term usefulness and behavior will be evaluated by taking into thought all tunnel options, like pure mathematics, geologic and hydrogeological conditions, age, construction techniques, operation conditions and material quality [1]. Road infrastructure affects the flexibility and quality of the personnel, that is reflected within the employment level. Furthermore, higher employment level makes the quality of living grow. The degree to that the road infrastructure is developed has a sway on many areas, like for example the event of commercial enterprise, inflow of foreign investments, regional development, etc. Eventually, all the indicators – employment, salaries, consumption, savings, investment, benefits of tourism – will have an impact on the volume of GDP (Gross Domestic Product), the key macroeconomic indicator, which measures the economic output of the state. In addition, transport is significant in international context in terms of foreign trade and cooperation in different areas. For transport infrastructure, like all other types of infrastructure, maintenance constitute an inevitable part of transport policies in fact tends to wear, tear, and deteriorate with age and use. Traditionally maintenance strategies are gradually shifting towards data-driven approaches, exploiting the power of digital technologies, big data analytics and advanced forecasting methodologies [2]. The Ministry of Infrastructures and Sustainable Mobility (Mims) has accepted the intervention strategies submitted by the 72 Inland Areas of the national territory to improve availability and road safety, for which 300 million euros have been allocated from the National Complementary Plan (NCP) to the National Recovery and Resilience Plan (NRRP). The protocols approving the operational plans prepared by the motorway concessionaires and the decree prepared by Anas for the implementation of dynamic monitoring systems for the remote control of bridges, viaducts, and tunnels in the main road network, involving an investment of 450 million euro.

In particular, the program for the 72 Inner Areas (which include 1,077 municipalities, with a total of 2 million inhabitants) envisages the improvement of mobility safety and accessibility through interventions on the secondary road network (provincial and municipal roads), also recovering the maintenance deficit recorded in past years. The objective is to upgrade about 2,000 kilometers of roads and related works of art (bridges, viaducts, etc.). The resources have been allocated among the Inner Areas according to criteria that take into account the resident population, the length of the roads, seismic and hydrogeological risks, and the availability of local public transport services. As far as the dynamic monitoring of bridges, viaducts and tunnels on the national road and motorway network is concerned, the 26 motorway concessionaires and ANAS have submitted their operating plans, which have now been approved by the Ministry. The investments financed by the NCP aim at improving infrastructure safety through the census, classification and risk management for 12,000 structures on the main road network, 6,500 of them will be equipped with remote control instrumentation, in this way, they will be subjected to safety management procedures involving network analysis, inspections, digitized system management, prioritization and implementation of interventions [3].

1.1.2 Electricity grid and microgrids

The electricity sector is crucial in supplying energy to society and make sure continuity for all structured, virtual, dynamic services. For this reason, networks must be resilient to the maximum. For Terna, in the 2020 development plan, the targets set in the proposed Integrated National Energy and Climate Plan envisage by 2025 the complete phase-out from coal, and in 2030 the cover half of gross electricity consumption (55.4%) with non-programmable RES, about 40 GW of new capacity. The actions identified by Terna for energy transition and de-carbonization reflect naturally reflect an approach from its own point of view and fall into four categories of intervention: long-term price signals, market evolution and integration, innovation and digitalization, grid investments, such as north-south backbone and reinforcements South and Islands networks, investments for voltage regulation and increasing system inertia, interconnections with foreign countries, resilience. Similarly, Enel, in its 2020-2022 strategic plan, approaches the energy transition process from the Group's point of view. The reality of the fast railway network to be extended to the entire national territory, in order to implement a real unification, requires the electricity grid to adapt its power supply capacity to the power necessary to meet demand. The necessary continuity of service requires redundant development throughout the territory, also considering the high seismicity. In areas at seismic risk, strategic facilities and those equated to strategic. Strategic structures (use class IV), which require maximum resilience of the technological systems (especially electrical) for continuity of service, are: hospitals, data processing, fire brigade headquarters, railway stations, airports, local coordination centers. These facilities are relevant in normal conditions and more relevant in situations of seismic events, when more advanced services are required, service restoration times from zero to a few seconds, as well as adequate and competent personnel. Depending on the level of protection required, mechanical and electrical design criteria are identified, installation selection and sizing, structuring of system with an electrical distribution system. Digitization, broadband and 5G communication networks will promote the spread of the Internet of things IoT, blockchain. The foreseeable impact of IoT on the use of energy electricity can enable an epoch-making evolution in the structure and operation of grids electricity grids and facilitate the efficient establishment of microgrids. The beneficial impact of IoT on electricity utilization is enabling an emancipated role of electricity from distribution, transmission and generation. The simultaneous use of energy will no longer be random but managed. The epoch-making evolution consists in the possibility of setting up microgrids 'dynamic' microgrids of tens of kilowatts, this systems could scale up to gigawatt 'virtual macro-grid' systems. IoT, at a general level, promotes the establishment of clusters of 'things enabled to communicate' involved in persistent interactions (society of things), such as household appliances, mobile phones, vehicles (IoVs) and countless other objects.

1.1.3 Railway Infrastructure

The railway infrastructure consists of the track and related civil works, as well as the technological installations for traction, signaling and safety systems. Currently, 90% of passenger traffic in Italy is by road (860 billion passenger-km per year), while only 6 % of passengers travel on the railways (compared to 7.9 per cent in Europe), with the consequence that the transport sector is among those most responsible for climate emissions, with a contribution of 23.3% of total greenhouse gas emissions (despite having decreased by 2.7% in the period 1990-2017, source ISPRA Yearbook, 2020). In the 'Strategy for smart and sustainable mobility EU's 'Strategy for smart and sustainable mobility' of 2020, the European Commission set as a goal the doubling high-speed rail traffic by 2030 and tripling it by 2050. The commitment, referred to Italian President Draghi refers to, requires rapid decisions to be taken on strategic issues including which includes the Italian High Speed Rail (HS). In this context, this would mean giving new life to a project that began twelve years ago and which today has almost 1,100 km of operational network (cf. Business Plan, 2021) intended for passenger traffic. Some characteristic data: against a unit infrastructure cost (millions of euros/km) more than double that of other European countries, the Italian HS network ranks sixteenth in the world ranking, for territorial coverage (km of line/km2) and in seventh place in terms of commercial speed of rolling stock (300km/h). On a European scale it is fourth in terms of extension of HS lines, after Spain, France and Germany. If, then, one considers the extension in terms of percentage of the high-speed network compared to the total, Italy takes third place (~6.50%), following, albeit at a distance, Spain (~24%) and France (~10%). A project, that of the Italian HS, today more than ever essential for the economic and financial subsistence and for the environmental and social sustainability of our country. A very ambitious, if we also take into account the opportunities for the transfer of technological know-how encouraged by a large-scale internationalization strategy implemented by Rete Ferroviaria Italiana (RFI), the national railway infrastructure manager. The training and innovation project undertaken by RFI over the years appears, however, to be congruent with the main strategic objectives outlined by the current government to support the recovery of the country's system. RFI's 2021-2024 Business Plan is divided into 3 business areas: public transport local, long-distance and freight transport. The interventions for local transport are aimed at improving quality standards for the relaunch of the sector, particularly in the large metropolitan areas. The planned measures are aimed, among other things, at enhancing rail-road integration, increase the capacity of saturated lines and nodes, resolve major interference between flows critical facilities, speed up suburban sections, develop urban interchange points and improve accessibility to stations, increase the regularity of services by implementing new technologies on the line and in stations. Investments on the long-distance network, aimed at improving network performance, are mainly oriented towards performance upgrading, the development of the HS/HC (High Speed/High Capacity) network and the speeding up of HS antenna sections. The interventions on freight transport, finally, pursue the objective of upgrading the rail corridors, as well as the main land and port terminals and their connections.

1.2 Sustainability as an infrastructure integrated factor

Sustainable infrastructure not only enables sound economic development, job creation and the purchase of local goods and services, it also enhances quality of life for citizens, increases positive impacts (benefits), helps protect our vital natural resources and environment, and promotes a more effective and efficient use of financial resources.
Approximately 70 % of global greenhouse gas emissions are produced by the construction, development and maintenance of infrastructure for energy, transportation and buildings. The strategy for a sustainable future must therefore entail prioritizing investments in certain key infrastructure sectors, that’s why sustainability must become an integrated factor in all phases of a project. According to some estimates, 75% of infrastructure projects that will be implemented by 2050 have not yet been planned, creating the opportunity to better integrate sustainability criteria.[4] Some of the priority goals to be pursued are: a greener

energy sector; greater energy efficiency of buildings; low-impact mobility; digital infrastructure and more efficient management of water resources and waste. In planning new infrastructure, as well as managing and maintaining existing infrastructure, sustainability objectives should be taken into account from a long-term perspective.

In Italy, according to the Italian Alliance for Sustainable Development, (80%) of emissions is produced by transportation (38%), buildings (27%) and industry (15%). In the transportation sector, the same grouping has calculated that financial needs amount to over 60 billion euro (of which 33 billion for mass rapid transit infrastructure and over 25 billion for the renewal and improvement of public transport vehicles for electric mobility and biking, pedestrians and safety). Furthermore, 60% of residential buildings in Italy are over forty-five years old and therefore not covered by the first law on energy savings dating from 1976, making the need to intervene in the construction sector evident [5]. To achieve these goals, TF proposed to develop a transparent legislative framework to ensure that sustainability criteria are included in planning, investment criteria and procurement phases across ministries and infrastructure sectors and to standardize sustainability requirements and studies on the impact of environmental factors on investment performance. Moreover, it is called to support the integration of sustainability criteria in ESG (Environmental Social Governance) standards for infrastructure and to facilitate funding mechanisms for sustainable infrastructure – such as "green bonds", green investments and finance for climate change. The infrastructure gap in Italy is very pronounced. Compared to other European countries. Italy is among those with the largest gap in investments in the infrastructure sector. The estimates of the Global Infrastructure Outlook of the G20 show a gap of over 373 billion US dollars from 2021 to 2040 (239 billion for railways, 39 billion for the energy sector, 37 billion for ports, 14 billion for airports and 1 billion for roads) [6]. The use of data and the most advanced analytics systems (machine learning, artificial intelligence and sensor systems) embodies a potential improvement in all processes of planning, design, delivery and operation of infrastructure [7]. Infrastructures are progressively connected to each other, which means that failure in one infrastructure asset will affect the performance of the entire system. Maintenance regimes are expected to ensure the performance and functionality for which the transport infrastructure assets were designed at the lowest possible costs. Performance can be defined in terms of quality, safety and environmental impacts. Maintenance is defined as a combination of all technical, administrative and managerial actions during the life cycle of an item intended to maintain it in or restore it to a state in which it can perform the required function. Infrastructure maintenance strategies are gradually shifting on data-driven approaches. They utilize the power of digital technologies, big data analytics and advanced forecasting methodologies. Data-driven approaches have achieved momentum in transport infrastructure maintenance as a result of four simultaneous technological innovations [8].

1. the development of digital technologies has resulted in the digitalization of society, industry and transport, which facilitates data sharing.
2. computing technologies have provided the necessary horsepower for running the digital infrastructure.
3. the Internet of Things and sensor technology have increased the potential for automating reporting from sensors that capture and measure new phenomena and provide data sets that flow through digital infrastructures.
4. artificial intelligence (AI) has helped to extract information from vast amounts of data, recognize patterns beyond the capacity of individual observation and exploit digital infrastructure and computing power.

2 Data analysis and use of BI

Business Intelligence (BI) is defined as a decision-making process supported by the integration and analysis of an organization's data resources, it plays an increasingly more critical role in companies because information is identified as fundamental resource for the development [14]. Data constitutes a new class of economic asset, similar to currency or gold [9], for this reason BI represent a challenge for information technology—Industry 4.0—as well as a very important management issue[10]. Business environments are becoming complex in the contour of Industry

4.0. Therefore, to provide quick responses in these dynamic markets, companies require innovations and advanced technologies [11]. In this perspective, technological tools, such as business intelligence (BI), are required both for processing information and for making correct decisions at corporate level. If this technological tool is implemented in an organization, it may provide several benefits such as architecture, efficient information and customer data management [12]. With this approach, companies may acquire a clearer picture of how important BI becomes in all different environments. The highly unstable business environment, as well as the opportunities arising within the economy, require a fast and efficient decision-making process. Tracking these dynamic changes within and outside organizations while maintaining sustainable goals is indeed a challenging feat. However, this is possible because of the different modern concepts and tools available such as Industry 4.0 and BI [13].

Traditional BI originally emerged in the 1960s as a system of sharing information across organizations. It further developed in the 1980s alongside computer models for decision-making and turning data into insights before becoming specific offering from BI teams with IT-reliant service solutions. About the definition of BI, is possible to say that it refers to capabilities that enable organizations to make better decisions, take informed actions and implement more efficient business processes, combines business analytics, data mining, data visualization, data tools infrastructure and best practices. Business Intelligence has evolved to include more processes and activities to help improve performance. These processes are:

- Data mining: using databases, statistics and machine learning to uncover trends in large datasets.
- Reporting: sharing data analysis to stakeholders so they can draw conclusions and make decisions.
- Performance metrics and benchmarking: comparing current performance data to historical data to track performance against goals, typically using customized dashboards.

- Descriptive analytics: using preliminary data analysis to find out what happened.
- Querying: asking the data specific questions, BI pulling the answers from the datasets.
- Statistical analysis: taking the results from descriptive analytics and further exploring the data using statistics such as how this trend happened and why.
- Data visualization: turning data analysis into visual representations such as charts, graphs, and histograms to more easily consume data.
- Visual analysis: exploring data through visual storytelling to communicate insights on the fly and stay in the flow of analysis.
- Data preparation: compiling multiple data sources, identifying the dimensions and measurements, preparing it for data analysis.

Industry 4.0 is a digital revolution marked by technology that takes advantage of big data and artificial intelligence (AI) to develop automatic learning systems. Manufacturers in today's marketplace seek to achieve business intelligence through the compilation, analysis and sharing of data across all key functional domains in order to achieve production excellence. Big data refers to data sets that are too large or complex to be dealt with by traditional data-processing application software. The collection of big data is huge in volume, yet growing exponentially with time. It is a data with so large size and complexity that none of traditional data management tools can store it or process it efficiently. Big data analytics is the complex process of examining big data to uncover information like hidden patterns, correlations, market trends and customer preferences with the aim of help organizations make informed business decisions. Big data analytics is a form of advanced analytics, which involve complex applications with elements such as predictive models, statistical algorithms and what-if analysis powered by analytics systems. Organizations can use big data analytics systems and software to make data-driven decisions that can improve business-related outcomes. The benefits may include more effective marketing, new revenue opportunities, customer personalization and improved operational efficiency. With an effective strategy, these benefits can provide competitive advantages over rivals.

The benefits of using big data analytics include:

- Quickly analyzing big quantities of data from different sources, in many different formats and types.
- Rapidly making better-informed decisions for effective managing, which can benefit and improve the supply chain, operations and other areas of strategic decision-making.
- Cost savings, which can result from new business process efficiencies and optimizations.
- A better understanding of customer needs, behavior and sentiment, which can go ahead to better marketing insights, as well as provide information for product development.
- Improved, better informed risk management strategies that draw from large sample sizes of data.
- Utility companies can utilize data analytics to identify energy consumption and energy saving to manage power outages, figure out peak times and to set energy pricing.

Businesses and organizations track performance against these goals, they collect the necessary data, analyze it, and determine which actions to take to reach their objectives.

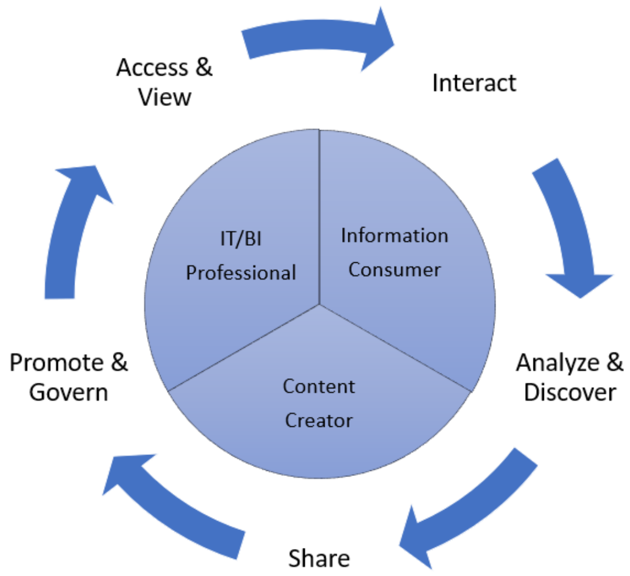


Figure 3. The modern analytics workflow

Nevertheless, companies can use the procedures of analytics to continually improve follow-up questions and iteration. Business analytics shouldn't be a linear process because answering one question will possibly lead to follow-up questions and iteration. Instead, thinking of the process as a cycle of data access, discovery, exploration, and information sharing Figure 3. A large amount of data is taken by organizations in different systems such as maintenance management, Enterprise Resource Planning (ERP), process control, process historians, condition monitoring, asset integrity management and a plethora of spreadsheets. Usually, these data sets are collected and analyzed autonomously, however, maintenance and reliability practitioners frequently have to bring data together from multiple sources to support decision making or to recognize improvement opportunities. The digital age provides us with a dizzying array of big numbers. A few keyword searches and clicks and you can find all type of numbers and statistics: Gas turbines generating 500+ gigabytes of data every day, more than 50 billion devices to be connected to the internet of things (IoT devices), 40,000 exabytes (trillion gigabytes) of stored data by 2020, and new terms invented to cope with the exponential growth – the dinosaur-like Brontobytes sloping the scales at 1027 bytes caught this father's attention [15] and [16]. Financial numbers are no less extraordinary, according to a recent McKinsey report [17], "the IoT brings with it a total potential economic impact of up to $11.1 trillion by 2025". Most suitably for us, the resources sector is likely to be affected significantly, where the economic effect of connected devices and analytics may reach $1T. Crucially, the report also shows a picture of winners and losers; winners are the companies that could find ways to obtain insights and value the data extracted from their installed IoT devices, and the stragglers are those that are losing out to competitors. The Accenture 2017 Digital Refinery Survey [18] confirms that the current focus is clearly on cost reduction, and while "new digital technologies are not currently the top investment priority", digital spend will increase in the upcoming years to support this. Of that digital spend, analytics has been identified as having the greatest potential effect on operational performance. Even though analytics is nothing new, what has changed is the volume and variety of data that can now potentially be analyzed. "Big data" essentially describes a new opportunity provided by the structured rows and columns stored in today's data warehouses, databases and spreadsheets, and the unstructured video, sound and images being captured by new technologies (drones, thermal cameras, etc.) and stored in new "data lakes". So it is possible to understand the benefits that these new data sets may deliver, "big data" challenge as a journey of developing capability (Figure 4) and realizing benefits from multiple smaller applications across many parts of the business.

Figure 4. Capability maturity model for analytics

In the context of BI software, data visualization is a fast and effective method of transferring information from a machine to a human brain. The idea is to place digital information into a visual context so that the analytics output can be quickly ingested by humans. The advanced technology is enabling companies to not just look at their own historical data, but also to predict future behavior or outcomes. The enormous development of sensors and measurement systems allows to collect a huge volume of data relating to the operation of each individual equipment and those relating to the operating status of the systems. Many of these data are linked to monitoring mechanisms of some key components, and therefore the analysis and data acquisition proceeds in real time. For example, it is compared with threshold values, the exceeding of which may indicate a deterioration in performance, or it can be used in a more sophisticated way for control purposes. Most of the data is stored and preserved, at least for a certain period, in the company's electronic archives, but this enormous amount of data and therefore information is often under-used, because the data is analyzed with classical statistical tools [19]. The scientific and industrial communities agree that intelligent exploitation of the huge amount of data available today in companies will be a source of competitive advantage in the global market, as well as a tool for improving the efficiency and sustainability of production cycles. Thanks to neural networks, artificial intelligence now allows the prediction or early recognition of operating anomalies and failures. These systems owe their suggestive name to a strongly interconnected architecture, inspired by that of the human nervous system, which, like this, breaks down a complex operation into many simpler operations carried out by elementary computing units, called “neurons”. Neural networks are equipped with "learning" mechanisms: algorithms that dynamically modify the internal parameters of the network based on experimental data. In the case of fault diagnosis, special neural networks can recognize within a very large number of measured variables, those factors that are the most significant "warning signs" of the fault itself and, on the basis of these signals, detect in advance of the occurrence of an anomaly. Specialized neural systems can also be employed to recognize rare events, since failures are much less frequent than normal operating conditions.

In order to respond to the required digitalization by PNRR, the dissertation topic is about the development of data-driven methods for specific infrastructure systems like motorway tunnels, electricity grid, and railways infrastructure. The study and research activities were mainly focused on the analysis of data coming from IoT sensors installed in tunnels and on the HV power lines conductors. The attention is also given to the importance of right KPIs, focused on the case of a railway infrastructure, since the goodness of an asset management system is based on the ability to assess the performance of the assets themselves.

3 Key Performance Indicators

KPIs are key performance indicators and are used by managers to understand whether the activities they manage are being conducted successfully. The points of observation can be multiple. Using the right KPIs allows them to highlight performance and highlight the areas that need attention and improvement, i.e. the critical areas in any given activity. In a sense, they quantify and measure what has been done in the course of the activity. Without the right KPIs, managers risk navigating in the dark with the risk of sinking.

It is therefore vitally important to understand and identify a few meaningful indices that, when measured appropriately, can provide insight into the performance of the managed business. One of the problems is that most managers, struggling to identify the few essential management metrics, consequently collect and report a large amount of data.

Therefore, it is necessary to define meaningful KPIs that are capable of analyzing the performance and most important aspects of the company as a whole. Failure to discern the right indices can often lead to errors in evaluation.

KPIs can therefore be seen as: 'the fundamental, critical, synthetic, meaningful and prioritized information that allows the company's performance to be measured in its most diverse aspects’.

Explicitly, they are defined as:

- critical, in that management makes its choices on them;
- synthetic, because they are expressed by a simple or compound variable;
- significant, in that they well represent the business phenomena to which they refer;
- priority, due to their indispensable nature in planning and control cycles and risk assessment at all corporate levels (strategic, management, operational).

Structures (companies, administrations) with established processes and strategies simply adapt their objectives to existing and established metrics. The development of KPIs starts from the knowledge of the objective that the structure aims to achieve and must provide information and answers to what is needed. The ability to define and correlate them provides the tools for rapid analysis and effective decision-making. It is essential to know what the information needs are and what questions need to be answered before introducing any KPIs.

One of the defining characteristics of data is the heterogeneity of the sources from which they come. Sources that, today more than ever, continue to change. Proper data management starts here: monitoring of sources and careful evaluation of new data sources. The flow of incoming data is a major challenge: the company must build a 'digital dam' to ensure that the huge flow of data is controlled and can flow intelligently into all departments of the company. Advanced data management tools enable the enterprise to channel data, manage high-speed streaming and master the catalogue of information it possesses. The enterprise must not feel overwhelmed by a large amount of data, but must also be aware that it must be managed carefully and strategically as any critical asset deserves. For that data to be useful, it needs to be given context. Raw data can only become constructive information if it is legitimized by a set of parameters, such as:

- where they come from
- how they can be used and what they mean in relation to other data.

Data are not always useful in the short term. Some of it may seem 'useless' for the company's current core business, but it would be a serious mistake to discard it. The opportunity offered by Big Data today, i.e. the analysis of huge amounts of data to derive useful information for business, is the development of innovation. Businesses today need to be able to grow their 'treasure trove', using Big Data management to combine structured and unstructured data, cataloguing these data intelligently and with some foresight so that they can be rapidly available in the future. A repository of Big Data could be exploited to expand an area of business or allow a company to enter a new business segment on the basis of solid market information. The Big Data base is the critical asset to leverage not only today, but also tomorrow. Intelligent Storage tools, supported by Artificial Intelligence algorithms, are fundamental for advanced data architecture models to properly manage data, protect it and make it available in an agile and fluid way.

The mass adoption of Big Data lives its full potential only if the data is made accessible and usable by every department of the enterprise, from sales and marketing to IT. Big Data Management, in short, ensures that this information becomes an integral part of the corporate culture: the more people who have access to it, the more opportunities there will be to give solidity to an insight. In this way, data-driven strategies enhance the potential of human resources. Raw data is analyzed and contextualized, generating information and knowledge that improves business performance.

Today, thanks to platforms such as 'data lakes' and 'Hadoop' for data storage, and technologies charged with extracting, managing and analyzing data in real time, it is finally possible to master this immense volume of data, Figure 5-6.

1. Collection
- Generation
- Acquisition
- Storage

2. Processing
- Extraction
- Integration
- Analysis

3. Interpretation
- Interpretation
- Decision

Figure 5. Phases to which the data are subject. [elaboration AGCM].

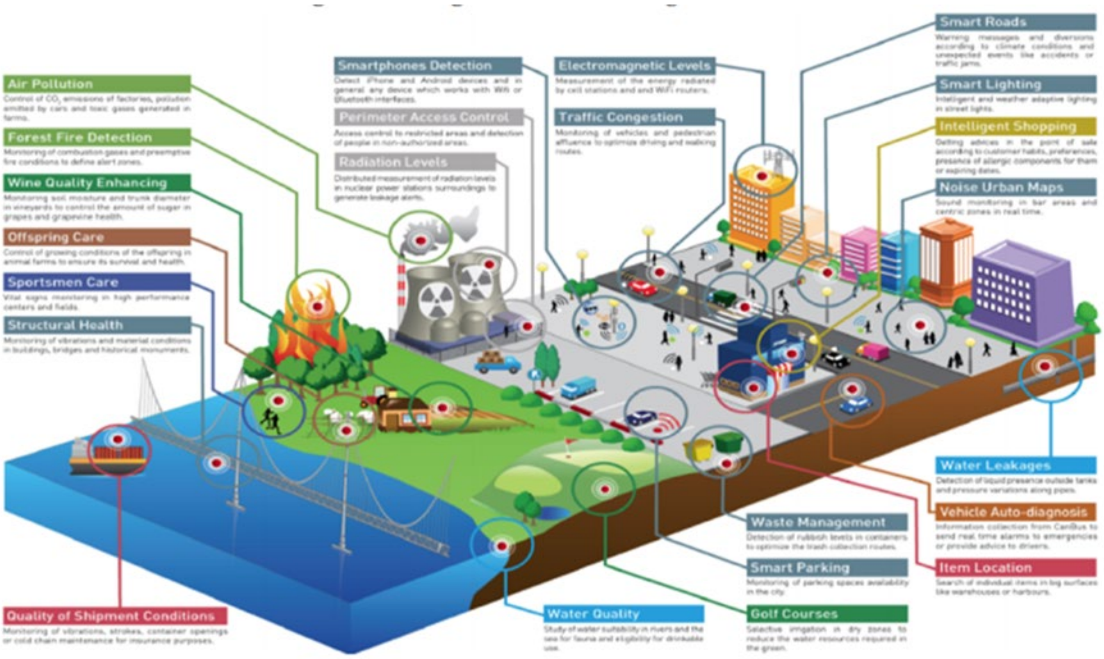


Figure 6. Libelium Smart World

The analysis activity makes possible to quickly extract knowledge from large masses of unstructured data in order to obtain information possibly in a compact and easily interpretable format.

After an initial extraction phase - during which the data is retrieved from the various available sources, selected and loaded into the memory of the processing system - and a subsequent integration of all information referring to the same elements or application domains, the actual data analysis takes place, which is done by means of analysis techniques and tools capable of bringing out from the unstructured raw data information susceptible of interpretation and practical use.

Generally speaking, analysis techniques mostly consist of algorithms, among which one distinguishes between querying and learning algorithms. While the former aim to respond to precise requests from users in the form of queries, the latter aim to extract new knowledge, new theses and make use of advanced Artificial Intelligence techniques such as machine learning.

The characteristic of these algorithms, whose functioning evolves with experience, is that they are time-varying, even at high speed. Moreover, the tendency to optimize computed models on the basis of analyzed data makes them increasingly precise and accurate. Such peculiarities make machine learning algorithms endowed with a certain 'autonomy' in their behavior.

It is precisely the 'intelligence' of the analysis techniques, together with the voluminousness and variety of the data, that is leading to an important innovation in the knowledge extraction process. In the new, so-called data-driven analytical paradigm, data contribute not only to verify theoretical hypotheses with statistical techniques, but also to explore new scenarios and derive new theories, as well as, more generally, to discover new knowledge through artificial intelligence algorithms. This is an approach to information acquisition and knowledge generation that is completely innovative from a methodological point of view, which recognizes the role of data as the guide and algorithms as the task of finding patterns that traditional methodology could perhaps only struggle to identify (except for having to subject them to subsequent verification). The innovative scope is such that some scholars speak of a true scientific revolution compared to the classical 'hypothesis, model, experiment' approach.

3.1 Steps required for the development of a generic KPI

Steps required for the development of a generic KPI are:

- determining the evaluation level;
- choice of reference variable (target variable);
- identification of the independent variables (variables that could influence the target variable;
- collection of historical data on the independent variables and the target variable;
- statistical analysis to study the link between target variable and reference variables;
- the baseline is set and the trend is assessed;
- research into typical cycles (time windows representing a production cycle);
- simulations to assess the presence of laws that can quantify the correlation between signals.

A graphical example for the evaluation of correlation between signals is presented in Figure 7.

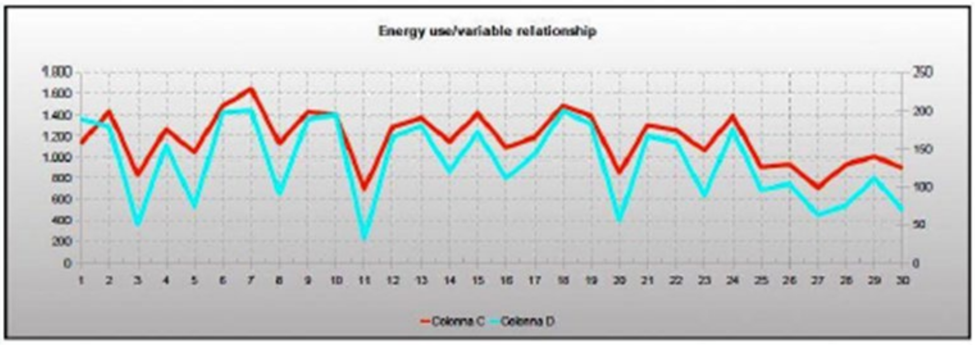


Figure 7. Useful simulations to assess the presence of laws that can quantify the correlation between signals

To quantify correlations between variables is possible to apply:

- simple ratio;
- simple linear regression (bi-variate);
- multiple linear regression.

- **Simple ratio:**

This methodology involves the calculation of an index based on a simple ratio that is the primary source of changes in systems performance (typically production outputs). This is equivalent to establishing a relationship of the type:

$$y = mx \tag{1}$$

y = target variable

m = slope

x = independent variable

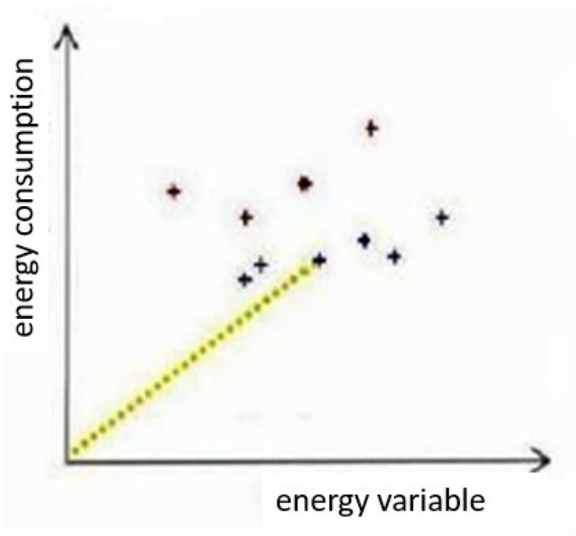


Figure 8. An example of a case where the relationship between energy consumption and energy variable can be represented by a simple ratio

where the slope (m) given by the ratio of y/x provides an assessment of process behaviour Figure 8.

- **Simple linear regression**

This methodology is based on the correlation between two variables:

$$y = mx + q \qquad (2)$$

If two variables X and Y are correlated with each other, and are both on equivalent interval scales or ratios, the statistical technique of linear regression makes it possible to calculate the expected (or estimated) value of Y, given a certain value of X. We speak of simple regression when the scores of Y (Dependent Variable) are estimated on the basis of a single independent variable X.

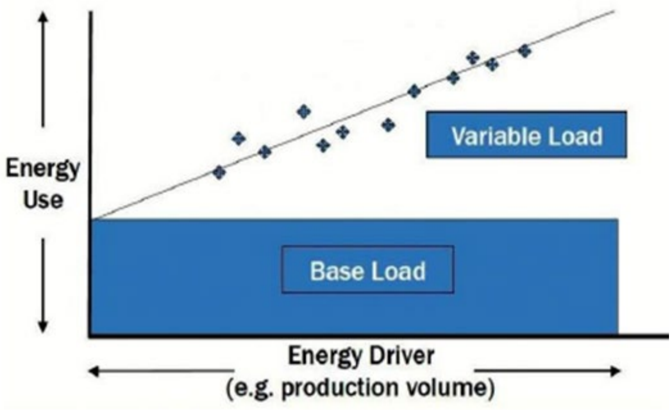


Figure 9. Example of a case where the relationship between energy consumption and energy variable can be represented with a simple linear regression. (Source: Focus on Energy)

With reference to Figure 9:

m = Energy intensity (represents the energy consumed per unit volume produced);

b = Base load (represents the energy consumed by compressors not related to the production of compressed air);

R^2= Correlation coefficient ($0 \leq R^2 \leq 1$). It expresses the share of deviance (variance) of energy consumption explained by the linear relationship with the energy variable.

It can be seen as a measure of the goodness of fit of the regression line to the observed points. The closer it is to 1, the smaller the dispersion of the points around the regression line and the better the fit.

The meaning of the two parameters m and q provides an assessment of the energy behavior for example of the compressed air production process in terms of inefficiency (expressed by parameter b) and energy performance per unit of production increase (expressed by parameter m).

The parameter R^2 expresses the goodness-of-fit of the model, representing the percentage of variation in electricity consumption (over the data sampling interval) that is actually reproduced by the model. For example, an R^2 equal to 0.84 indicates that the linear regression is able to express 84% of the variation in electricity consumption. It follows from the above that the closer R^2 is to 1, the higher the goodness of the model.

In general, linear regression is a law that allows many processes to be simulated. Figure 34 shows an example in which net production and energy consumption have a similar trend over time. In this case, linear regression lends itself very well to representing the link between the two variables:

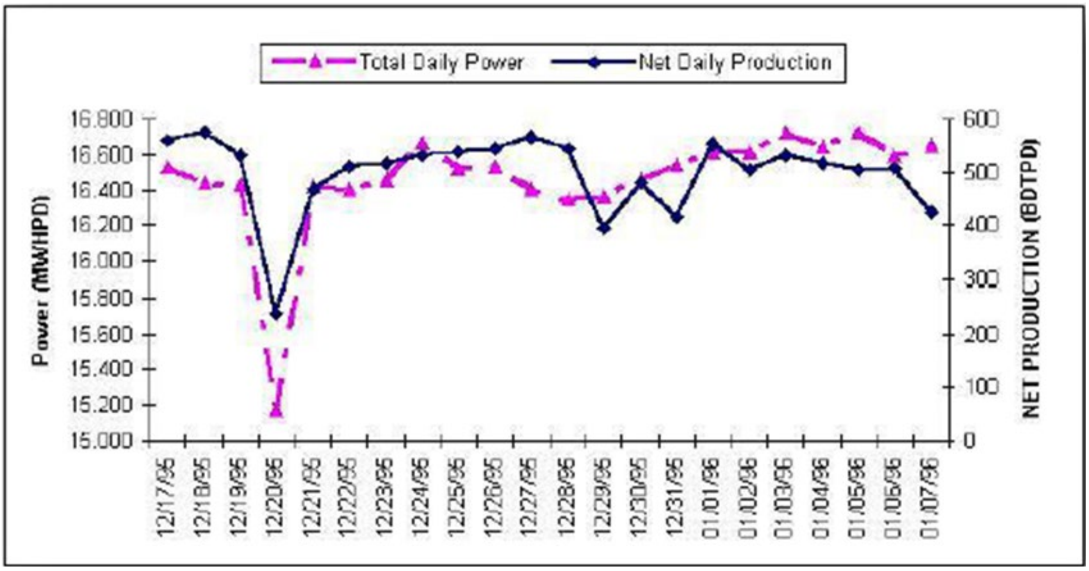


Figure 10. Net production and energy consumption trend(R^2>0.75)

- **Multiple linear regression**

The example shown Figure 10 highlights the presence of other 'complicating factors' influencing energy consumption other than the selected energy variable (i.e. production output). "The presence of these factors is indicated by an $R^2 \geq 0.75$".

Complicating factors may include:

- multiple variables (energy drivers) that 'drive' the energy consumption trend;
- a multiple or variable product composition (the output of one product depends on another);

- a production volume that cannot be easily characterized;
- upgrades of the main system or changes in operations (in this case, the index structure and sampling interval must be reworked).

In the case of the presence of multiple "energy drivers", the consumption trend is analyzed with respect to several variables by considering the superposition of the individual effects (influences) to the overall consumption.

For this purpose, the most widely adopted model in current energy management practices is the multiple linear regression.

In the multiple linear regression model (fig. 11), it is assumed that each observed value of the dependent variable (energy consumption) can be expressed as a linear function of the corresponding values of the explanatory variables plus a residual term that translates the inability of the model to accurately reproduce the observed reality.

Assuming k energy variables are considered, the general equation of the model will be of the type:

$$y = b_0 + b_1 x_1 + \cdots + b_k x_k \qquad (3)$$

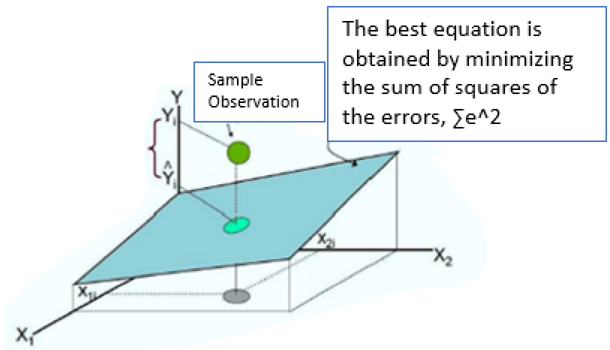


Figure 11. Multiple linear regression model

Where:

y = energy consumption

x_1= energy variables (energy drivers)

b_1= partial regression coefficients

e= random error

Partial regression coefficients quantify the partial effect of a generic variable on total energy consumption, assuming the other variables to be constant.

In the case of two independent variables, the equation represents a regression plan evaluated by minimizing the sum of the squares of the errors.

The partial coefficients obtained through the regression can have a positive or negative sign depending on the effect they have on total consumption, and do not allow us to determine which of the selected parameters has the greatest influence on energy consumption. This is because they are expressed with different units of measurement (unit of consumption/unit of measurement of the energy variable).

The dissertation consists of 7 sections. First three sections are about introduction and contextualization. Section IV is on motorway tunnels with particular attention to risk analysis and on artificial intelligence application to a specific Italian motorway tunnel for detection and prediction of failure (nowcasting and forecasting). Section V presents a multi-variable DTR algorithm for the evaluation of HV lines temperature, it also describes the materials and methods. Moreover, there is the model description and approach used for identification and validation of HV line temperature. In section VI is analyzes the case of an Italian railways infrastructure operators with the presentation of the international standards (ISO5500X) and UIC guidelines. Finally, section VII concludes the research.

4 Motorway tunnels

Artificial intelligence is an innovative application used like an important tool that can be helpful for improving and optimizing the safety level of road tunnels. Tunnels longer than 500 m facilitates the communication of the great region of Europe, they have a decisive role for the functioning of the regional economy. On November 30, 2001, the transport ministers of Austria, France, Germany, Italy and Switzerland met in Zurich and adopted a joint declaration recommending that national regulations aligned with the latest harmonized requirements aim to strengthen safety in long tunnels. The European road tunnels, which are in service in a lot of years ago, had been designed when the technical possibility and the conditions of transport were very different from the current ones, for this, they imposed a series of measures inherent to the geometry and design features of the tunnel, safety installations, compressing the signs, traffic management, emergency response training, accident management, information to communicate. Safety measures should enable the people involved in accidents to escape to safety, allow users immediately to avoid more serious consequences, ensure the effective action of emergency services, protect the environment and limit material damage. In order to define a balanced approach considering and in view of the high cost of the proposed measures, it is appropriate to establish the minimum safety equipment taking into account the typical characteristics and the expected traffic volume of each tunnel. International organizations such as the World Road Association and the UNECE have long made valuable recommendations for improving and harmonizing the legislation on safety equipment and traffic in road tunnels. To maintain a high level of safety, adequate maintenance of the safety installations in tunnels is required. The exchange of information on modern safety techniques and data relating to accidents/events between Member States should be systematically organized. For tunnels already in operation or for tunnels whose design has been approved but which have not yet been open to the public, Member States are allowed to accept the adoption of risk reduction measures as an alternative to the requirements of the Directive [20] , if the characteristics of a tunnel do not allow to realize structural solutions at reasonable costs [Directive_CE_number_2004-54]. It is very complicated managing tunnel safety and organizing maintenance activities in order to comply with the minimum safety requirements imposed by the directives. Artificial Intelligence techniques can support the maintenance operators, it's also possible to extract relevant information from large volumes of data in an efficient, fast, dynamic and adaptive manner, and make it immediately usable to those who manage machinery and services enabling them to make effective and quick decisions.

4.1 Risk analysis in road tunnel

The risk analysis is carried out, if necessary, by a body that is functionally independent of the tunnel manager. The content and results of the risk analyzes are included in the safety documentation sent to the administrative authority. The risk analysis of a tunnel considers-all the elements inherent to its design characteristics and traffic conditions that affect safety, and in particular the characteristics and type of traffic, the length and geometry of the tunnel, as well as the number expected of heavy vehicles in daily transit. The IRAM methodology allows the use of the risk analysis tool with comparative value as it is possible to define the performance conditions of the devices and subsystems that implement the safety measures in terms of reliability and efficiency as well as the management measures compensating for any degradation and assess the impact on user safety. The accident scenarios and their evolution in the tunnel in terms of danger are represented by models that include the tree of causes, the initiating critical event and the tree of events, characterized in terms of probability of occurrence of the critical initiating and conditional probabilities of evolution along the individual branches, as an expression of the reliability and efficiency of the safety measures installed or envisaged.

The Risk Model (IRAM) uses known and codified techniques:

- Probabilistic techniques for identifying and characterizing relevant incidental events relevant to the system (distribution functions, event trees);
- Probabilistic techniques of representation of possible danger scenarios, conditioned in the evolution by the reliability and efficiency of the safety systems that implement protective safety measures in emergency conditions (event trees);
- Analytical and numerical solution techniques of the models formulated to represent the flow of danger in the structure, determined by the thermal and fluid dynamics phenomena induced by specific accidental events, in order to characterize the environment inside the structure in which the process of exodus of the users involved and the action of rescue workers (simplified thermo-fluid dynamic models, models formulated and solved by adopting the Computational Fluid Dynamic method);

- Statistical techniques for solving the models of users leaving the structure in emergency conditions (Monte Carlo techniques);
- Analytical and graphic techniques for representing the risk associated with a road tunnel (complementary cumulative curves);
- Risk assessment criteria consistent with known and codified doctrines of risk acceptability.

As part of IRAM risk analysis procedure, the social risk measures are determined through the convolution operation between the distribution functions of the frequency of critical events and expected consequences determined based on the analyzes and simulations described in the paragraphs previous.

The quantification results of the risk are expressed through the indicators established by Legislative Decree no. 264/2006:

- Social Risk represented as Complementary Cumulative Curve reported on plan F – N;
- Expected Damage Value (VAD) determined as the area subtended by the Complementary Cumulative Curve.

The Complementary Cumulated Curves represent, on a logarithmic scale, the function:

$$1 - F_n(X) = P(N > x) = \int_x^\infty f_n(x)dx$$

(4)

Where F_n (X) is the probability distribution function of the number of fatalities for year f_n (x), is the probability density function of the number of fatalities per year. Complementary Cumulated Curves are, by definition, decreasing monotone continuous curves. The Expected Damage Value is the defined integral of a Complementary Cumulated Curve. The Expected Value of Damage, being the Time of the First Order of the Distribution Function defined by a Complementary

Cumulated Curve, provides limited information on the Social Risk associated with a Tunnel System. The Expected Value of Damage is indicated by the Legislative Decree as the Global Risk Indicator to be used in the Verification of the Equivalence Criterion for Tunnel Systems that have Deficits in the Minimum Safety Requirements. The risk acceptance criteria, in the legislative decree, are established in accordance with the ALARP principle. The risk acceptance criteria, translated into a tolerable risk level and an acceptable risk level, are represented in terms of frequency-consequences by lines of fixed intercept and unit negative slope (degree of risk aversion).

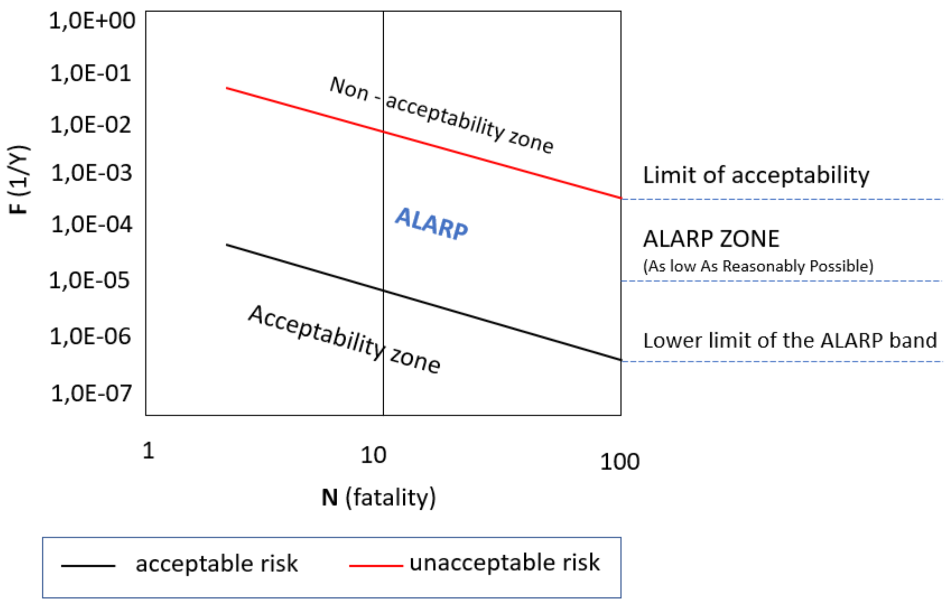


Figure 12. Risk acceptance criteria

The tolerable and acceptable risk levels delimit the following three areas (figure 5):

- "Unacceptable" risk area. A risk that falls in this region cannot be justified in any case;
- "Acceptable" risk area. If the risk associated with the activity or work in question falls in this region, no further investigations and actions are necessary as the value is to be considered acceptable;

- ALARP area (As Low As Reasonably Practicable). Further investigations and mitigating actions must be carried out in order to reduce, as far as reasonably practicable, the risk value, by implementing additional safety measures that ensure a global level of safety equivalent to that of the associated virtual tunnel.

4.2 The risk

The risk associated with a road tunnel is obtained by adding the contributions relating to each individual hazard identified. The value obtained is a risk distribution that must be represented in the form of a complementary cumulative curve. The risk associated with a single hazard is obtained as the combination between the frequency of occurrence f expressed on an annual basis and the distribution of the number of fatalities N considering the uncertainties σ associated with the period itself, as shown by this equation:

$$R = f \cdot N + \sigma(R) \quad (5)$$

The risk curve obtained as defined is compared with the risk acceptance criteria defined in attachment 3 of Legislative Decree 264/06. The risk acceptance criteria are based on:

- The social risk represented as a complementary cumulative curve (Curve F-N) on the Frequency -Number of Fatalities (F-N) plane referred to the year and km of line,
- The Expected Value of Damage defined as the overall risk value referred to the year.

4.3 Calculation of the occurrence frequencies

The occurrence frequencies are calculated starting from the occurrence rates of the accidents associated with each hazard. The occurrence rate is assessed by both statistical analysis of the data and on the sector literature. The frequency associated with each hazard m is calculated as:

$$f_m = 365t_i \cdot TGM \cdot (1 - e)$$

(6)

Where:

t_i : is a base occurrence rate;

TGM: is the average daily traffic;

e: is the effectiveness of preventive measures and is defined between 0 and 0.9999.

The occurrence rate values are derived from the statistical analysis of accident data, from the sector literature and from the results of the analysis of the cause tree according to the type of danger and system.

4.4 Event tree

Event trees are formulated for each hazard identified; a sufficient number of scenarios is associated with each branch of the event tree for each of which the value of the consequences in terms of number of fatalities will be calculated. The number of scenarios to be calculated for each branch of the tree is variable according to the types of hazards and must be aimed at considering a sufficient number of possible cases. The probabilities of malfunction to be attributed to each branch of the event tree are derived from the effectiveness of the safety systems. The probability associated with the individual sub-events, which refer to the different subsystems, is identified with the effectiveness of the system. The values of the probabilities associated with each branch consider the conditional probabilities associated with the different branches of the event tree. The frequency of occurrence of each branch n of the tree of events is calculated starting from the frequency of occurrence with the following relationship:

$$f_{mn} = f_m \cdot P_x$$
(7)

where P_x is the probability associated with branch x, given by the product of the conditional probabilities associated with the single events.

Each branch n of the event tree to which a hazard m is associated is named R_{mn}; for each branch a number j of scenarios is defined.

Considering the high uncertainty connected to the category of thermo-fluid dynamics hazards indicated by Legislative Decree 264/06, each branch of the event tree is associated with several scenarios for which the consequences are calculated according to the Monte Carlo method (Fig. 6).

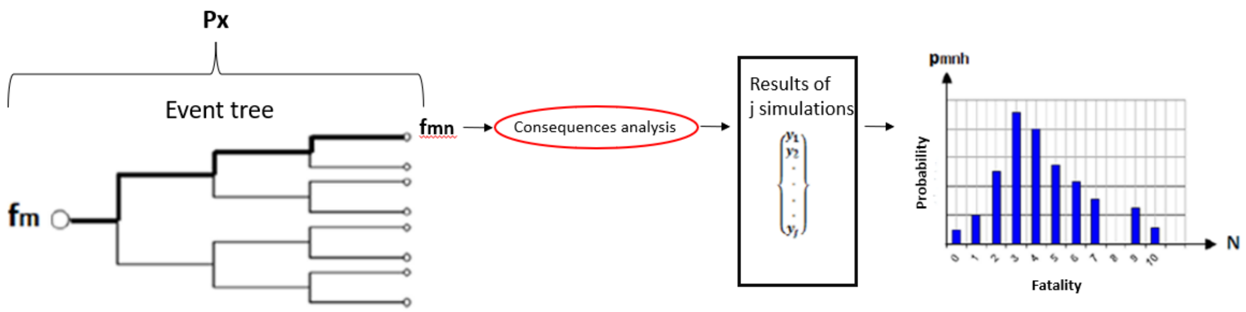


Figure 13. Event tree, scenarios

The number of scenarios to be analyzed must be statistically significant, i.e. it must not be less than 6000 for each hazard as a whole and not less than 100 for each branch of the event tree. The event tree is characterized by an extended number of sub-events and considers at least the following events / systems (Tab.1).

Table 1. Sub-events

Fire							
1. Light vehicle 2. Heavy vehicle 3. Dangerous cargo	Drainage effectiveness	Effectiveness of detection systems	Effectiveness of ventilation systems	Communication effectiveness	Effectiveness of signposting and communication	Fire - fighting system effectiveness	Effectiveness of emergency procedures

4.5 Calculation of risk

The risk is calculated by adding the contributions in terms of frequency of occurrence for each fatality value of the various hazards, obtaining a distribution of frequency of occurrence as a function of each value of the consequences or of the f-N pairs. To construct the complementary cumulative curve associated with each hazard, each pair of numbers must be formed by the value of the fatality N_h and the relative frequency F_{Nh}, calculated as the sum of the frequencies associated with the fatality N_h and all the frequencies to which they are associated the fatalities $k > N_h$. The frequency relating to the fatality N_h is therefore determined with the following sum:

$$CF_n = \sum_{k>N_h} f_k = F_{Nh}$$

(8)

Each point of the complementary cumulative curve will be identified by the pair of fatality values N_h and Cumulative frequency F_{Nh}.

The overall risk for each hazard is defined as the integral of the complementary cumulative curve which is the area under the curve itself up to the maximum number of fatalities calculated, the overall risk represents the Expected Value of Damage (VAD) defined by Legislative Decree 264 / 06.

Instead of calculating the integral, the large number of values available allows the overall risk to be calculated as the sum of the cumulative frequencies associated with each fatality value.

$$VAD = \sum_{i=1}^{Nmax} F_{Nh}$$

(9)

4.6 Artificial Intelligence Applications: Failure Prediction

Today's advanced technology is enabling companies to not just look at their own historical data, but also to predict future behavior or outcomes. The enormous development of sensors and measurement systems allows collecting a huge volume of data relating to the operation of each individual equipment and also those relating to the operating status of the systems. Many of these data are linked to monitoring mechanisms of some key components, and therefore the analysis and data acquisition proceeds in real time. For example, it is compared with threshold values, the exceeding of which may indicate a deterioration in performance, or it can be used in a more sophisticated way for control purposes. Most of the data is stored and preserved, at least for a certain period, in the company's electronic archives, but this enormous amount of data and therefore information is often under-used, because the data is analyzed with classical statistical tools and often for a posteriori analysis.

The scientific and industrial communities agree that intelligent exploitation of the huge amount of data available today in companies will be a source of competitive advantage in the global market, as well as a tool for improving the efficiency and sustainability of production cycles. Thanks to neural networks, artificial intelligence now allows predicting or early recognition of operating anomalies and failures. These systems owe their suggestive name to a strongly interconnected architecture, inspired by that of the human nervous system, which, like this, breaks down a complex operation into many simpler operations carried out by elementary computing units, called “neurons”. Neural networks are equipped with "learning" mechanisms: algorithms that dynamically modify the internal parameters of the network based on experimental data, which have the function of "external stimuli." In the case of fault diagnosis, special neural networks are able to recognize within a very large number of measured variables, those factors that are the most significant "warning signs" of the fault itself and, on the basis of these signals, they detect in advance the occurrence of an anomaly. Specialized neural systems can also be employed to recognize rare events, since failures are much less frequent than normal operating conditions.

The tunnels managed by the concessionaire Autostrade per l’Italia S.p.A. have been divided into groups. The subdivision into groups, shown below, is based on the length of the tunnels (different minimum requirements required by the legislation) and on the value of 10,000 vehicles / day / lane (tunnels with special characteristics), and the most representative tunnels of each group have been identified on the basis of these factors and the results of the risk analyzes (table 2) .

Table 2. Tunnel clusters

<table>
<tr><th>Group</th><th>Lenght</th><th>TGM
(vehicles/day/road)</th><th>N°Tunnels</th><th colspan="3">%Tunnels</th></tr>
<tr><td>1</td><td>500m<L<1000m</td><td>< 10000</td><td>47</td><td>38,2</td><td rowspan="2">63,4</td><td rowspan="4">91,9</td></tr>
<tr><td>2</td><td>500m<L<1000m</td><td>> 10000</td><td>31</td><td>25,2</td></tr>
<tr><td>3</td><td>1000m<L<2000m</td><td>< 10000</td><td>21</td><td>17,1</td><td rowspan="2">28,5</td></tr>
<tr><td>4</td><td>1000m<L<2000m</td><td>> 10000</td><td>14</td><td>11,4</td></tr>
<tr><td>5</td><td>2000m<L<3000m</td><td>< 10000</td><td>5</td><td colspan="2">4,1</td><td rowspan="2">6,7</td></tr>
<tr><td>6</td><td>2000m<L<3000m</td><td>> 10000</td><td>3</td><td colspan="2">2,4</td></tr>
<tr><td>7</td><td>L>3000m</td><td>-</td><td>2</td><td colspan="3">1,6</td></tr>
<tr><td colspan="3"></td><td>123</td><td colspan="2"></td><td></td></tr>
</table>

Furthermore, the service levels and compensatory measures that will be implemented by the Operator following a system degradation of the tunnel equipment that could occur during operation have been identified, in order to guarantee a level of infrastructure safety equivalent to that of its own of the tunnel in the absence of deterioration. The service levels of the tunnels have been defined starting from the conception of the tunnel as an integrated system to guarantee the safety of the users who travel through it. Each system present in the work has a very specific function and the set of all systems contributes to ensuring 4 safety macro-functions:

- Prevent breakdowns and / or accidents;
- Limit the consequences of a breakdown and / or accident;
- Evacuate and shelter users.

The logic with which the degradation levels are proposed is based on the fact that the tunnel is subject to the maximum level of degradation when the functionality of all the safety systems defined by Legislative Decree 264/06 is compromised. The macro safety functions have been further classified into "functionality" and "functions" with the aim of identifying the system and / or systems that allow their implementation. By then applying a "reverse" approach, for each plant or part of the plant, its contribution was taken into consideration, identified in the function it is called upon to perform. This reasoning made it possible to evaluate the general safety architecture of the tunnel system, highlighting how and with which redundancies the systems guarantee the necessary safety features / functions. This summary made it possible to assess the impact of any loss of a plant on the management and safety of users. This logic is the basis for the classification of the degradation levels, the sum or combination of which defines the operating level of the tunnel. Following the logic described above, the following have been identified and reported below:

The main "*functionalities*" that characterize the proper functioning of a tunnel compliant with the dictates of Legislative Decree 264/06 and that the tunnel systems must always guarantee:

- Power supply;
- Fire detection;
- Driveway door;
- Functionality Remote management;
- Evacuation ;
- Ventilation;
- Fire-fighting water system;
- Video surveillance;
- Radio system;
- Active drainage;
- Accident prevention;
- Passive drainage.

The main "*functions*" that the tunnel systems must perform, and which may determine consequent levels of degradation (compromise of a functionality) depending on their functioning:

- Ordinary power supply Active signage;
- Emergency power and safety Continuous fire detection;
- Driveway door operation Punctual fire detection;
- User info;
- Supervision and control system;
- Management of escape route or safe place Data network;
- Pressurization of the filter area / safe place / escape route SOS management;
- Air quality escape passage Detection of ventilation parameters;
- Water pumping system Smoke management;
- Water reserve RAI form;
- Radio user Monitoring;
- Radio aid Drain pumping system;

- Radio ASPI Accumulation;
- Permanent lighting Hydraulic protection;
- Reinforcement lighting.

The main "*subsystems*" within which the possible level of degradation generated by the failure to perform a function and / or functionality is displayed (table 3):

Table 3. Abbreviation

Ventilation	VENT
Power supply	ALIM
Fire Fighting	ANT
Lighting	ILL
PMV	PMV
Pressurisation	PRES (EVAC)
Cameras Fire Evacuation	RAI
SOS/Rescue	SOS
Remote management	TEL

We therefore proceeded to:

- Associate with each *''functionality''* identified, all the relative *''functions''* to be performed which, in the event of degradation of the systems / elements that compose it, may compromise the functionality itself;
- Identify within each *''function''* the elements and / or systems that are needed for the function to be fulfilled;
- Develop in matrix form (and / or according to a possible event tree) the possible combinations of faults from which to give rise or not to levels of degradation and / or alarms and / or malfunctions;
- Carry out specific analyzes and considerations for each part of the plant analyzed in relation to the design, regulatory, good practices and / or assumptions of the operator;

- Define the operating levels resulting from the aforementioned iterations of possible events / failures and their combinations based on the following assumptions and definitions:
  - Level 1: The tunnel has no degradation, the system works normally;
  - Level 2: Partial loss of function;
  - Level 3: Total loss of function;
  - Level 4: Loss of function.

In view of the possible levels of degradation, defined as above, while awaiting the restoration of the performance levels of the systems, mitigation measures are introduced that must be able to compensate for the increase in risk induced by the degradation compared to that which characterizes the operating condition nominal.

4.7 Road Tunnels Monitoring

In the specific case of motorway tunnels, carrying out a 'Predictive Risk Analysis' represents an important technological innovation, which would simplify the management activities of the tunnels and therefore the restoration of any degradation activities, keeping the risk within the tolerance. The new idea envisages the creation of a predictive algorithm capable of acquiring real-time data from the sensors of the individual tunnel systems and using them to predict faults and then identify the tunnel status and its service level.

This research describes how Artificial Intelligence techniques can play a supportive role both for maintenance operators in monitoring tunnels and for safety managers in operation. It is possible to extract relevant information from large volumes of data from sensor equipment in an efficient, fast, dynamic and adaptive way and make it immediately usable by those who manage machinery and services to aid quick decisions. Carrying out an analysis based on sensors in motorway tunnels, represents an important technological innovation, which would simplify tunnels management activities and therefore the detection of any possible deterioration, while keeping the risk within tolerance limits. The idea involves the creation of an algorithm for fault detection by acquiring data in real time from the sensors of tunnel sub-systems and using them to help identifying the service state of the tunnel. The AI models are trained on a period of 6 months with one hour time series granularity measured on a road tunnel part of the Italian motorway systems. The verification has been done with reference to a number of recorded sensor faults.

Road tunnels are key infrastructures to facilitate inter-regional transportation with a significant direct economic impact. Minimum safety requirements have been recently updated [12] to be applied to existing as well as new tunnels, including a series of measures inherent to design, safety installations, traffic management, emergency response, accident management and to the communication of information [21]. Among the diverse factors, risk mitigation measures have been often proposed to be linked to the empowerment of tunnel monitoring systems to keep an adequate maintenance of the safety installations.

Advances in data intensive technologies are enabling the valuation of historical data while, at the same time, broadening the potential outcomes of data analysis in the perspective of forecasting [22,23]. The continuous development of sensors and measurement techniques allows collecting a large volume of data relative to each individual equipment in any complex engineering systems, in the attempt of unveiling real-time correlations of data and operating status of the systems. The data-driven causal analysis is most of the time motivated by fault-detection and diagnosis goals [24], or it can be used in a more sophisticated way for control purposes [25]. With the rapid development of sensors technology, wireless transmission technology, network communication technology, cloud computing and smart mobile devices, large amounts of data have been accumulated in almost every aspect of our lives [26]. Moreover, the volume of data is growing rapidly with increasingly complex structures and forms [27]. However, this huge amount of data, therefore the potential content of information, is often underutilized because data is analyzed with classical statistical tools. The scientific and industrial communities agreed that the data explosion in companies' businesses will be a source of competitive advantage able to lead the improvement of efficiency and sustainability of production cycles [28,29]. Technology infrastructure can be monitored and operated even over huge physical distances. Networking enables simultaneous control and optimal coordination of a wide variety of complex technological processes. Digitalization is facing various challenges in the world of infrastructure, such as challenges in operational efficiency and cost control [30,31], system stability and reliability [32], renewable energy management [33], energy efficiency and environmental issues [34], as well as consumer engagement and service improvement [35]. Data driven and artificial intelligence methods can be developed to help detecting and even anticipating anomalies and failures during the operations [36,37]. Specifically, nowcasting systems can be equipped with learning mechanisms based on monitored time series evolution from the tunnel sensor network. The idea presented in this first project advocates the detection of faults by acquiring data in real time from the sensors of tunnel sub-systems and using them to help identifying the service state of the tunnel. Tunnels sensors have their own specific models based on multivariate regression to model the reciprocal influence among sensor signals. The proposed innovative application handles the use of Artificial Intelligence as an important tool that can be helpful for improving and optimizing the managing of road tunnels.

This first case study focuses specifically on the use of data from sensor network equipping tunnel auxiliary plants in a view to define service state, contribute to tunnel safety management and data-driven maintenance. The large volume of data, derived from sensors, gives us relevant information and makes it usable to those who are managing the machinery and services, enabling them to make effective and quick decisions [38]. In motorway tunnels, carrying out a data analysis, simplifies the management activities of the tunnels and therefore the restoration of any degradation, managing road tunnels. The proposed idea envisages the creation of a regression algorithm capable of acquiring data from the tunnel sensors and made detection of faults. The regressor model is built starting form data exploration, in an attempt to understand which, the recurring dynamics are, to discover patterns in data trying to find subgroups, and to identify the subsystems of variables that exhibit the same dynamics.

4.8 Literature Review

The maintenance operations on the equipment could be preventive or corrective (Figure 14). Preventive maintenance is carried out at fixed intervals with the objective of maintaining the equipment in a good operating condition. Preventive maintenance leads to high costs if the interventions are too frequent. Corrective actions instead are carried out when a system or a part of a system has failed or has been damaged, it offers the advantage of using a system to the maximum extent of its service life. Its disadvantage however, is that it cannot be planned and therefore emergency repairs are normally carried out with a significant surplus cost and consequences for the traffic flow. It may be noticed nonetheless, that even when preventive maintenance is carried out the operator cannot avoid corrective interventions, they therefore need to be suitably optimized with predictive maintenance [39-40]. Many publications focus on data-based maintenance, while others describe the general inspection of the equipment and service of the tunnels by inspectors [41]. To this end predictive failure detection has not yet been explored [42], especially in tunnels. Several papers describe how to use predictive maintenance for specific systems in mechanical engineering, manufacturing processes, and other fields, for example, [43–44]. Even though tunnel systems are the subject of analysis for maintenance purposes, this analysis usually focuses on the structural part instead of on the technological part. Currently, the technological part of tunnel system consists of many different devices and technologies, some of them critical to the tunnel safety. Tomáš Tichý et al.[45-53] recently presented the results of the research on predictive maintenance of technological devices in tunnel systems. This investigation has shown that predictive maintenance for technological devices in tunnel systems might bring benefits. In view of this survey, the main goal of this project is to assess the approaches and possibilities that could be applied for tunnel systems in the future, in particular on the basis of data captured in tunnels.

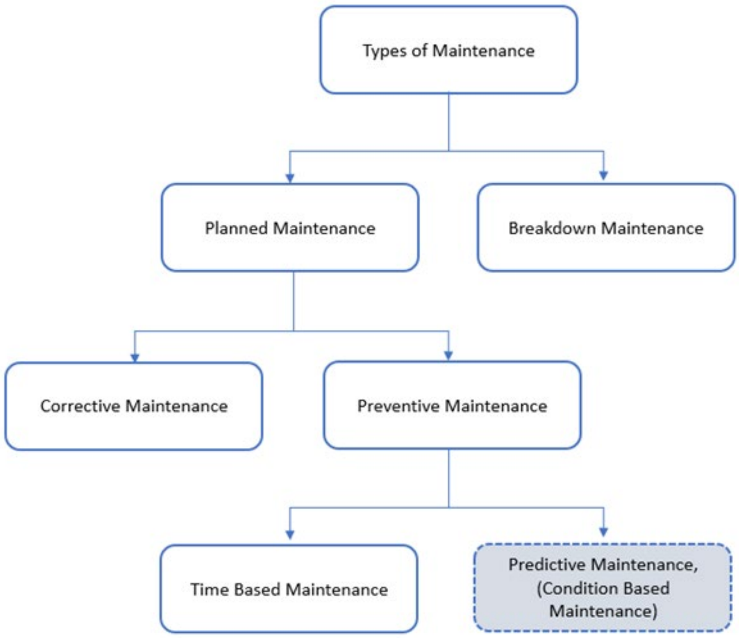


Figure 14. Types of Maintenance

4.9 Methods

The methodology consists of a first step entailing the labeling of available time series (from sensors) and traffic data [95]. The labeling makes use of the information from the system status data (bi-hourly) and from the historical levels of service of galleries. The outputs of this last step are processed time series and traffic data, as shown in Figure 15.

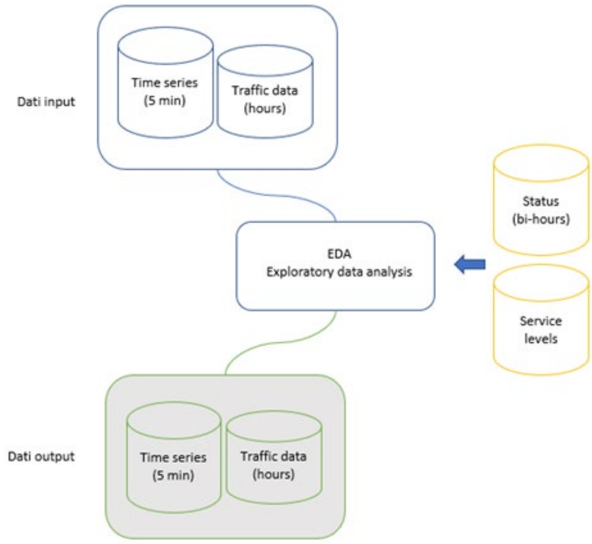


Figure 15. Data labeling and pre-processing

The processed input is then divided to obtain training and test datasets. In so doing, the learner model is developed following the rational illustrated in Figure 16.

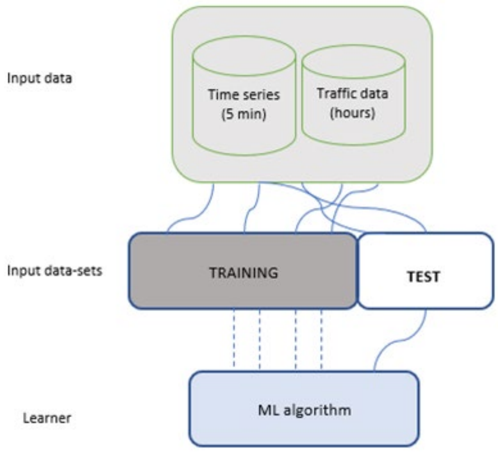


Figure 16. Data flow

Concerning the regressor, it is based on a Multivariate regression scheme [47] used to predict the value of a variable y (dependent) based on the value of n variables x_i (independent), with i = 1, n.

The mathematical formulation of the multivariate regressor reads as:

$$y = \beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n, \tag{10}$$

being the purpose of multiple regression equation the estimation of the coefficients j with j = 0, n. Specifically the regressor coefficients are computed by means of a least square estimation by minimizing, during the training phase, a function that assigns a cost to instances where the model y deviates from the observed data h. The cost function is in the form of a MSE:

$$J(\theta_0, \theta_1, \dots, \theta_n) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^i) - y^i\right)^2 \tag{11}$$

as the summation of square of difference between our predicted value and the actual value divided by twice of length of data set. Here the cost function is used along with the Gradient Descent algorithm to find the best parameters [40].

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \dots, \theta_n) \tag{12}$$

4.10 Data collection and processing

This article is based on the data measured in a specific tunnel part of the Italian motorway network. Specifically, the sample tunnel for the present study is a twin-tube tunnel over 1.000 m long. The analysis refers to a 6 month period, from November 2019 to April 2020. The initial investigations consist of patterns recognition, individuation of spot anomalies, test hypothesis and check assumptions with the help of summary statistics and graphical representations. The analysis has been carried out with reference to the sensor network which monitors the tunnel ventilation sub-system (including smoke management function and ventilation parameters detection). Figure 17 illustrates the flow chart of the ventilation sub-system monitoring.

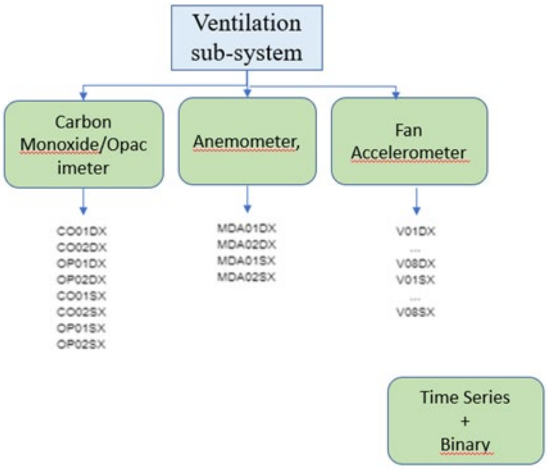


Figure 17. Ventilation sub-system sensor network nomenclature (SX and DX suffices indicate respectively left and right tube; CO: carbon monoxide, OP: opacimeter, MDA: anemometer, V: fan accelerometer)

Concerning the traffic data, characteristic patterns were recognized on a global scale as indicate in Figure 18. Notably, traffic data, either on light or heavy vehicles, did show a discontinuity during the lockdown period i.e. March – April 2020.

The time series from the sensor network were made available through the motorway concessionary with 1 hour sampling interval. By analyzing the time series from the sensors, the trends reveal particular dynamics in the period under scrutiny. Figure 19, as an example shows the anemometer Carbon monoxide sensors and opacimeters data series as recorded by the tunnel monitoring system.

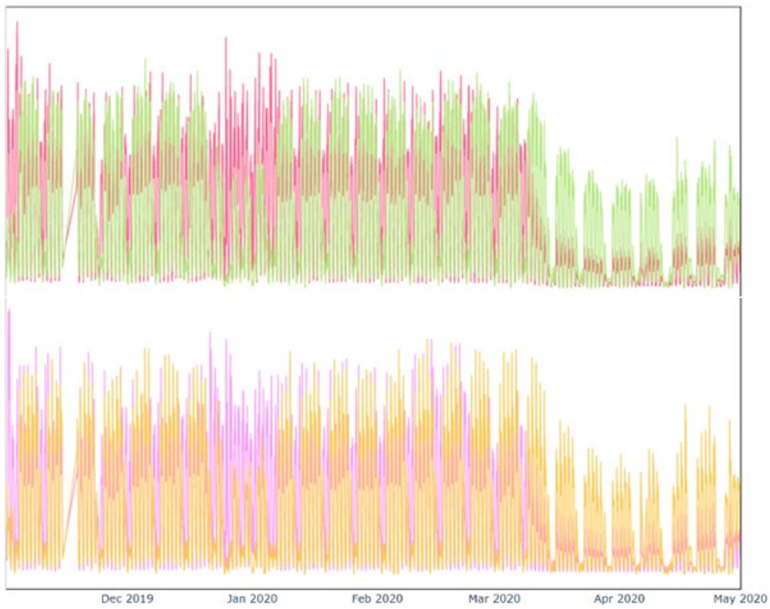


Figure 18. Normalized traffic trend of the sample tunnel, a) SX tube (heavy: pink, green: light), b) DX tube (heavy: purple, yellow: light)

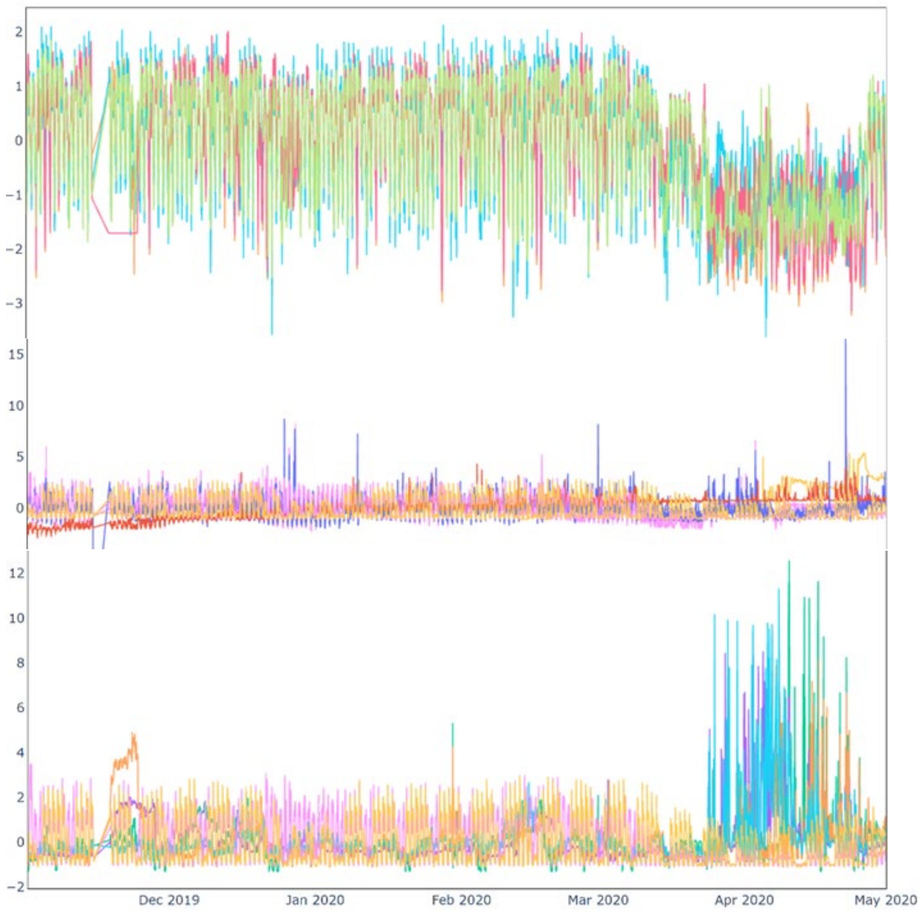


Figure 19. Normalized sensor time series trends: a) anemometer, b) Carbon monoxide sensors and c) opacimeters.

Concerning data preprocessing, the available sensor time series have been corrected with missing values substitution using data interpolation technique [49]; moreover, outlier detection using sigma-rule [50] and z-score (also called standard score) for data normalization [51, 52].

4.11 Results and discussion

On the basis of pre-processed datasets, we developed a learner for each sensor in the ventilation sub-system of the sample tunnel. Sensor nowcasting models aimed at the determination of dis-ambiguous information on the level of degradation corresponding to sensor failure events, in order to guarantee a reduction in response times and accuracy of the intervention.

As for the training data sub-set we did consider the period from November 2019 to April 2020 by eliminating all time interval corresponding to sensor failure events. On such data sets, specific models have been trained for each sensor to predict the sensor signal based on all other sensor behaviors in the short term (i.e. 1 hour). The quality of the training of sensor-specific learners is shown in Table 4, by introducing the principal metrics of the multi-variate regression. In particular, Table 1 collects the R-score and the error per type of sensor.

Concerning the testing phase, the data set is extended to include the failures recorded during the monitoring interval. To this end, Table 5 collects the statistical information that characterize the corrective maintenance carried out during the period under scrutiny. While, Table 5 confirms a high level of availability of the tunnel monitoring system, it also demonstrate the occurrence of a sufficient number of failure events to motivate the present study.

Table 5. Summary of the ventilation sub-system maintenance data

MTBF	*Average Downtime*	*Availability*
(hours)	(hours)	-
312	36	0.9

Sensor	*R*	*Error*	*Samples*
Anemometer DX	0.96	0.01	4065
Anemometer SX	0.93	0.02	2716
CO meter DX	0.75	0.03	4065
CO meter SX	0.70	0.04	2716
Opacimeter DX	0.77	0.03	4065
Opacimeter SX	0.75	0.03	2716

Table 4. Training results

To this end, Table 7 lists the failure events used to populate the testing datasets.

Table 6. Fault events

Sensor category	*Sensor code*	*Event date*	*Type of event*
Anemometers	MDA01DX	24/03-25/03	Loss of Communication
	MDA02DX	14/11-24/11	Fault: Alarm Switch
	MDA02SX	14/11-18/11	Fault: Alarm Switch
		24/03-25/03	Loss of Communication
Carbon monoxide sensors	CO01SX	1/11-21/11	Generic fault
		13/02-14/02	Generic fault
		17/02-19/02	Generic fault
		9/03	Generic fault
		24/03-25/03	Loss of Communication
	CO02SX	24/03-25/03	Loss of Communication
	CO01DX	24/03-25/03	Loss of Communication
Opacimeters	OP01DX	24/03-25/03	Loss of Communication
	OP01SX	14/11-18/11	Generic fault
		21/11	Generic fault
		24/03-25/03	Loss of Communication
	OP02DX	14/11-18/11	Generic fault
	OP02SX	24/03-25/03	Loss of Communication

The nowcasting performance of the developed models have been tested introducing into the data sets the actual series of fault occurred to the sensors in the period under scrutiny.

To give more hints on the results of the sensor-specific nowcasters the following figures show details of the behavior of predicted against actual sensor time series in the vicinity of the ensuing period: sensor CO01SX in December 2019 (Figure 13), sensor OP02DX on November 14th 2019 (Figure 14), and sensor MA02DX on November 14th 2019 (Figure 15).

Figure 20, first, illustrates the behavior of the Carbon monoxide sensor CO01SX during a period of stable operation coinciding with December 1st to December 31st 2019.

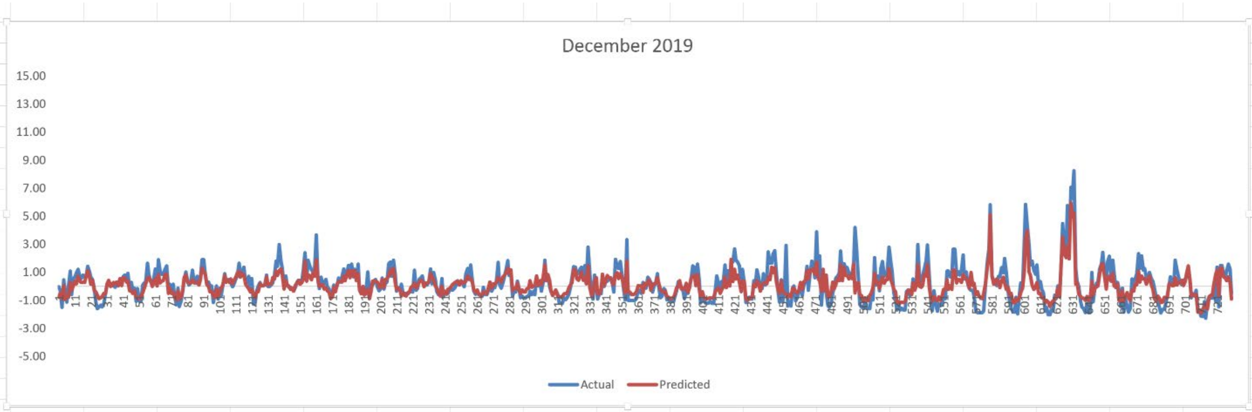


Figure 20. Normalized CO01 SX signal during December 2019: actual (blue) and predicted (red).

It is worth noting that the quality of the multi-variate learner is confirmed by the capability of reproduce the short-time signal dynamics as well as the long-term ones driven by the weekly cycles or to the traffic increment around the December vacation time.

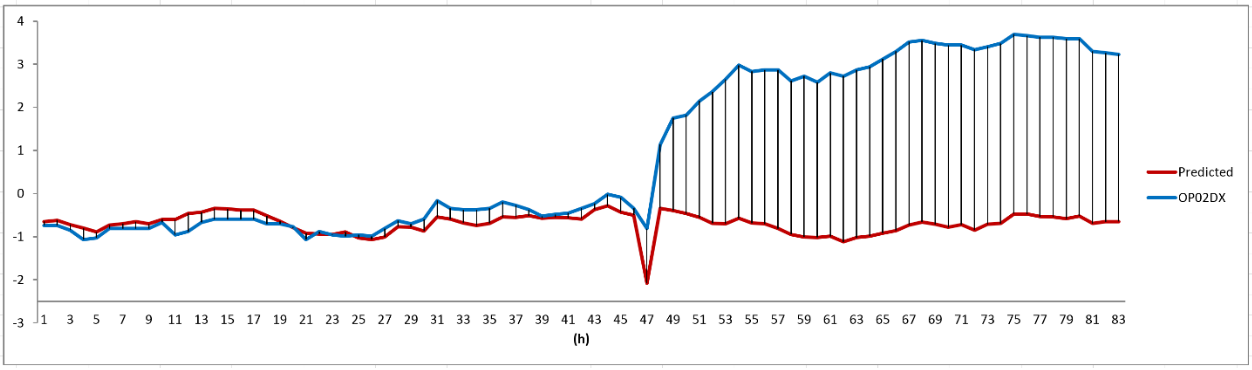


Figure 21. Normalized OP02 DX signal on November 14th 2019: actual (blue) and predicted (red).

Figure 21, on the other hand, shows the OP02DX signals around November 14th 2019. Specifically, the plot demonstrates the intervention of the nowcaster for sensor OP02DX at the occurrence of the fault on November 14th 2019. The evidence of the failure is proven by the departure of the actual signal from the predict one, that in this specific circumstance starts over-predicting the CO concentration.

Similarly, Figure 22 shows the behavior of the nowcaster for the sensor MA02DX during ten days, i.e. November 14th to November 24th 2019.

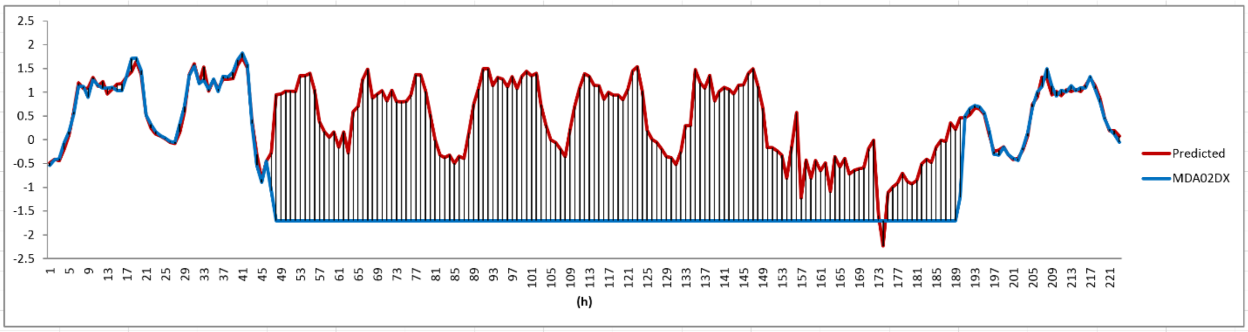


Figure 22. Normalized MDA02 DX signal November 14th 2019 to November 24th 2019: actual (blue) and predicted (red).

Notably, in the selected sample the prediction of the nowcaster returns to the actual value of the sensor signal after the maintenance intervention as such giving a further evidence of the robustness of the multivariate learner.

4.12 Proposed Improvements

The created regressor models are a start point that well implemented could be a robust predictive learner, making possible to have a reliable forecast of breakdowns. So the future steps of this preliminary work are improve the algorithm with more data for managing real time tunnel safety, giving the possibility to organize maintenance activities before a system failure occurs, for avoiding the adoption of compensatory measures now necessary during the failure of a plant, to ensure tunnel operation with an equal level of safety (ALARP criterion) [53]. Moreover, it would be convenient to create a single model by type-category of sensor (no longer for each sensor of the same category) by extending the input data to different road tunnels.

4.13 Remarks

About nowcasting is possible to conclude that the presence of a fault (where the intervention of the maintenance technician is recorded) is detected by the models created for the sensors. For the period 24/03 - 25/03 we hypothesized a malfunction of the communication system as more than one sensor was involved but the plots do not show a flattening of the signal curve. To improve the performance, future work aims at gathering at least one year of data, in order to include a greater number of cases and phenomena typically associated with seasonality.

5 Italian electricity grid

The transfer capabilities of High Voltage (HV) Overhead Lines (OHL) are often limited by the critical power line temperature that depends on the magnitude of the transferred current and the ambient conditions, i.e., ambient temperature, wind, etc. To utilize existing power lines more effectively (with a view to progressive decarbonization) and more safely with respect to the critical power line temperatures, this chapter proposes a Dynamic Thermal Rating (DTR) approach using IoT sensors installed on some HV OHL located in different Italian geographical locations. The goal is to estimate the OHL conductor temperature and ampacity, using a data-driven thermo-mechanical model with the Bayesian probability approach, in order to improve the confidence interval of the results. This work highlights the possibility of estimating a space-time distribution of temperature for each OHL and an increase of the actual current threshold values for optimizing OHL ampacity. The proposed model is validated using Monte Carlo method.

One of the main causes of the transformation of the Italian electricity grid is certainly the rapid and widespread expansion of renewable source plants, with particular attention to generation from wind, photovoltaic and hydroelectric sources. This characterizes the evolution of the electricity production park in the last decade, both in Italy and in Europe. The highly distributed nature of these energy sources means that the user, exchanging energy flows, is not just a consumer but also a producer, thus becoming an active node in the network. The injection into the power grid occurs most of the time in areas of the grid with unknown magnitude power, due to the non-programmability of renewable sources. To achieve the national decarbonization purpose, digitalization and innovation of the network are needed. The keys are electrical infrastructures as an integrated system for monitoring the environment with innovative digital tools placed on the pylons and the support of IoT technologies.

5.1 Literature Review

DTLR (Dynamic Thermal Line Rating) systems are classified as indirect and direct methods. Indirect methods measure weather-related data [54–55], while direct methods measure either conductor sag [56], conductor ground clearance [57-58-59], line tension [60-61], or conductor temperature [62-63].

In Ref. [64], considering the growth in RES (Renewable Energy Source) installation, DTR is being investigated as a way to connect the new intermittent generation, expanding the possibility to increase the rating of non-thermally limited lines (long lines). In Ref. [65], the paper discusses the wide range of real-time line monitoring devices which can be used to determine the DTR of an overhead transmission line in normal or contingency operation. In Ref. [66], the dynamic values of the line current are evaluated as a function of the variations due to the high penetration of intermittent RES in the case where consistent forecast errors occur. In Ref. [67], an optimal algorithm is proposed for the management of congestion on the electric transmission system in real time, considering quasi-dynamic thermal rates of transmission lines. In Refs. [68] and [69] some types of commercially available DTR systems are described and also results from the use of DTR systems in an important 220 kV connection has been presented.

5.2 Multi-variable DTR Algorithm for the Estimation of Conductor Temperature and Ampacity on HV Lines.

One of the most interesting areas for ensuring network security is represented precisely by the monitoring of lines through IoT sensors. In fact, Terna launched a project in the third quarter of 2019 for the monitoring of its assets called IoT4TGrid. In particular, the monitoring started from the asset that presents the highest risk in terms of its regards its exposure to natural and calamitous events, the power lines in high voltage. The positioned sensors on the pylons, in fact, make it possible to collect monitoring data from the power lines, which are then processed via a central platform. Through a central platform are then processed. The use of the sensors, thanks to the capillary spread of the electrical infrastructure over the territory allows a significant increase in the ability to observe the state of the state of the electricity grid and ensure efficient management and more timeliness of intervention in case of need.

Extreme weather events, such as those related to snowfall with the formation of ice sleeves along overhead lines, have more frequently affected certain areas of our country, making it necessary for grid operators to pay greater attention. One of the parameters that requires particular attention in monitoring is mechanical resilience, i.e. the ability to withstand stresses that exceed the tightness limits of the system. For overhead lines, weathering is a major problem. Resilience level is given by the design limits of the lines in relation to the loads from ice, wind or snow, and the situation and the area in which the fault occurs. The use of a sensor system makes possible to monitor assets more effectively and to manage events more easily. Furthermore, data provided by the sensors can be used to indirectly analyze quantities of primary importance for power lines from the point of view of transit and safety parameters.

This case study 2 proposes a dynamic thermo-mechanical model approach that utilizes the weather data measured by IoT sensors through which the conductor temperature and ampacities of power grids can be properly estimated. A significant enhancement in transmission ampacity of power grids when the thermo-mechanical approach is used. Moreover, for the validation of this dynamic model, the Monte Carlo simulation of weather input data is used.

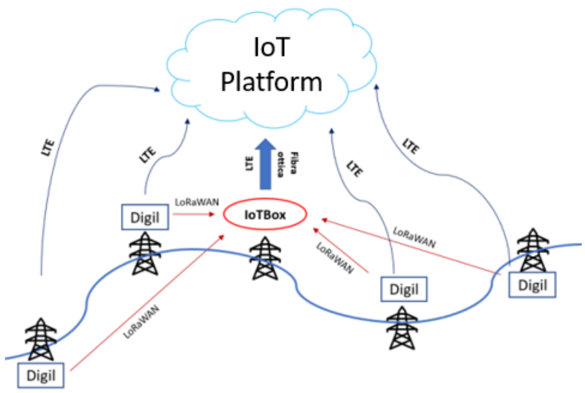
5.3 Materials and Methods

The data collection is made by an infrastructure, which is based on a wireless sensor network. These sensors (Digil) are installed directly on the pylons of the lines and send the collected data to a concentrator (IoTBox), with a star topology network. IoTBoxes send the recorded measurements with an aggregation time of 15 minutes. The data are sent finally from the IoTBox to the central processing platform, as shown in Fig. 16.

Figure 23. Data acquisition scheme.

- *Weather unit: measurements of wind speed and direction, irradiation, ambient temperature, relative humidity of the air.*
- *Mechanical sensors: tension monitoring on the 3 phases, measurement of acceleration / vibration and inclination of the trellis.*

Atmospheric agents represent a considerable problem for overhead lines, therefore the use of IoT sensor system allows to monitor assets and manage events more effectively. Furthermore, the data provided by the sensors can be used to analyze and estimate quantities of primary importance for OHL from the point of view of transits and safety parameters. The ampacity of the OHL is closely related to conductor temperature, in a view of increasing the capacity of the lines and is defined as the maximum electric current that a conductor can carry continuously



before deterioration. The current range is limited by several factors: the structure and the geometry of conductors, the surrounding environmental conditions, and the operating conditions of the line.

The temperature of the conductors depends on the current and local meteorological conditions, therefore the dynamic evaluation of the range of an overhead line requires the estimation of the maximum time interval in which the line can withstand a given load current.

The most substantial restriction on the power delivery via an Extra-High Voltage (EHV) grid is the thermal limit of the line conductor. The indirect measurement of the conductor temperature can be done using two analytical models:

- Thermal model, from which we derive an ex ante estimate;
- Mechanical model, from which we derive an ex post estimate.

Thanks to the combination of these two estimations, it is possible to create a temperature probability distribution (Bayesian approach), characterized by a certain degree of confidence. [96]

5.4 Thermal balance equation

The thermal balance equation is used to uncover the relation among the ampacity of a line conductor, conductor temperature, and weather conditions [70], [71]. According to the IEEE Std. 738-2006 [70], the relation between conductor current and temperature can be expressed by a thermal balance equation of heat gains and losses in the conductor (per unit length), i.e.,

$$P_j + P_S = P_c + \mathrm{P_r} \tag{13}$$

P_j = heat generated inside the conductor due to the Joule effect [W / m]

P_s = density of heat transmitted to the conductor by solar radiation [W / m]

P_c = density of heat dissipated by convection [W / m]

P_r = density of heat dissipated by radiation [W / m] where all the physical quantities and their units in (13) are defined in [17].

5.5 Mechanical model

Most of the conductors used on overhead lines for the transport of electricity consist of a core and a mantle of different metal materials. By exposing the conductor to a heat source or applying a tension force, it tends to stretch proportionally to the elastic modulus (E) or to the thermal expansion coefficient (α) of the material. To maintain the integrity of the conductor, the elongation of the two components must be the same, but the thermal expansion coefficients α of the core and cladding are different, therefore the tensile stresses are distributed differently on the internal and external part of the conductor.

By indicating with T the tension to which the conductor is subjected, the latter is divided between the mantle Tm and the core Ta. When the conductor is in place at temperature θ and tension T, it must be:

$$\frac{T_m}{E_m A_m} - \frac{T_a}{E_a A_a} + (\alpha_m \alpha_a)(\vartheta - \vartheta^*) = 0 \qquad (14)$$

A_m = theoretical section of the cladding [mm^2]

A_a = theoretical section of the core [mm^2]

A = total section of the conductor [mm^2]

E_m = modulus of elasticity of the shell material [daN / mm^2]

E_a = modulus of elasticity of the material making up the core [daN / mm^2]

E = $(E_m A_m + E_a A_a) / A_m + A_a$: modulus of elasticity of the conductor [daN / mm^2]

α_α = thermal expansion coefficient of the core [1 / ° C]

α_m = thermal expansion coefficient of the cladding [1 / ° C]

α = $(\alpha_m E_m A_m + \alpha_a E_a A_a) / (E_m A_m + E_a A_a)$: thermal expansion coefficient of the conductor [1 / ° C]

a: span length [m]

p: unitary transverse actions acting on the conductor [daN / m]

To apply the equation of state (14) it is necessary to know the operating temperature of the conductor, to compare it with the transition one and establish in which stress regime we are working.

$$\frac{a^2}{24}\left[\left(\frac{p_c}{T_c}\right)^2-\left(\frac{p_0}{T_0}\right)^2\right]=\frac{T_c-T_0}{EA}+\alpha(\theta_c-\theta_0) \tag{15}$$

To determine θc it is possible to apply the equation of the change of state (15).

5.6 Bayesian approach

In the Bayesian approach, a certain probability is assigned to a given event before carrying out ex ante temperature estimation. After observing the experimental frequencies, probability is modified, to arrive at the a posteriori probability, that is a conditional probability.

The parameters calculated with the generalized Bayes equations describe the Gaussian distribution with which the probability distribution of the conductor temperature is represented for each time interval. The final estimation therefore has both a temporal and spatial distribution, to which a certain degree of confidence is attributed.

$$\mu_{\mathrm{estimated}}=\frac{(\mu_{ante}\,\sigma_{post}^2+\mu_{post}\,\sigma_{ante}^2)}{\sigma_{\mathrm{post}}^2\sigma_{\mathrm{ante}}^2} \tag{16}$$

$$\Sigma_{\mathrm{estimated}}=\sqrt{\frac{\sigma_{ante}^2\sigma_{\mathrm{post}}^2}{\sigma_{ante}^2+\sigma_{\mathrm{post}}^2}}$$

(17)

In Fig. 24 the complete methodology applied for the derivation of the conductor temperature is reported.

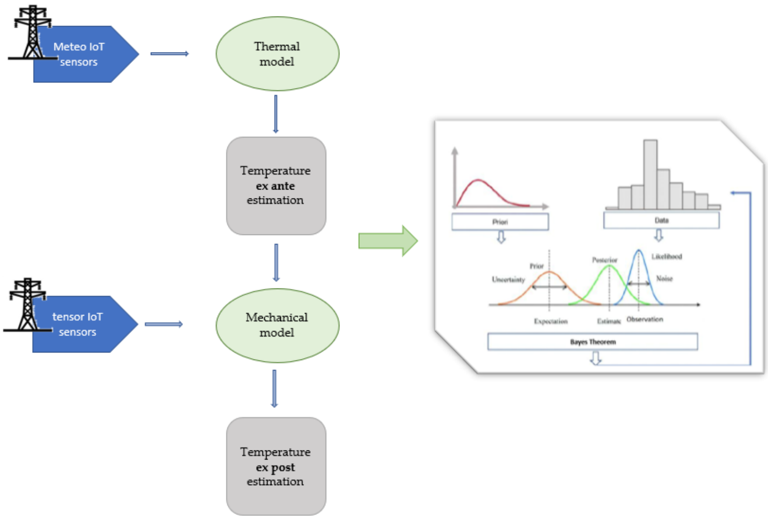


Figure 24. Schematization of the methodology used for the estimation of conductor temperature.

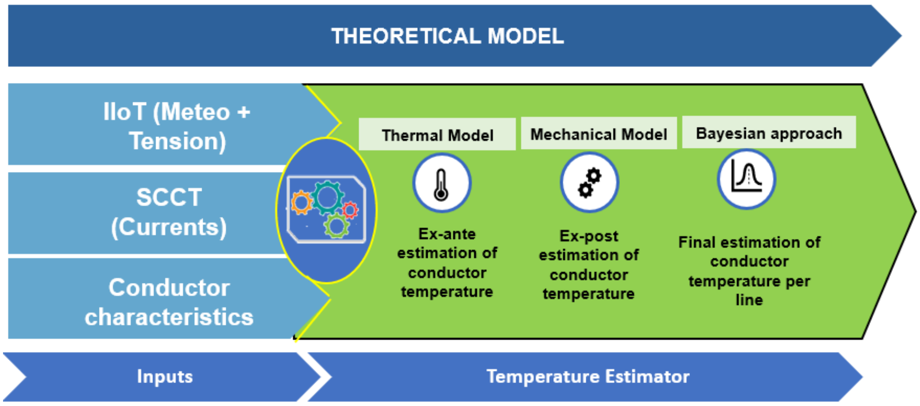
According to the IEEE Std 738 [73], the conductor temperature is an important parameter, which will directly influence the limit current flowing of the line. This work ends with the determination of the ampacity value for each line analyzed.

5.7 Results

5.7.1 Evaluation of conductor temperature

According to the IEEE Std 738 [73], the conductor temperature is an important parameter, which will directly influence the limit current flowing of the line.

At the theoretical level, data from IoT sensors were used as input data for the realization of the model (Figure 18). In particular, Meteo and Tension data, SCCT Currents data and geometric-physical characteristics of conductors. All these data were used for the implementation of the thermal model (Section 2.1) and also in the mechanical model (Section 2.2). The output temperature of the thermal model (ex



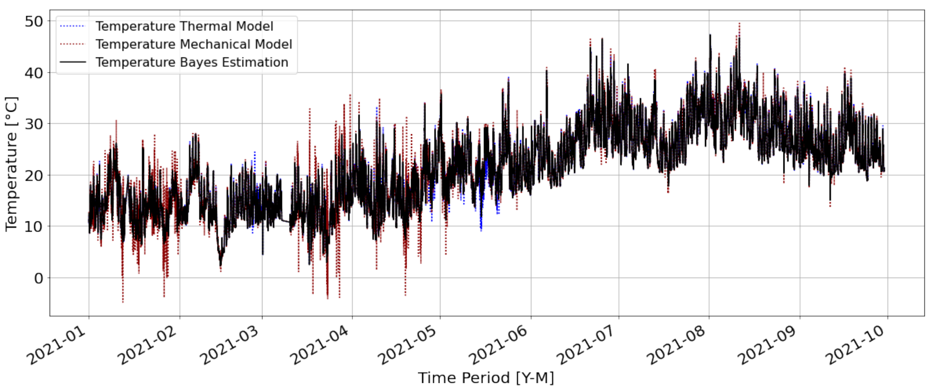
ante) is used as input of mechanical model that return ex post temperature. Once the two temperatures were estimated, they were combined with the Bayesian approach, with the aim of obtaining the final estimate of the conductor temperature for the entire line (spatial distribution).

Figure 25. Theoretical temperature model

Once the model in figure 25 has been applied, we obtained the following results.

In Figs. 26-27 the mean value of temperature of the considered HV Italian line coming from the thermal model (dashed blue line) is represented, together with the mean value of temperature coming from the mechanical model (dashed red line), as well as the mean value of Bayesian temperature (black line).

The temperature value deriving from the thermal model differs from the temperature value obtained from the mechanical model by an average value (in



absolute value) of about 2 degrees.

Figure 26. Temperature trends for all analyzed period: thermal model (dashed blue line); mechanical model (dashed red line); Bayesian temperature (black line).

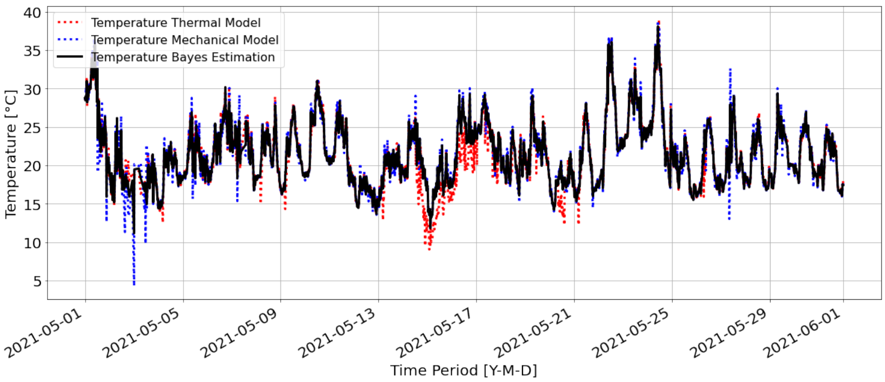
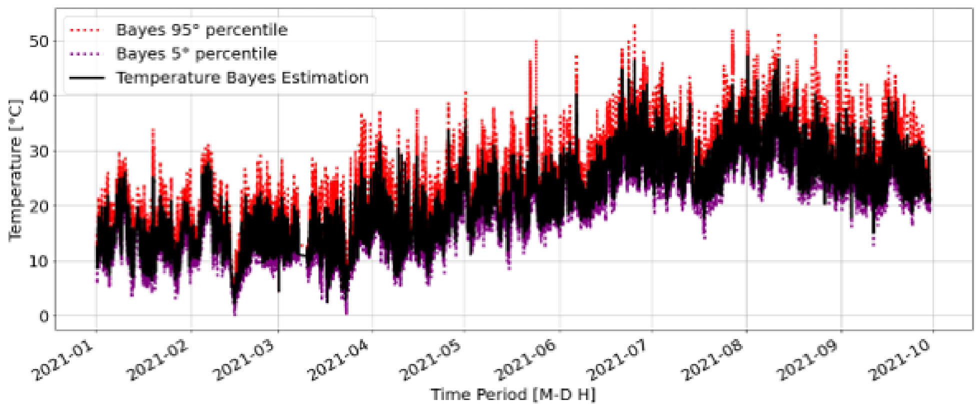


Figure 27. Zoom temperature trends for a specific period: thermal model (dashed red line); mechanical model (dashed blue line); Bayesian temperature (black line).

In Figs. 28-29 it is possible to observe the estimation of the temperature for a HV Italian line, derived from the generalized Bayes equation (black line) to which a 95%



confidence range has been attributed.

Figure 28. Bayes temperature trend and confidence range in total analyzed period: Bayes equation (black line).

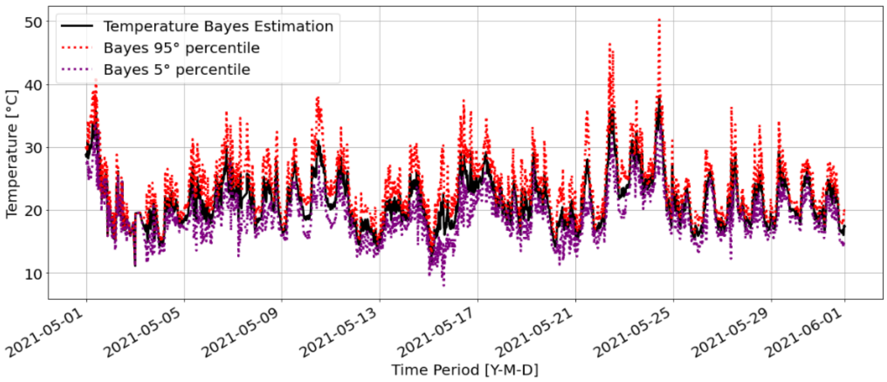


Figure 29. Zoom Bayes temperature trend and confidence range for a specific period: Bayes equation (black line).

5.7.2 Evaluation of ampacity

The use of the theoretical model for the evaluation of ampacity is the same of the temperature estimation model described before. In Figure 30, the input data being used are shown: IoT sensors, Meteo and Tension data, SCCT Currents data and geometric-physical characteristics of conductors. In this work the authors did not add, as input data, the conductor distance from the ground (mechanical constraint).

Usually, the ampacity is used like threshold values, derived from the technical catalog: it is calculated without considering the weather conditions associated to the different localization of the lines; the only characterization is the generic division into summer and winter period.

For the determination of optimized ampacity, an ampacity value for each line must be identified, because the limit current value depends on the weather parameters around pylons.

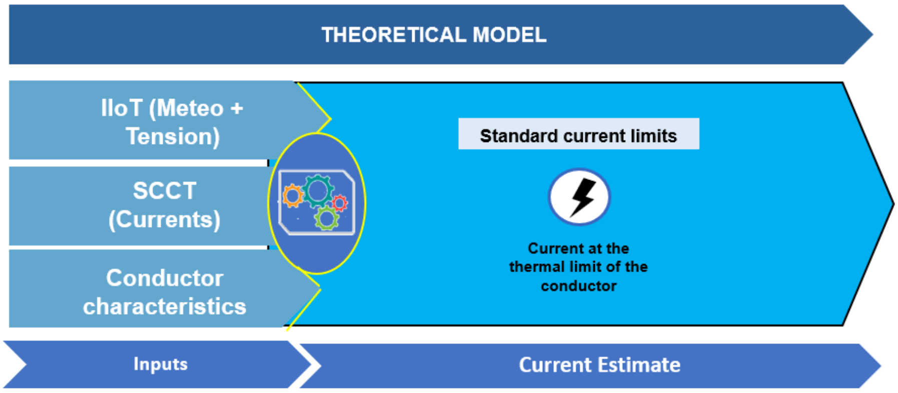


Figure 30. Theoretical model for ampacity estimation.

To overcome this problem and obtain ad hoc limit current values for each line, the DTR model was exploited by setting the temperature of the limit conductor to T_{cl} = 75 °C. This value represents the limit temperature tolerable by the conductor material. The limit current associated with each line will be selected as the minimum current value between the three conductors of the HV Line for each side of the pylon, calculated for every point of measure on the line. This value is evaluated for each timestamp and for each line.

Fig. 31 shows the current trend for the summer period of a generic HV Line, Fig. 32 shows the cumulate current value for summer period of a generic HV Line, Fig. 33 shows the current trend for winter period of a generic HV Line, and at last Fig. 34 presents the cumulate current value for winter period of a generic HV Line.

In Fig. 31 and Fig. 33 the first evidence of the results is the conductor current range reached at the imposed thermal limit, which is much higher than the current values required by the standard.

In Fig. 32 and Fig. 34 it is worth noting that, in a significant period of time, it could be possible to increase the actual current threshold values to optimize OHL ampacity. Considering all the lines analyzed, on average it is optimizable for 17% on summer periods and 44% on winter periods (Table 1).

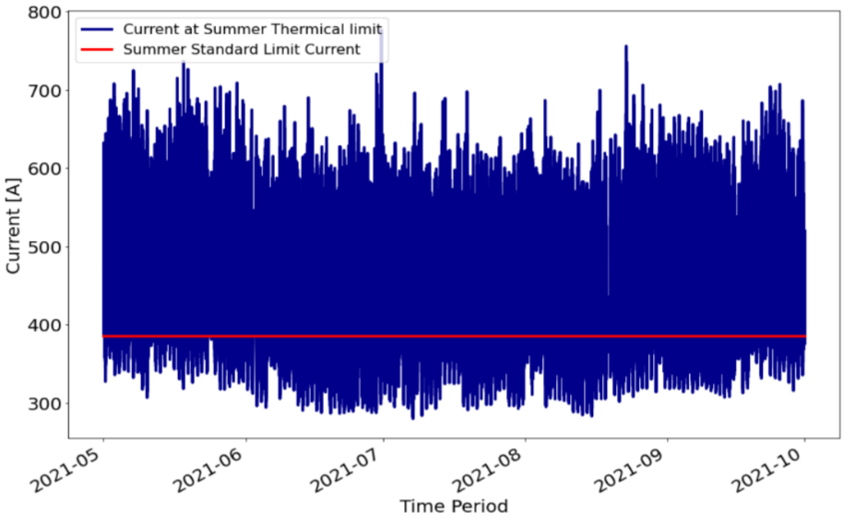


Figure 31. Current trend for summer period of a generic HV Line.

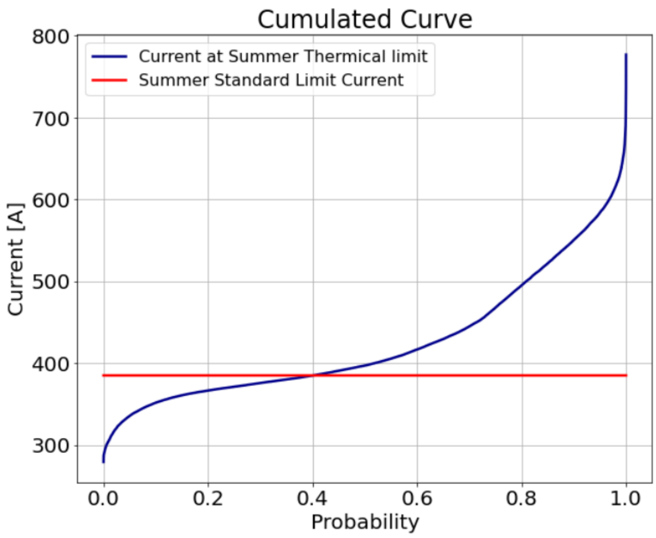


Figure 32. Cumulate current value for summer period of a generic HV Line.

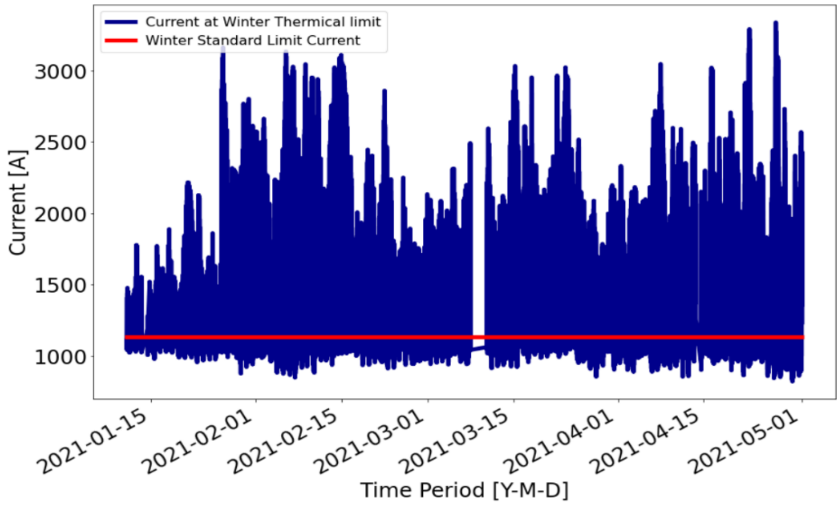


Figure 33. Current trend for winter period of a generic HV Line.

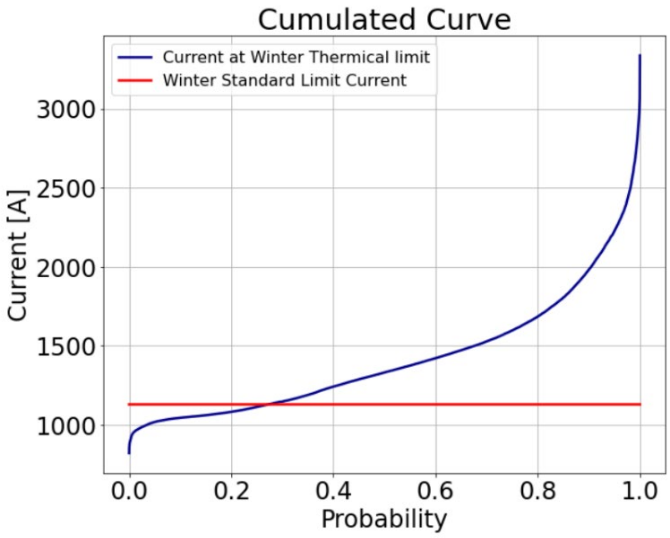


Figure 34. Cumulate current value for winter period of a generic HV Line.

Lines	standard_value_termal_model	standard_value_meccanical_model	mean_standard_deviation_bayes	mean_diff_bayes_95	std_diff_bayes_95	cumulated_winter	cumulated_summer	mean_summer_limit	mean_winter_limit
1	1.980	2.527	1.342	4.911	2.783	28.429	8.266	369.274	463.147
2	1.010	1.137	0.615	2.250	2.504	40.205	3.694	172.560	103.157
3	1.230	2.827	0.921	3.370	2.462	34.174	6.993	288.907	398.028
4	1.298	1.445	0.872	3.191	2.660	50.753	20.459	71.782	79.996
5	0.795	0.870	0.516	1.887	2.318	47.527	24.429	54.273	88.309
6	1.463	1.736	1.015	3.717	3.042	64.274	40.096	83.131	89.161
mean	1.296	1.757	0.880	3.221	2.628	44.227	17.323	173.321	203.633

Table 7. Outputs obtained for each line analyzed and the average values obtained.

Table 7 shows the outputs obtained from analyses carried out on each line. The variables 'mean_diff_bayes_95' and 'std_diff_bayes_95' respectively represent the mean and standard deviation of the difference between the value of bayes temperature [°C] and the value of 95° percentile. The variables 'cumulated_summer' and 'cumulated_winter' represent the intersection (evaluated as a percentage of the total time) between the cumulative curve of the calculated ampacities and the standard current limit for the summer and winter periods respectively. Instead, the variables 'mean_summer_limit' and 'mean_winter_limit' represent the average of the differences between the calculated current [A] and the thermal limit's current [A] for the summer and winter periods respectively.

5.8 Monte Carlo Validation

The validation of the model is based on the Monte Carlo method (a computational method based on random sampling to obtain numerical results). For each value measured by the sensors, the average value ($\bar{x}$) and its standard deviation (σ) were computed. With these parameters, the normal distribution associated with each sensor was obtained. Randomly, a large number of values (about 500) were extracted from the normal distributions obtained every 15 minutes. This extractions represent the input data that allow to calculate, for a high number of times (namely, equal to the number of values taken from the normal distributions) the temperatures of the conductor for every single quarter of an hour. The values found were then averaged, obtaining the mean temperature (T_m) and the mean standard deviation (σ_m).

Table 8. Sensors' accuracy.

Sensor	Accuracy
wind speed [km/h]	if <35: 0.02*wind_speed, else: 0.03*wind_speed
wind direction [°]	±2 + wind_direction
air temperature [°C]	±0.15 ± 0.1*air_temperature
relative humidity [%]	± (1.5+1.5*humidity)

solar radiation [W/m²]	10 ± 1*solar_heating
ST401Sy datasheet160221 [kN]	±1*sensor_pull
ST413 datasheet160221 [kN]	±1*sensor_pull
ST461.1 datasheet160221 [kN]	±1*sensor_pull
ST461.2 datasheet160221 [kN]	±1*sensor_pull

For the values of the absorption (ε) and emission (α) coefficients, the Monte Carlo method was applied, as previously discussed, obtaining normal distributions starting from the average value $\overline{x}$= 0.5 and standard deviation σ = 0.01.

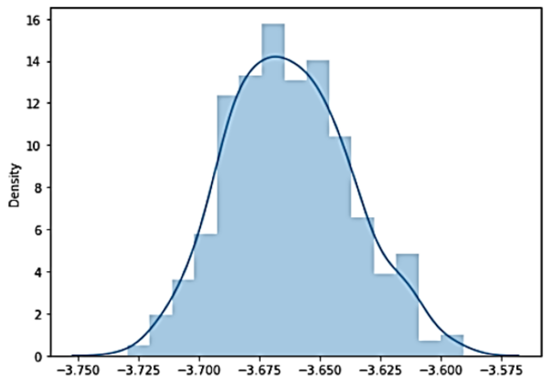


Figure 35. Example of normal distribution for generic input data.

Table 9. Results of temperature [°C] value obtained before and after the application of Monte-Carlo methods.

Timestamp	Montecarlo	Model	Difference
0	-3.168	-3.200	0.032
1	-2.874	-2.900	0.026
2	-1.170	-1.200	0.030
3	-0.565	-0.600	0.035
4	-3.701	-3.700	0.001
5	-3.173	-3.200	0.027
6	-1.071	-1.100	0.029
7	-0.681	-0.700	0.019
8	-3.530	-3.600	0.070
9	-3.600	-3.600	0.000
10	-1.667	-1.700	0.033
11	-0.677	-0.700	0.023
12	-2.900	-2.900	0.000
13	-3.374	-3.400	0.026
14	-2.135	-2.200	0.065

Table 9 shows the results obtained with the application of Monte Carlo method ('montecarlo' column) and the results from the model without having applied the Monte Carlo Method ('model' column). The average of the differences ('difference' column) between the values obtained is around 0.028: there is a minimum difference, so this highlights the good temperature estimation achieved by the proposed model.

5.9 Future work

Dynamic Thermal Rating systems and the georeferencing of the electrical system represent an important evolution of the high voltage network towards an intelligent system. The possibility to continuously check some fundamental parameters of the system, such as the temperature and the tension of the conductors, allows a more flexible operation of the rating of the overhead power lines. The analysis of the results of the proposed model shows the high model reliability for the estimation of temperature and ampacity of the lines. The model implemented considers only the thermal limit of the conductor material and its associated technical catalog ampacity value.

Future work may be aimed at augmenting the proposed model with the data related to the conductor distance from the ground in order to have an even more precise evaluation of the current ampacity. Moreover, to better assess the reliability of the model, it would certainly be necessary to carry out a validation by installing direct temperature sensors and comparing the measurements with the outputs of the proposed model. Finally, it is also possible to think about an implementation of a machine learning algorithm that would certainly make the model less heavy in computational terms and could also allow the forecasting of line temperature values.

6 Asset Management in railway infrastructure

Performance evaluation is a fundamental principle of Asset Management. As a consequence KPIs are used by managers to understand if the activities they manage are being successfully conducted to maintain and improve the performance [74].

Therefore, is vitally important to understand and identify a few meaningful indices that, when properly measured, are capable to understand the trend of the managed activities.

KPIs can measure the company's performance in its most varied aspects and they should be defined as [75]:

- critical

- synthetic
- significant
- priority

Critical because the management makes its own choices based on them, synthetic because they are expressed by a simple or compound variable, significant as they well represent the business phenomena to which they refer and priority due to their indispensable nature in the planning and control and risk assessment cycles at all company levels (strategic, managerial, operational).

In general KPIs can be grouped in order to provide an immediate overview of the progress of the business [94]. The subdivision proposed in this project is as follows:

- financial perspective;
- customer perspective;
- marketing and sales perspective;
- operational processes and supply chain perspective;
- employee perspective;
- corporate social responsibility perspective.

This work proposes a railway AM optimization using the framework presented by UIC Guideline[78].

6.1 International Standard

In 2014, the British standard (BS) of PAS 55 were translated into international legislation by the ISO:

- ISO 55000 - Overview, principles and terminology- which aims to provide a general vision on asset management and establishes its specific terminology and basic principles[66];
- ISO 55001 - Requirements- defines which are the requirements of an efficient asset management system [68];

- ISO 55002 - Guidelines for the Application- is a useful guide for the application of ISO 55001.

The international standard express the fundamental requirements of Asset Management:

1. Context of the organization;
2. Leadership;
3. Planning;
4. Resources;
5. Operation;
6. Performance evaluation;
7. Continuous improvement.

The principle of performance evaluation makes the use of KPIs to fulfill its purpose. Transforming data into information is the key of measuring asset performance. Monitoring, analysis and evaluation of this information should be an ongoing process.

ISO 55000 states that the performance of asset management should be evaluated with respect to the achievement of the Asset Management objectives. It is also advisable to examine any opportunities arising from exceeding these objectives, as well as any failure to achieve them [74]. ISO 55001, regarding the performance evaluation [76] and ISO 55002 express which one should consider for the monitoring [77]. Below (Figure 36) AM framework is presented.

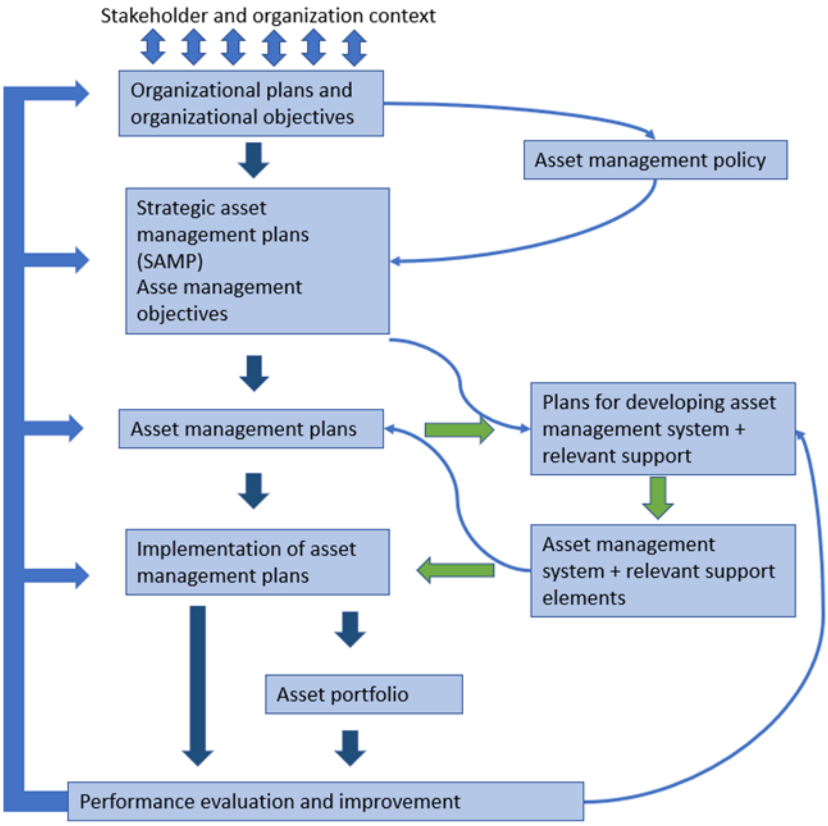


Figure 36. AM Framework ISO 5500X

6.2 The UIC Guidelines

In 2016, the Guidelines for the Application of Asset Management in Railway Infrastructure Organizations (UIC guideline) [78] was updated. It contains the guidelines for the application of the principles of Asset Management, imposed by the international legislations, to the railway sector. The application of these principles to the infrastructure must allow to maximize the profit for main stakeholders and users, in a sustainable way and under the most economically advantageous operating conditions.

This guidelines underline the importance to provide a measure of the effectiveness of implementation of each component of the resource management system, for example, the execution of work against plans and budgets; measurements of the impact of the Asset Management System implementation on infrastructure performance, e.g. conditions, failures, capacity, service impact, costs, etc.

Top management must control the wealth management system in a systematic and regular manner like:

- identify the gaps in the implementation of the Asset Management System;
- identify the root causes of deviations in performance measurements from target values;
- confirm that the implementation of the resource management system is driving sustainable performance, costs and risk levels;
- identify the actions for the short-term improvement of the infrastructure performance, where required, and the long-term continuous improvement of the components of the Asset Management System, including any changes to the general framework.

UIC guideline aim is to ensure that appropriate processes, requirements and technology are in place, to allow the monitoring and measurement of the Asset Management Plans, the implementation of the Asset Management System, the achievement of the Asset Management objectives. In Figure 37 UIC framework is presented.

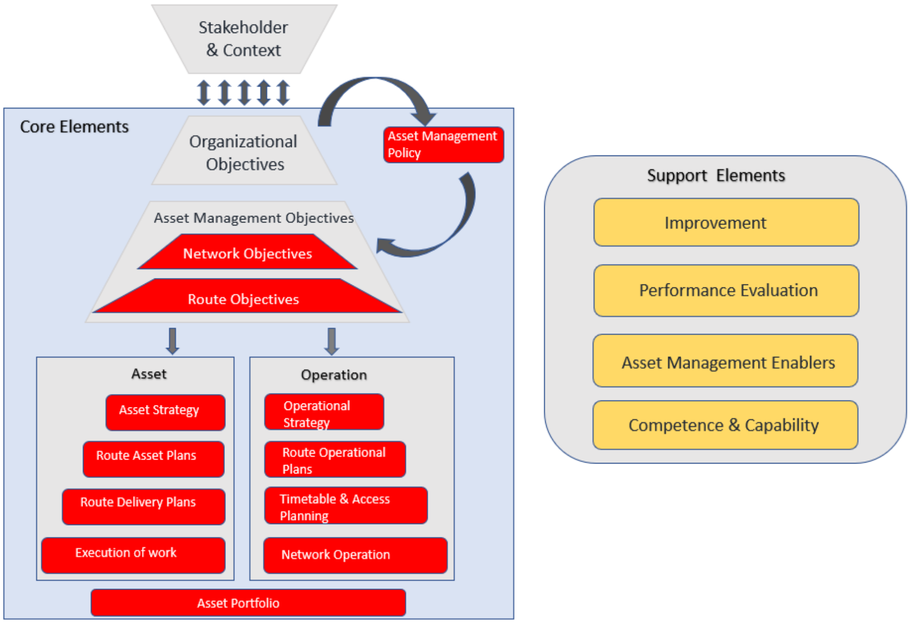


Figure 37. AM UIC Framework

6.3 Objectives

The aim of this study is to improve, using BI, the ability to evaluate the performance of the assets, to ensure the optimization of management and provide the guarantee that the organization (manager) is monitoring the aspects that can compromise the business objectives, through a systemic vision of the management system KPIs that allows an integrated reading of the performance results

A well-structured evaluation system should include metrics and indicators that are associated with objectives and that are above all aligned with the objectives of Asset Management and corporate strategy.

The company should monitor the performance of the asset management system itself, in order to evaluate the effectiveness of its management system. The gap analysis between asset management KPI's and those currently used will allow to define implementations in terms of new KPI to be introduced; verify the correct use of the KPI's in terms of improving the monitoring and improvement processes on the entire asset management systems.

6.4 Literature Review

This section deals with the overview of literature related to KPIs. Major facility performance measurement practices include benchmarking, a balanced scorecard approach, post occupancy evaluation, and measurement through metrics of key performance indicators (KPIs). Douglas [80] asserts that benchmarking is vital in building performance measurement. Some of the articles referenced in this paper discuss evaluating the performance of an organization and its services. Preiser [81] said that organizational performance is closely related to a facility's performance. Cable and Davis [82]affirm that measuring performance by establishing key performance indicators helps the Top Management to make important strategic decisions. Baldwin et al., [93] underline that performance metrics indicate long-term and short-term financial and performance goals, and are for a healthier relationship between customer and service provider.

Lebas [84] claims the measurement of performance expands the possibilities of examining the past and present and inferring future strategies for the proper functioning of the organization and for the achievement of its strategic objectives. Alexander [85] explains that facility management has a major impact on organizations, and its significance is increasingly being recognized.

Amaratunga et al. [83] argue that performance measurement is vital to the organization because it provides much-needed direction for decision-making.

Cable and Davis [82] explain that KPI's are useful for warn the presence of inefficiencies and unavailability. According to Amartunga and Baldry [87], the Procurement Executives' Association, described "performance management" as, 'the use of Performance Measurement (PM) information to effect positive change in organizational culture, systems and processes, by helping to set agreed-upon performance goals, allocating and prioritizing resources, informing managers to either confirm or change current policy or program directions to meet those goals, and sharing results of performance in pursuing those goals'. Neely et al. said that a

PM system can be described as the set of metrics used to quantify both the efficiency and effectiveness of actions [90].

Neely et al. [90] claim that performance measure can be defined as one used to quantify the efficiency and/or effectiveness of an action.

Porter and Lawler [93] described a model where performance consists in 'efforts, ability and role perception'. As Neely et al. [90] PM can be well-defined as the process of quantifying the efficiency and effectiveness of action. Thus, performance is the ability of an organization to implement a chosen strategy.

Developing performance metrics is an important step in the process of performance evaluation as it includes relevant indicators that express the performance of the facility in a holistic manner. Consequently, it is tremendous important to identify a set of KPIs to establish effective performance evaluation metrics. Performance Measurement (PM) and its framework areas are continually changing and developing.

6.5 Methods

The first task of this phase was the identification of the generic KPIs, starting from what the ISO 5500X regulation provides. In the Table 10 below are expressed KPIs identified.

Table 10. KPI's for a generic infrastructure

KPI			
Net profit	Total Return to Shareholders (TSR)	Debt / equity ratio (D/E)	Level of online customer engagement
Net profit margin	Economic added value (EVA)	Cash conversion cycle (CCC)	Online voice sharing (OSOV)

Profit margin	Return on investment (ROI)	Working capital index	Footprint on social networks
Operating profit margin	Return on investment (ROCE)	Operating cost index (OER)	Klout score
EBITDA	Return on assets (ROA)	CAPEX in relation to sales	Six Sigma Level
Revenue growth rate	Return on capital(ROE)	Price / Earnings Ratio (P / E Ratio)	Capacity Utilization Rate (CUR)
Promoter Net Score (NPS)	Customer satisfaction index	Customer Lifetime Value (CLV)	Process waste level
Customer loyalty rate	Customer profitability score	Customer turnover rate	Order fulfillment cycle time (OFCT)
Customer involvement	Relative market share	Conversion rate	Full, on time delivery rate (DIFOT)
Customer complaints	Brand equity	Positioning in search engines (by keyword) and click-through rate	Inventory Shrinkage Rate (ISR)
Market growth rate	Cost per lead	Page views and bounce rate	Change in project planning (PSV)
First Contact Resolution (FCR)	360-degree feedback score	Average duration of employees	Change in project cost (PCV)
Added value of human capital (HCVA)	Wage Competitiveness Index (SCR)	Bradford absenteeism factor	Earned value metric (EV)
Turnover per employee (RPE)	Return on investment in training	Waste reduction rate	Strength of the innovation pipeline (IPS)
Employee satisfaction index	Ecological footprint	Waste recycling rate	Return on investment in innovation (ROI)
Employee engagement level	Water footprint	Quality index	Market time
Staff defense score	Energy consumption	Overall Equipment Effectiveness (OEE)	First pass performance (FPY)
Employee churn rate	Levels of savings through conservation and improvement efforts	Product recycling rate	Rework level
Machine or process downtime level			

As a second step, the AM framework for a railway infrastructure was analyzed (Figure 37), going to explain all its contents. Then the company provided was asked to collect in a database all their KPIs currently used. The database had to specify the following items:

Table 11. KPIs items

Process
Sub-process
Activity
Perspective examined
Importance-Definition of the index
How to measure (formula, percentage...)
Data collection
Target
Frequency of verification

In table 11 there are the necessary information to make known the usefulness of each indicator, and its use. Until today, from corporates point of view, the organization is structured by business functions. This work want to change the point of view, restructuring the system according to the processes. To do this the actions start from the AM framework's components. Each KPI has been associated with the core element monitored (red elements in the figure 36 of the framework).
A critical analysis of the indicators was then conducted on the basis of this database, aimed at verifying how they support the management phases, to:

- keep the objectives under control;
- make business decisions;
- keep risks under control.

These macro views are ensured in the framework by the components that collect the objectives of the Infrastructure Manager, useful to the Top Management, while the decision-making aspects are used in the strategic processes where the choices of intervention are made, planning them at the strategic level, used by the managers responsible for management, and, finally, in the risk control levels are made the operational processes of execution of activities, used by management (resource manager).

Then the different KPIs can be aggregated into a pyramid view as shown in figure 38.

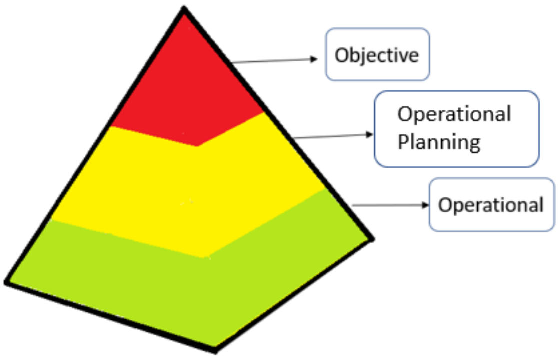


Figure 38. Pyramid macro-area view

Each area is characterized by external (stakeholders) and internal (structures employees) references with their own risks to be kept under control. Business objectives are the results that Top Management intends to achieve over a period of time. The objective must be:

- clear and specific so as not to run the risk of thwarting efforts to achieve it;
- measurable through pre-established quantitative parameters.

Once the objectives have been outlined, the management proceeds with the strategy (operational planning), planning the actions to achieve them; considering the resources available, it draws up a strategic plan to achieve the objectives. This can be done through the use of different tools.

6.6 Results and discussion

For a company operating in the field of Concessions of Public Assets (as in the case of RFI) one of the main objectives must be to create value from the asset granted

without depleting it. At the top of the pyramid, as already specified above, we have the objectives and descending respectively strategy and operational KPIs.
Once the area to which the individual KPIs belong has been identified, the next step was to make the associations of the individual KPIs to the framework component of the reference process. It is possible for each macro-area to identify its framework elements, therefore each KPI must choose its unique framework element.
After the restructuring/systematization of the performance measurement system according to the asset management system processes, the possibility of updating the KPI database was then evaluated. Gap Analysis completes the work by comparing how a company should measure its management system performance, according to standard and best practice, and how it is currently evaluated in the organization.
Below is presented an example of the simulation of the KPI distribution on AM Framework components for the railway infrastructure manager examined in this work. Each colors indicate a different company’s areas of responsibility (Figure 39).

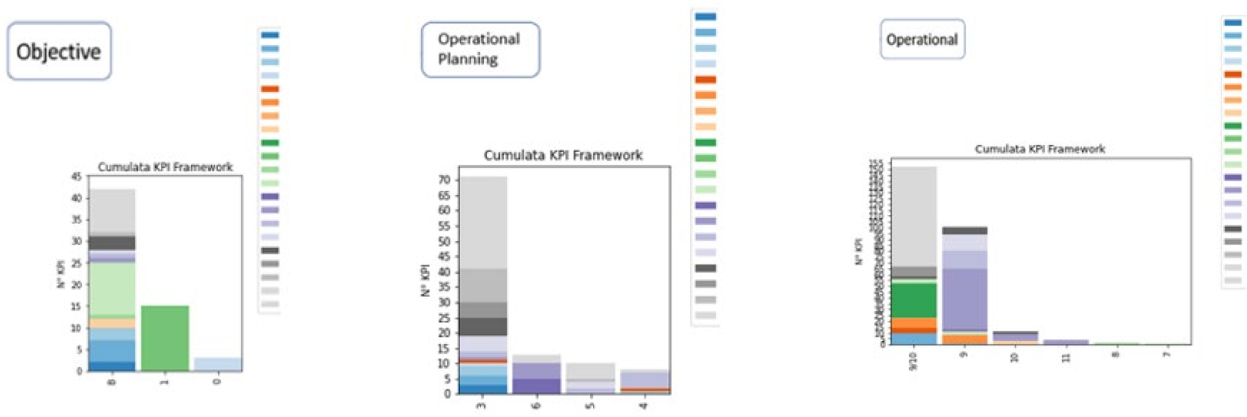


Figure 39. KPI distribution on AM Framework components

6.7 Proposed Improvements

Particular attention was given to the category of KPIs in the field of Sustainability: Environmental Social Governance (ESG), a theme considered central in this era. In addition to traditional perspectives, the most innovative are environmental and social aspects, with the aim of giving a coherent answer to the following questions:

- What is the value of environmental management and corporate social responsibility?
- How can companies plan and control the implementation of their sustainability strategy?
- How does this contribute to core business processes?

It's possible to think on a balanced scorecard [89] that favors and optimizes behaviors in line with the principles of environmental compatibility, first of all considering the company as a set of causal relationships between four interconnected visions (financial perspective, training and innovation, knowledge of customer and internal processes), and then assign a weight to intangible resources, which, although not immediately quantified in money and therefore not directly controllable with traditional management systems, play a fundamental role in determining a successful strategy for modern enterprise.

The Sustainability Balanced Scorecard aims to further expand the aforementioned vision by studying the integration of the environmental and social component within the system and assessing its contribution to the creation of value for the company, according to the three dimensions of sustainability:

- economic;
- social;
- environmental.

What is more, another key element that can act as a connector between strategical objectives and objectives delivery could be the value framework, a tool that declines the asset management system value elements that are connected to sustainability.

6.8 Comments

The use of the correct KPIs allows companies to highlight performance and sectors that need attention and improvement. In this study the key indicators were placed in the optimal management systems for the research of the value of a specific company, examining at first an optimal management system, as specified by the ISO standard of AM and then in a railway infrastructure management system, as specified by the guideline "UIC Railway Application Guide - Practical implementation of Asset Management through ISO 55001" - November 2016.

It was also possible to deduce that the KPIs definable are various and therefore it is very important to be clear about the use made of them in order to guide the improvement actions resulting from performance.

The development of KPIs starts from knowing the goal to achieve: they must provide information and answers to what is needed. The ability to define and correlate them provides the tools for quick analysis and effective decision making. The indices in use are therefore analyzed to understand the real use, any redundancies or uncovered areas.

7 Conclusions

This thesis described the projects carried out during the three years of the PhD program, aimed at researching data-based methodologies for design, validation and analysis of energy and industrial assets, in Industry 4.0 contexts. Considering that all used data in the presented experiments in this thesis are real data coming from installed sensors in industrial fields.

Through the implemented systems, it is now possible to detect and distinguish tunnel anomalies (nowcasting), thus enabling diagnostic functions. The large volume of data, derived from sensors, gives us relevant information and makes it usable to those who are managing the machinery and services, enabling them to make effective and quick decisions.

Furthermore, it is possible to construct a virtual sensor capable of detecting the temperature of high-voltage conductors (HV lines) with good accuracy, using sensors already installed on the lines and thus obtaining the following advantages:

1. Cost reduction: The efficiency of the lines is increased, resulting in lower costs;

2. Scalability: The virtual temperature sensor can be used to estimate the entire line;
3. Maintainability: The statistical model reduces the deterioration over time to which direct measurement sensors are subject;
4. Distributed Measurement: temperature measurement is extended to the entire line, reducing the problems associated with point measurement.

Indirect measurement expands the perimeter of measurement monitoring at zero cost.

By using sensors that monitor the resilience of overhead lines, it is possible to indirectly estimate quantities for which there are no field sensors. The quantities taken into consideration for the use of IoT sensors are conductor temperature and current at the thermal limit.

1. The temperature value obtained on a statistical basis using the Monte Carlo method is very close to the value obtained from the theoretical model;
2. The range of conductor currents reached at the imposed thermal limit, which is much higher than the current values predicted by the standard.

The last part of the PhD, a management system of an infrastructure manager was analyzed and systematized according to processes using the framework described in the ISO5500X standards.

Effectiveness, reaching one's objectives, efficiency, achieving them at the lowest cost, for a service provider, as in the case of a railway infrastructure manager, is determined by the overall quality of the service produced. Quality, a combination of effectiveness and efficiency, mean the relationship between the company's performance, and therefore the rendering of a service, and the needs/expectations of the customer/user. It is a relative and time-varying concept that strongly depends on the company's performance, determined by its Management System (SG), the quality of the work of each resource, which for an infrastructure manager are above all human resources, and the quality of the organization in general. The quality of a company's products/services is nothing more than the result of the processes put in place to make the product and/or deliver the service.

By having clear processes/sub-processes/activities, putting in place to realize products/services, organizing them with the requirements of ISO 5500X, we guarantee having all risks under control and making decisions in line with objectives (effectiveness) and at the lowest cost (efficiency), i.e. guaranteeing the grantor of the asset to create value from the asset granted, at least without making it lose value (e.g.: Bridge over the Polcevera). Making decisions in infrastructurally complex situations, such as railway infrastructure, and with the high number of interlocutors/data providers, requires the need of providing intelligent systems to support the decision-making phase, which is based on historical data from the use of assets. The activity carried out and thus steering the improvement of the management system. Above all, the indicator must monitor the risks in the management of the assets:

- Own risks arising from the Management System;
- Risks related to the supply in general (of products and services);
- Risks shared with the user of the service;
- Risks arising from the activities of other parties outside the railway system.

Starting from the AM framework, is possible to think, after a series of analyses and evaluations, of identifying, among them all, some indicators that are more significant or more aligned than others with what is the strategy of the moment in order to be able to form the reference dashboard for the company manager.

To conclude, it can be notice that: the use of machine learning systems, in combination with big data and the Internet of Things (IoT), enabled by today's digitization technology, has facilitated the sharing of a large amount of data. Digitization before being a new technology is a cultural change, a paradigm shift.

The following is a significant sentence by James Harrington (1611 - 1677) who already in the 17th century had specified the importance of data knowledge and gave a complete definition from measurement to improvement:

"Measurement is the first step that leads to control and finally to improvement. If you cannot measure something, you cannot understand it. If you cannot understand it, you cannot control it. If you can't control it, you can't improve it."

- James Harrington

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