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multi-Risk sciEnce for resilienT commUnities undeR a changiNgclimate

Codice progetto MUR: **PE00000005** – CUP LEAD PARTNER

Deliverable title: IT tools for advanced and integrated Situational Pictures

Deliverable ID: DV 6.6.3

Due date:30/11/2025

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1. Technical references

Project Acronym	RETURN
Project Title	multi-Risk sciEnce for resilienT commUnities undeR a changiNg climate
Project Coordinator	Domenico Calcaterra UNIVERSITA DEGLI STUDI DI NAPOLI FEDERICO II domcalca@unina.it
Project Duration	December 2022 – November 2025 (36 months)

Deliverable No.	DV 6.6.3
Dissemination level*	PU
Work Package	WP 6.6 - Integrated technologies and solutions for holistic risk reduction
Task	T 6.6.3 - Applying situational awareness to real-time approaches to risk reduction
Lead beneficiary	ENGINEERING
Contributing beneficiary/ies	UNIROMA1.

* PU = Public

PP = Restricted to other programme participants (including the Commission Services)

RE = Restricted to a group specified by the consortium (including the Commission Services)

CO = Confidential, only for members of the consortium (including the Commission Services)

Document history

Version	Date	Lead contributor	Description
0.1	30.09.2025	Giuseppe Cammarata (ENG)	First draft
0.2			Critical review and proofreading
0.3			Edits for approval
1.0			Final version

2. Abstract

This paper describes the Situational Awareness (SA) component developed within the RETURN prototype, aimed at ensuring resilience and safety in critical infrastructures exposed to natural hazards and NaTech events. The approach adopted is based on an integrated and holistic view, combining theoretical SA models, advanced information fusion techniques, risk assessments, and AI-based predictive strategies. The platform is designed to rapidly integrate and analyze data from diverse sources and in different formats, creating a dynamic and layered representation of infrastructure conditions to support accurate and timely decisions.
The modular system architecture, based on event-driven paradigms and microservices, is illustrated and facilitates real-time data collection, normalization, storage, and analysis. Particular emphasis is placed on the integration of the ETL framework via Node-RED, which allows for the orchestration of heterogeneous and flexible data flows. Data Visualization and Exploratory Data Analysis capabilities complete the system, offering interactive analysis tools and continuous monitoring that increase situational awareness and response capabilities.

This deliverable defines the functional and non-functional requirements, architectural structure, and operational processes needed to provide an advanced and reliable representation of the situation, laying the foundation for intelligent and proactive management of critical infrastructures, with the goal of minimizing risks and maximizing business continuity.

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4. Introduction

This document aims to define and explore the concept of Situational Awareness (SA) applied to both linear and point-based critical infrastructure exposed to natural hazards and NaTech events (technological disasters caused by natural phenomena). In a landscape characterized by increasing risks and vulnerabilities, the ability to acquire, integrate, and interpret heterogeneous data in real time is crucial for the efficient and resilient management of these vital systems. To address these needs, the document proposes a theoretical and methodological model that improves situational awareness through the fusion and overlay of information from various sources, thus supporting timely and shared decision-making processes.

SA represents up-to-date knowledge of the status of a complex system and its operational context. In the case of critical infrastructures, it requires constant monitoring of the physical and environmental status of assets and networks, the evolving risk scenarios, and the interactions that can lead to adverse events. Effective SA allows for anticipating future developments, identifying vulnerabilities, and adopting mitigation strategies. The awareness is based on data collected in real time through monitoring systems, IoT sensors, GNSS data, warning platforms and contextual sources, integrated and analyzed synergistically to provide a holistic and detailed view of the situation.

This paper explores the enabling technologies used to protect critical infrastructure, highlighting how a detailed understanding of both the internal functioning of systems and their interactions with the external environment is essential for effective management. In this context, data collection and analysis play a strategic role in ensuring security, operational efficiency, and resilience. Continuous monitoring allows for the timely detection of anomalies and malfunctions, while predictive analytics support informed decisions and proactive risk prevention. Furthermore, data collection, cleansing, and enrichment are essential elements for ensuring the sustainability and operational continuity of critical infrastructure.

The technologies considered—when synergistically integrated—enable advanced risk management and reliability optimization strategies providing benefits such as protection from natural events and NaTech, reduced failures, reduced costs and downtime, and increased operational safety. The proactive approach includes predictive maintenance and the adoption of data collection frameworks, which enable the creation of informative "datalakes" through the integration of sensors, IoT devices, and monitoring software. This data, once normalized and enriched with contextual information, provides operators with a solid and up-to-date basis for decision-making, maximizing performance, security, and business continuity. The implementation of a well-designed data gathering framework is an enabler for intelligent and resilient management of critical infrastructure.

5. System Requirements

The system designed to build and represent SA for critical infrastructures must meet both functional and non-functional requirements to ensure effectiveness, reliability, security, and adaptability in acquisition, integration, analysis, and visualization of data.

From a functional perspective, the system should:

- collect information from heterogeneous sources (physical and virtual sensors, APIs, files, databases),
- support various protocols and data formats (JSON, CSV, GeoJSON, shapefiles),
- automatically normalize and historicize information, aggregate and correlate data in real time, and provide advanced and customizable visualizations through dashboards and interactive maps.
- manage alarm generation, event traceability, and support operators in the decision-making process with simulation and risk assessment tools.

From a non-functional perspective, the system should ensure:

- operational reliability and fault tolerance,
- horizontal and vertical scalability, reduced response times, data and access security, modularity and architectural extensibility,
- ease of maintenance, interoperability with other systems and environments,
- usability of interfaces, as well as system availability and resilience even under critical conditions.

These integrated requirements ensure that the system is able to effectively manage large volumes of data, foster up-to-date situational awareness, and support the business continuity and resilience of critical infrastructure, in compliance with industry best practices and regulations.

Table 1 Functional Requirements

ID	Functional Requirement	Description
RF-01	Acquisition from heterogeneous sources	The system must acquire data via REST API, MQTT, file system, FTP/SFTP.
RF-02	Support for multiple formats	It must handle JSON, CSV, GeoJSON, Shapefile, with the possibility of extension to other formats.
RF-03	Data normalization	The system must convert heterogeneous data into a consistent and standardized format.
RF-04	Advanced normalization	Coordinate transformations, reference systems, and format conversions (e.g. SHP → GeoJSON) must be supported.
RF-05	Historicization in datalake	All data (raw and normalized) must be stored in MongoDB and/or MinIO.
RF-06	Extensibility and modularity	The system must allow easy addition of new flows, modules and formats without altering the core.
RF-07	Data fusion and correlation	It must integrate, correlate, and interpret data from multiple sources, enabling contextual analysis.

RF-08	Advanced View	The system must offer interactive dashboards, maps, and customizable situation views.
RF-09	Alarm and notification management	It must generate automated alarms and track interventions and maintain a history of critical events.

Table 2 Non- Functional Requirements

ID	Functional Requirement	Description
RNF-01	Reliability	It must guarantee operational continuity, error retry and event logging.
RNF-02	Scalability	The system must handle increasing loads and support the addition of new sources.
RNF-03	Performance	It must ensure adequate response times for both real-time and batch data flows.
RNF-04	Safety	Authentication, authorization and data encryption mechanisms must be implemented
RNF-05	Maintainability	Flows must be modifiable through the interface, with configurations kept separate from the code and properly documented
RNF-06	Interoperability	REST APIs and standard formats for external integration with other systems must be supported.
RNF-07	Availability and resilience	The system must support distributed environments, containerization, and automated backups.
RNF-08	Usability and customization	Simple and configurable interfaces according to the operator's role, with filterable and adaptable views must be implemented

6. Reference Architecture

Interoperability is a fundamental requirement for any complex IT system, particularly for platforms dedicated to protecting critical infrastructure. A useful and maintainable system must ensure that its components, often heterogeneous and distributed, can communicate effectively through well-defined interfaces. These interfaces can involve both hardware components, such as connectors and buses, and software, such as middleware, databases, operating systems, and communication protocols. In the design context, to ensure high levels of interoperability, aspects such as the heterogeneous nature of the components, the type and quality of information exchanged, the services provided, the dependencies between modules, portability, and the communication protocols adopted are considered.

The communication paradigm plays a primary role in the design of system architecture. There are synchronous communication modes, characterized by the simultaneous exchange of information between sender and recipient, and asynchronous communication modes, where such exchanges do not necessarily occur simultaneously. Often, especially in complex systems such as those supporting critical infrastructures, mixed models are adopted that combine these two modalities, using message brokers that simplify the management, sorting, and distribution of messages among the various components of the system.

This project adopts an event-driven architecture (EDA), which has proven particularly well-suited to managing parallel processing and resource monitoring in distributed and dynamic environments. The key feature of an EDA system is the use of events to communicate state changes within the system, promoting low dependency between the event producer and consumer modules. Message brokers, such as Eclipse Mosquitto, which implements the MQTT protocol, play a central role in ensuring efficient, fast, and scalable communication, mediating between producers and consumers in publish-subscribe mode. This model also supports temporary event persistence to ensure robustness in case of network instability or temporary outages.

The microservices architectural component (Figure 1) represents a further distinctive element, allowing the application to be divided into independent, stateless, and autonomous services.

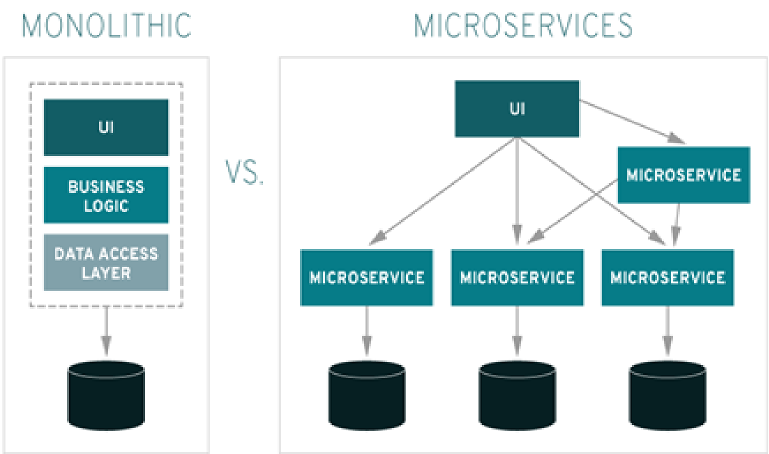

Figure 1 Microservices

Each microservice performs specific functions and communicates through APIs or events, thus promoting modularity, ease of maintenance, and dynamic scalability. The microservices approach integrates SOA architectural principles and leverages containerization technologies such as Docker and Kubernetes, which enable the entire application ecosystem to run flexibly and portably.

The architecture is divided into three main functional levels (Figure 2):

The **first level** involves data collection, acquisition, and homogenization, integrating physical sensors, software probes, and legacy components through automated ETL connectors such as Node-RED. This level collects data from a wide range of sources, normalizes it into standard formats, and manages its historicization in scalable datalakes using technologies such as MongoDB and MinIO. Asynchronous management of flows and data through brokers ensures efficiency and resilience.

The **second level** is dedicated to information processing and the generation of the actual SA. Here, event correlation engines, semantic fusion modules, and artificial intelligence algorithms are implemented to detect patterns and anomalies and generate integrated knowledge. The system builds dynamic and up-to-date situational images, producing a holistic and risk-based picture of the infrastructure's status, thus supporting timely, data-driven decisions.

The **third level** represents the user interface and service delivery, ensuring the availability of interactive dashboards, geolocated maps, notification systems, and APIs for integration with external applications or mobile devices. Customizing views by role and end user makes the platform accessible and actionable across different operational scenarios.

Overall, this distributed, modular, and scalable architecture, based on event-driven paradigms and microservices, offers a robust and flexible technological environment capable of effectively meeting the needs of acquiring, integrating, analyzing, and representing information to support the real-time maintenance and management of critical infrastructure.

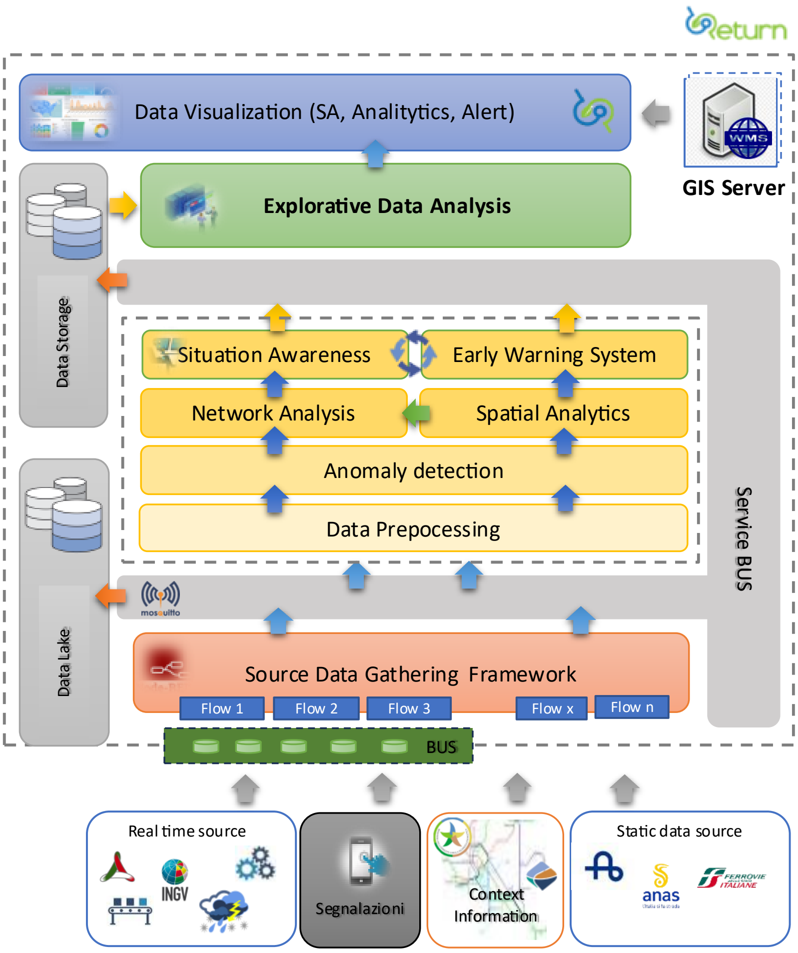

Figure 2 Overview of the reference layered architecture

After describing a complex and functional architectural model (Figure 2), it is useful to also introduce a more concise and linear representation of the system, illustrated in Figure 3. This version emphasizes the main data flow, from ingestion to visualization and alert systems, offering a clear and direct view of the information path through the platform's main modules.

The architecture highlights how data sources, which include both static data from different organizations and infrastructures and real-time data from monitoring systems, are collected, reconciled, and normalized through the "Source Data Gathering" framework. The processed data is then stored in a datalake and dedicated storage systems, available to the exploratory analysis, processing core, and SA construction modules (DIVA core). The latter encompasses all the key functions of preprocessing, anomaly detection, network analysis, and construction of the overall situational picture.

Finally, the processing results are sent to visualization and dashboard systems, GIS servers, and alert modules, thus completing the information and decision-making cycle. This architecture, although less detailed than the one seen previously, represents a complete and immediately understandable functional framework of the main components and their interaction, facilitating overall communication among stakeholders with different levels of technical expertise.

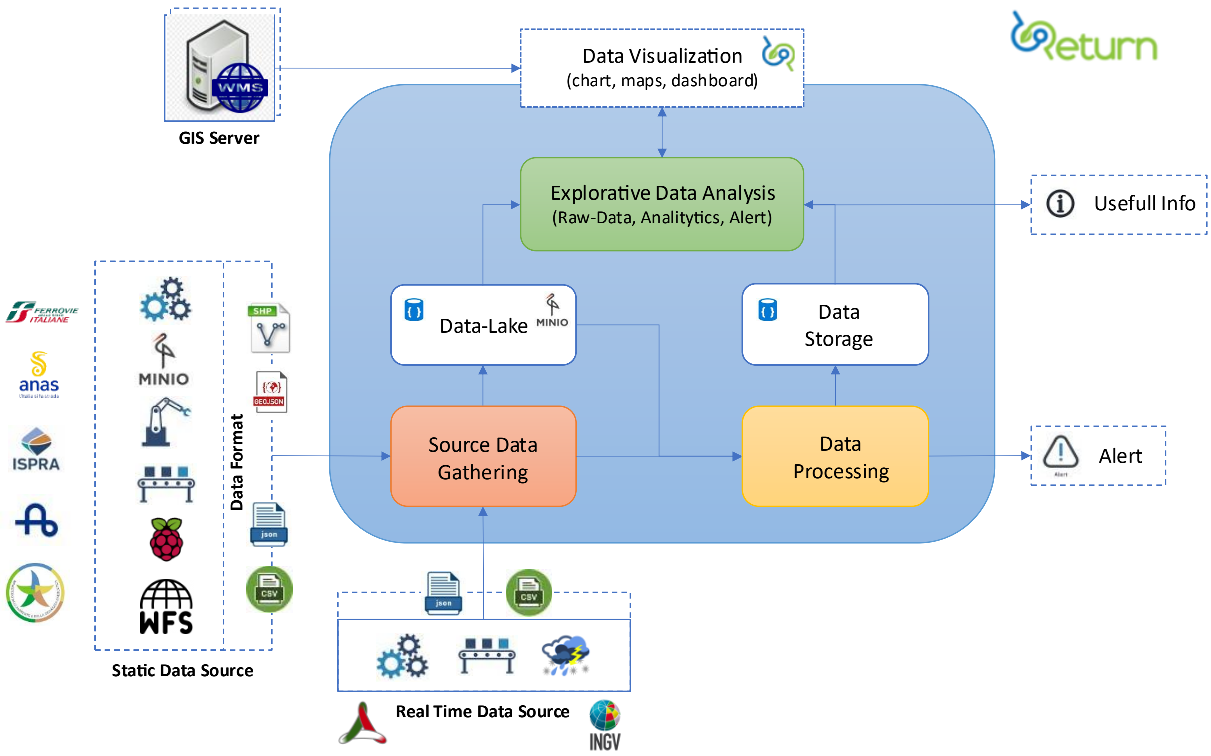

Figure 3 Reference architecture highlighting the data flow between components

6.1. Service BUS

The Service Bus, implemented through a generic message broker, is a fundamental component for orchestrating and enabling communication between the various components of a distributed system built on an event-driven architecture and microservices. This middleware acts as an intermediary, facilitating the asynchronous and reliable exchange of messages, events, and data between producers and consumers without requiring direct point-to-point connections. The service bus enables intelligent message routing, content-based routing, data transformation, and transaction management, ensuring that information reaches the appropriate recipients in a timely manner.

In the context of data acquisition and SA construction, the service bus integrates information flows from both physical sensors and software systems, acting as a technological backbone that supports resilient, scalable, and low-latency communications. By adopting standard protocols such as MQTT or AMQP, the broker ensures message persistence, support for the publish-subscribe pattern, and queue management with features such as automatic retry, sorting, dead-lettering, and status monitoring. In this way, the service bus enables a decoupled communication model, allowing sensing, processing and interface systems to interact in a synchronized but independent manner, improving the flexibility, modularity and maintainability of the system as a whole.

6.2. ETL

ETL (Extract, Transform, Load) platforms are fundamental tools used to manage the flow of data from heterogeneous sources, performing extraction, transformation, and loading operations into a target system, typically a data warehouse or datalake. These solutions ensure connectivity to multiple sources, data cleansing and normalization, error management, and operational scalability. Furthermore, ETL platforms offer visual interfaces that simplify the design and management of data pipelines, facilitating rapid integration and automation of data processing processes.

After careful analysis of the state of the art and the various available solutions, Node-RED was chosen as the primary ETL platform for this project. Node-RED is a visual development tool based on Node.js, designed to create automated workflows through a browser-based graphical interface. Its flexibility and customization capabilities make it ideal for integrating various data sources, such as IoT devices, web applications, databases, and cloud services, simplifying the creation of customized data automations.

Node-RED's graphical interface allows users to configure flows by simply dragging and dropping nodes, each configurable to perform specific actions and set connection and transformation parameters. Flows can be executed directly in the Node-RED environment or exported in JavaScript code for execution on Node.js servers. Thanks to a large developer community, Node-RED is enriched with numerous predefined and customizable nodes, offering debugging and monitoring tools that ensure reliability and process control.

In the context of the project, the ETL functionality attributed to Node-RED is divided into three levels. The first level collects and filters incoming data. The second handles normalization and transformation, adapting the data to the requirements of other system components. Finally, the third is dedicated to communication and information sharing with other platform modules. This approach allows for the effective integration of even highly heterogeneous components, facilitating customization and extension in complex environments. Node-RED thus represents a strategic choice for orchestrating the data flows necessary to ensure effective and consistent construction of the SA.

6.3. Data Visualization

Data Visualization is an essential element for effectively understanding and interpreting data and analytical results in any complex system. Through visual representations, large amounts of data can be synthesized into easily interpretable forms, facilitating the identification of patterns, correlations, trends, and anomalies that might not emerge from textual or tabular analysis. It also allows complex information to be communicated intuitively, supporting decision-making processes and continuous monitoring.

Modern visualization platforms enable the creation of multidimensional dashboards that aggregate and represent data from various sources. These dashboards integrate various types of graphs, such as time series, pie charts, summary tables, heat maps, and real-time indicators. Thanks to dynamic customization capabilities, users can interactively filter and modify views, exploring the most relevant information in depth. Real-time visual data analysis, combined with configurable alerting systems, enables proactive management of critical events and continuous improvement of operations.

In this context, data visualization tools are essential for the holistic representation of the performance of systems, applications, and services, making information easily accessible and usable by operators with different roles and responsibilities.

7. Source Data Gathering

The source data gathering process involves collecting data from specific sources and preparing it for subsequent analysis. This activity involves extracting information from databases, CSV files, web services, and other sources, based on the analytical objectives being pursued.

In some contexts, this process is similar to ETL (Extract, Transform, Load), whose goal is to acquire data from heterogeneous sources, transform it into a consistent and usable format, and finally make it available for effective analysis.

Data collection is the first crucial step and can involve two categories of sources: primary and secondary.

Primary data comes from direct observations, such as field sensors or log files used for infrastructure and environmental monitoring. It is often presented in a raw form and requires considerable effort to collect and process, resulting in increased costs.

Secondary data, on the other hand, has already been acquired previously by other parties for different purposes. Compared to primary data, it is generally more refined but less reliable and accurate. While finding accurate information can be more complex, collecting secondary data is quicker and more cost-effective. Secondary sources include books, journals, government publications, institutional websites, and academic articles.

In the context of critical infrastructure, data collection and integration pursue security, efficiency, and resilience objectives, providing information on system performance, vulnerabilities, and potential risk scenarios.

7.1. Context and Objectives

The growing complexity and vulnerability of critical infrastructure, exacerbated by the effects of natural events and NaTech (technological hazards triggered by natural causes), requires the adoption of proactive and technologically advanced approach to risk and resilience management. In this context, the availability of accurate, up-to-date, and easily accessible data is key for planning monitoring, maintenance, and timely response to adverse events.

This document is part of a broader analysis of enabling technologies for the protection of critical infrastructure, with a particular focus on the development of a modular system for acquiring, normalizing, and historicizing data from heterogeneous sources. The goal is to enable the systematic and automatic collection of operational and environmental information to support evidence-based management strategies, improve decision-making, and optimize operational efficiency.

The technologies described allow data to be acquired from IoT sensors, web services from institutional bodies (such as INGV, ISPRA, Protezione Civile, MASE), historical datasets, and files distributed in various formats (JSON, CSV, GeoJSON, Shapefile, etc.), through different access methods (REST API, MQTT, local or remote file system). Such data, often heterogeneous in structure, content, and quality, must be normalized and structured consistently to ensure usability in analytical or application contexts.

To this end, the system relies on an ETL engine built with Node-RED, which allows for the visual configuration of data acquisition and transformation flows. Node-RED is suitable for basic normalization operations, such as payload restructuring, redundant fields removing, and timestamp conversion. For more advanced needs such as geographic coordinate transformation, reference system changes, or Shapefile to GeoJSON conversion, custom Python modules can be integrated to perform more complex or intensive processing.

The normalized data is then stored in a datalake based on MongoDB (for structured and queryable data) and MinIO (for binary and document data). This architecture allows for the preservation of both the original information and its processed version, ensuring flexibility in future analyses, traceability, and process repeatability.

In summary, the proposed system represents an enabling infrastructure for the integrated and resilient management of critical infrastructures, capable of enhancing prevention, forecasting, and intervention capabilities through the efficient and intelligent use of data.

7.2. Purpose of the Data Acquisition System

The data acquisition system described in this document is designed to provide a flexible and scalable technological infrastructure capable of collecting, normalizing, and historicizing data from heterogeneous sources to effectively support the analysis, monitoring, and risk management activities associated with critical infrastructures.

The primary objective is to create a modular and interoperable framework that allows data acquisition in different formats (**JSON, CSV, GeoJSON, Shapefil**e) using multiple channels (**REST APIs, MQTT** protocols, local or remote file access), while ensuring the preservation of both the original information and its normalized version.

By using **Node-RED** as the primary **ETL** engine, the system enables the automation of data acquisition and pre-processing workflows, enabling the seamless integration of new sources and simplified management of operational workflows. For more advanced normalization needs, such as geospatial transformations or complex format conversions, the system can be extended with dedicated Python components, ensuring maximum flexibility and processing capacity.

Data historization is achieved through a dual datalake infrastructure: **MongoDB** for structured and queryable data, and **MinIO** for the secure storage of binary files and large datasets. This solution guarantees complete information traceability, raw data preservation, and the ability to perform retrospective or comparative analyses over time.

In summary, the system's purpose is to:

- **Ensure interoperability between heterogeneous data sources**, regardless of format or access method;
- **Support predictive maintenance and resilience management strategies** by providing reliable and timely data;
- **Promote the automation of data collection and transformation processes**, reducing operational overhead and manual errors;
- **Build a solid and long-lasting database**, suitable for analytical systems, operational dashboards, early warnings, or decision-making models.

This system is configured as a **fundamental enabling element** for the adoption of proactive and data-driven approaches in the protection and sustainable management of critical infrastructures.

7.3. Definition and Objectives of the Data Collection Process

Data collection is an activity aimed at acquiring information from various sources to meet specific needs. It includes tasks such as manual or automated extraction, cleansing, transformation, integration, and sometimes even encryption and compression, to ensure security and efficiency in transmission.

The main objectives are:

- obtaining accurate and reliable information for informed decisions;
- selecting relevant data based on the application context;
- ensuring protection and privacy, preventing unauthorized access;
- minimizing errors through appropriate collection methodologies;
- maximizing efficiency, reducing the time and resources required.

In the RETURN project, the complexity and heterogeneity of the modules necessitated data-level integration, adopting a single and consistent schema. This way, the various sources can be implemented independently, simplifying the entire process.

7.4. Data Collection Sources

Data collection sources are divided into internal and external.

Internal sources: These include data generated by the organization itself, useful for analyzing the status of its systems. This category includes:

- Infrastructure monitoring sensors and devices (motion, vibration, temperature, humidity, crack meters, inclinometers);
- Industrial control systems (SCADA and production management systems), which record and control the operations of the critical infrastructure.

External sources: These include data from the surrounding environment or from third parties, including:

- Environmental sensors and devices (similar to internal sensors, but installed outdoors);
- Geographic data relating to the territory and topographical features;
- Meteorological data for forecasting extreme events (hurricanes, floods, storms, etc.);
- Seismic data for assessing the potential impact of earthquakes or seismic activity;
- Third-party sources, such as government agencies, security agencies, and risk analysis organizations.

The quality and relevance of sources are crucial aspects of data gathering: the choice must take into account the project needs and available resources, with particular attention to the reliability and consistency of the collected data.

> **Benefits of adopting a data gathering model**

The widespread availability of data in modern systems has made data collection models indispensable tools for managing critical infrastructures. A well-structured model achieves significant benefits:

- Structure: clearly defines what data to collect and how to organize it;
- Accuracy: reduces errors and improves information quality;
- Optimized management: ensures consistency and standardization in storage and sharing;

- Efficiency: reduces the time and resources required for data collection and analysis;
- Adaptability: can be modified based on specific project needs;
- Scalability: applicable to data collection environments of varying size and complexity.

In the RETURN project, an effective data collection and integration model enables continuous infrastructure monitoring, the timely identification of anomalies and threats, and the activation of rapid countermeasures, with concrete benefits in terms of resilience, reduced downtime, resource optimization, and reduced overall management costs.

7.5. System Architecture for Data Acquisition

The data acquisition system is designed to operate as a **modular**, **scalable**, and **interoperable framework**, capable of collecting data from heterogeneous sources, normalizing it, storing it, and making it available for analysis, predictive processing, or integration into external systems.

The architecture is based on an **ETL (Extract – Transform – Load)** pipeline (Figure 4).

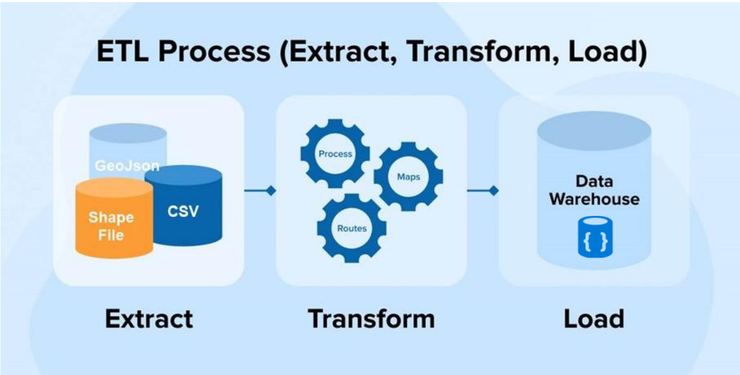

Figure 4 ETL

which leverages:

- Node-RED for managing ingestion and normalization workflows;
- Python for advanced transformation operations (e.g., geospatial conversions);
- MongoDB for structured data storage;
- MinIO for scalable storage of files and unstructured data.

This structure allows to:

- Acquire data from any source (institutional systems, sensors, static datasets);
- Apply customizable transformation logic;
- Save both raw and normalized data, maintaining complete traceability.

7.6. Logical Scheme of the Components

Here is a simplified representation of the architecture:

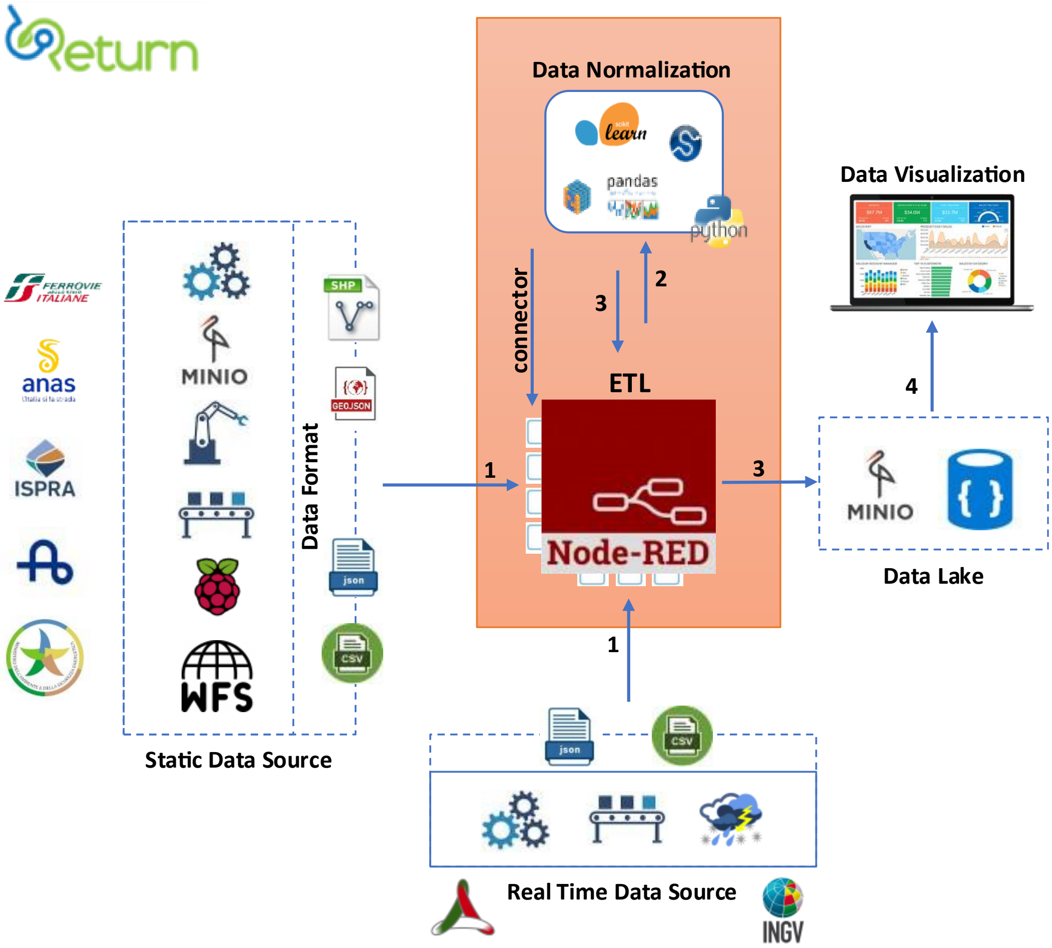

Figure 5 Scheme of components

7.7. Technical Description of the Modules

7.7.1. Acquisition Module

The acquisition module represents the initial component of the system and plays the crucial role of collecting data from heterogeneous sources, ensuring a constant and controlled flow to subsequent processing modules. Based on Node-RED, this module uses a graphical flow development environment, particularly suited to managing complex and variable pipelines, enabling the rapid integration of new data sources and customization of the behavior of each flow.

The system can interface with a wide range of sources, starting with web services exposed via REST APIs. These interfaces are queried according to configurable logic, with support for standard (Basic, Token, OAuth2) or custom authentication mechanisms, ensuring compatibility with major institutional data providers, such as INGV, ISPRA, MASE, and the Civil Protection Department. Pagination, query frequency, and error management are also included, ensuring acquisition continuity even in the event of temporary service interruptions.

In parallel, the module supports real-time acquisition through MQTT broker subscriptions, a key feature for receiving data from sensor networks and IoT devices installed in the field. Message management is based on configurable topics, and the system ensures automatic reconnection in the event of a disconnection, with the option to set the Quality of Service (QoS) level to ensure reliable reception.

Another acquisition mode includes reading local or remote files, by monitoring directories on the file system or connecting to remote sources such as FTP/SFTP servers. In this scenario, the system automatically detects the presence of new files in supported formats (such as CSV, JSON, shapefiles, GeoJSON), imports them, and activates the associated processing flows. Integrity checks, automatic renaming of acquired files, and temporary file management are also provided.

To ensure flexibility and operational continuity, the system allows for customized scheduling of acquisition activities, with the option of cyclic scheduling (cron-based), polling at configurable intervals, or triggered by external events (such as file creation or the arrival of an HTTP request via webhook). All these modes are configurable via the interface and allow for fine-grained control over the system's behavior based on the type and criticality of the data source.

Overall, the ingestion module provides a robust, extensible, and reliable foundation for ingesting data from disparate sources, serving as an enabler for a truly flexible, responsive, and operationally resilient critical infrastructure analytics and protection pipeline.

7.7.2. Parsing and Normalization Module

The parsing and normalization module is the heart of the system's data transformation phase. This component translates, harmonizes, and enriches the acquired raw data, making it compliant with internal standards and ready for storage and analytical processing. To ensure maximum flexibility and expressiveness in manipulation operations, the module is implemented using Python scripts integrated into Node-RED flows, which manages its invocation and data transfer.

One of the module's main functions is the conversion of geospatial data, specifically the transformation of shapefiles into GeoJSON format, with the aim of standardizing the format of territorial data and facilitating its integration with GIS applications and web-based analysis tools. This transformation is managed using established libraries such as GDAL, Fiona, and GeoPandas, which ensure reliability and accuracy in the processing of complex geospatial formats.

Complementing this activity, the module is capable of transforming geographic reference systems, for example, converting coordinates from EPSG:3857 (metric projection) to EPSG:4326 (WGS84, the standard format for geolocation). This operation is essential to ensure spatial consistency between datasets from different sources and to enable their overlay and integration in subsequent processes.

In addition to formal data normalization, the module performs advanced geospatial calculations, such as buffer generation, layer intersection, clipping of territorial portions, and overlay operations. These processes allow for the extraction of relevant geographic information based on the system's analytical or predictive needs.

Finally, the module includes a pre-processing phase for predictive models, which can include temporal aggregation, data cleansing, missing value interpolation, synthetic index calculations, or any transformation needed to prepare input data for machine learning models or risk analysis algorithms.

Thanks to the use of Python, the advanced transformation module combines expressive power and operational versatility, allowing for the efficient management of heterogeneous data and complex structures, transforming them into information assets ready for archiving in the datalake and use in subsequent analytical modules.

7.7.3. Historical Storage Module

The historicization module ensures the structured, secure, and traceable preservation of acquired and normalized data. It plays a key role in the entire system, particularly for retrospective analysis, transformation verification, and process auditing. This module is based on the synergistic integration of two complementary technologies: MongoDB for managing structured and semi-structured data, and MinIO for storing raw files and binary objects.

The data, once normalized, is saved within MongoDB according to a consistent structure that preserves its original semantics, enriched by metadata generated during the acquisition and transformation process. The choice of MongoDB, a document-oriented NoSQL database, allows for efficient storage of data in JSON and GeoJSON formats, while maintaining the flexibility needed to manage the variability of the original sources and formats. The saved documents also contain cross-references to the archived raw versions, ensuring full traceability and reversibility of the ETL process.

At the same time, the system stores the raw data and original binary files (such as shapefiles, CSVs, or unnormalized JSON dumps) within the MinIO system, an S3-compatible object storage solution. This approach allows the original state of the information to be preserved, which is useful in validation, debugging, or reprocessing scenarios for future improvements to the parsing modules. Each object stored in MinIO is associated with a metadata structure that describes its origin, acquisition date, source type, and processing status.

The entire historicization process is accompanied by advanced metadata management maintained in MongoDB and synchronized with MinIO. This metadata includes key information for data governance: unique source identifier, acquisition timestamp, normalization version, any errors or process notes. In this way, the system guarantees not only data preservation, but also its traceability, accuracy, and temporal reconstruction.

Overall, the historicization module creates a consistent, queryable historical data infrastructure ready to feed subsequent analysis, visualization, and predictive modeling phases.

7.7.4. Orchestration and Monitoring Module

The **orchestration and monitoring module** serves as the central mechanism that coordinates and supervises all data acquisition and transformation processes. Its primary function is to ensure the correct functioning of operational flows, synchronize activities between modules, and provide real-time visibility into the status of operations, promptly intervening in the event of anomalies or malfunctions.

Process orchestration is handled by **Node-RED**, which, in addition to serving as an ETL flow development tool, allows you to configure and manage the execution of activities in a modular and reactive manner. Thanks to its event-driven architecture, Node-RED allows you to define conditional processing paths, activate sub-processes in parallel or sequentially, manage flows dependent on external events (such as file uploads or data arrival from MQTT), and schedule executions according to defined rules (cron or dynamic triggers). This ensures fluid and adaptive management, capable of responding to the variability of sources and the frequency of incoming data.

From a **monitoring** perspective, the system integrates multiple levels of observability. At the runtime level, customized dashboards allow operators to view the status of active nodes, the number of events processed, execution times, and any errors that occurred during operations. These tools are essential for ensuring continuous operation and verifying system performance.

In addition, a **centralized logging subsystem** is provided, which collects and stores logs generated by each system component, including information on executions, errors, warnings, and completed flows. Logs can be accessed via dedicated interfaces or integrated with external tools (such as Grafana or Kibana) for more in-depth analysis and automatic alerts.

The orchestration module also manages **notification mechanisms**, which can be activated in the event of critical events such as acquisition failure, missing expected data, or parsing errors. Notifications can be sent via email, webhooks, or integrated into messaging systems (e.g., Slack, Telegram), allowing operators to intervene quickly.

Finally, the module supports **centralized configuration management**, allowing operating parameters (sources, frequencies, output paths) to be modified without interrupting services, making the system highly maintainable and scalable.

In summary, the orchestration and monitoring module ensures effective system governance, combining automation, visibility, and the ability to intervene—essential requirements for operating in a critical and dynamic context such as protecting strategic infrastructure.

7.8. Operational Flows

Operational flows describe the set of coordinated activities that the system performs to acquire, process, normalize, and store data from heterogeneous sources. These flows are implemented using the Node-RED platform, which allows the system's behavior to be modeled through logically connected nodes in an event-driven structure.

7.9. Startup and Scheduling of Operations

The process starts in response to three possible triggers:

- Time-based scheduling (e.g., hourly, daily): typical for REST sources.
- Real-time events (e.g., new incoming file, new MQTT message).
- Manual request (debugging or relaunching failed acquisitions).

This phase is managed by the orchestration module, which dynamically activates the flows provided for each configured source.

7.10. Data Acquisition

Once started, the flow activates the acquisition module, which connects to the specified source using the appropriate protocol:

- **REST API** with optional authentication (API key, token, OAuth).
- **MQTT** broker for receiving continuous or push streams.
- **Access to remote file systems** or directories for reading static or periodically updated files.

The acquired data, in its original format (JSON, CSV, Shapefile, etc.), is temporarily stored in memory or on local disk for subsequent phases.

7.11. Parsing and Normalization

The **parsing and normalization module** comes into play immediately afterward, converting the raw data into a uniform format (typically JSON/GeoJSON) and enriching it with metadata. This phase includes:

- Content parsing and data structure identification.
- Geospatial conversions (e.g., EPSG, buffering, shapefile-to-GeoJSON transformations).
- Removal of inconsistencies or redundancies.
- Application of normalization rules defined based on the data type and application domain.

For complex or georeferenced data, external Python scripts are activated to perform more complex transformations.

7.12. Storage and Preservation

Once normalization is complete, the data is managed in two parallel directions:

- **Writing to MongoDB**, where each document represents normalized data, complete with metadata and information about the source, timestamp, and process status.
- **Archiving of the raw file in MinIO**, which preserves the original version as a binary object, accessible at any time.

The association between normalized data and the original file is tracked using unique IDs and cross-references.

7.13. Logging and Notifications

During all previous phases, the orchestration and monitoring module tracks the operations performed:

- Technical logging with details on execution times, anomalies, network errors, or parsing.
- Issuing notifications in the event of significant events or detected problems.
- Recording of execution status and outputs in a centralized system accessible via a web interface.

7.14. Use Cases and Exemplary Data Sources

The acquisition system's flexibility allows it to be used in a variety of real-world applications. Some illustrative use cases are illustrated below, with reference to specific official data sources (Figure 6), field sensors, and historical datasets.

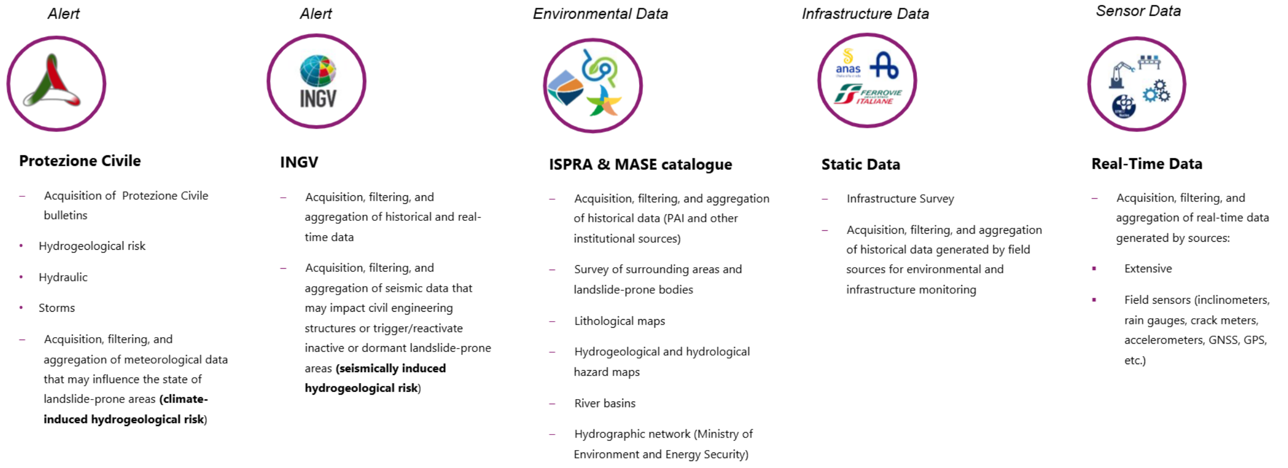

Figure 6 Official sources

The system can interface with numerous institutional sources that provide data relevant to the protection of critical infrastructure:

INGV (National Institute of Geophysics and Volcanology): provides real-time seismic data via REST API, with detailed information on epicenter, magnitude, depth, and event (Figure 7).

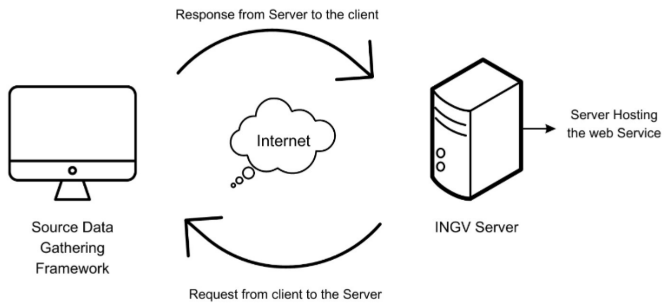

Figure 7 INGV Architecture

The table below shows the information made available by the INGV source for "earthquake" events, relevant to the RETURN project:

Table 3 INGV source attributes

Field	Description	Type	Example
#EventID	Earthquake ID	int	33975051
Time	Timestamp	datetime	2023-01-25T08:00:04.230000
Latitude	Earthquake latitude	float	43.1735
Longitude	Longitude of the earthquake	float	13.0502
Depth/Km	Depth of epicenter	float	14.3

Author	Entity that provided the data	string	SURVEY-INGV
Magnitude	Earthquake magnitude	float	0.9
EventLocationName	Location of the epicenter	string	4 km S Castel Raimondo (MC)
EventType	Event Type	string	earthquake

By querying the database provided by INGV and applying a filter based on a set of infrastructure-specific rules, the data gathering framework is able to produce an "earthquake" event as output.

Civil Protection: provides weather and risk alert bulletins (Figure 8), often in PDF or CSV format, which can be consulted and converted using automated parsing. The daily Civil Protection bulletin is an official statement that provides information on the evolution of emergency or crisis situations, such as natural events, including earthquakes, floods, fires, or health emergencies such as epidemics or pandemics. The National Criticality/Alert Bulletin reports the assessment of the criticality/alert levels for hydraulic, storm, and hydrogeological events expected on average until midnight on the day of issue (today) and within 24 hours of the following day (tomorrow) for the 156 alert zones into which Italy is divided.

The document is generally published daily by 4:00 PM. If, in specific cases, the Regions and Autonomous Provinces make new criticality assessments after the 4:00 PM Bulletin is published, the Department issues a new National Criticality Bulletin/Alert to reflect the relevant changes. In this case, two bulletins with the same date are published in the archive, one of which is labeled "Update."

The information contained in the "PC Bulletin" source is provided below:

Table 4 Civil Protection source attributes

Field	Description	Type	Example
Hydraulic risk	Hydraulic risk assessment	string	Moderate / ORANGE ALERT
Storm risk	Storm risk assessment	string	No significant foreseeable phenomena / NO ALERT
Hydrogeological risk	Hydrogeological risk assessment	string	Ordinary / YELLOW ALERT
Area name	Area name	string	Northern and north-western ridge, Valgrisenche and Valdigne
Municipalities	Municipalities in the area	string	Allein, Arvier, Avise, Bionaz, ecc
Publication date	Publication timestamp	datetime	20230210_1524

Once the information of interest has been extracted, the data gathering framework maps the events related to the three types of risk as defined by the Civil Protection Agency itself.

Figure 8 Criticality-alert mapping provided by the Civil Protection for hydraulic, storm and hydrogeological risks

ISPRA (Higher Institute for Environmental Protection and Research): distributes thematic shapefiles on hydrogeological risk, landslides, floodplains, soil, and land consumption.

MASE (Ministry of the Environment and Energy Security): provides open environmental data (emissions, air quality, energy consumption) via public portals and APIs.

> **Sensors in the field**

The system is designed to collect data from edge devices distributed across the territory, connected via lightweight protocols such as MQTT. These sensors can monitor environmental parameters (temperature, humidity, vibrations, water level, etc.) and transmit data at variable frequencies, from seconds to hours, in JSON or binary format.

The collected data is immediately processed to verify consistency, timestamps, and units of measurement, and then normalized for storage in the datalake.

> **Integration with historical datasets**

To enable retrospective analysis and predictive model training, the system allows for the bulk import of historical datasets. This data can be loaded from CSV or shapefile files, manually or through automated batch processes. During import, the data is parsed, cleaned, and normalized before being written to storage systems.

This approach enables consistent integration between current and historical data, which is essential for trend analysis and predictive risk management.

8. Situational Awareness

8.1. Theoretical Models

Several Situational Awareness (SA) representation models have been implemented based on the Endsley model. Their goal is to represent the situation and derive important knowledge about emerging threats, ongoing incidents, and their potential impact on security from the vast amount of available information. Although the Endsley model forms the basis of all SA representation models, it was necessary to conduct an analysis of the most frequently cited models. Endsley's cognitive SA model, adopted as the reference model, is divided into six components or levels: Perception, Comprehension, Projection, Decision, Execution, and Feedback. These levels are necessary for reconstructing the situation and provide a highly informative situational framework necessary to support the decision-making process. The models analyzed below, as mentioned above, are based on the reference model but use different names for the same levels.

8.2. Endsley's Situational Awareness Model (SAM)

Endsley's SAM model is based on the definition of SA as: "the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their state in the near future" (Endsley, 1988). According to the author, for a given operator/decision maker, SA is defined in terms of the goals and decisions to be made to manage a given task. The operator, therefore, does not need to know everything, but does need to know a large amount of information related to the goal to be achieved.

Figure 9 illustrates the definition of SA, which helps establish what "knowing what is happening" entails. Endsley's SA model defines SA as a state of knowledge that derives from a mental process, consisting of three levels of representation: perception, comprehension, and projection. The entire process can, of course, vary from individual to individual and from context to context and is referred to as situational assessment or as the process of achieving, acquiring, and maintaining SA.

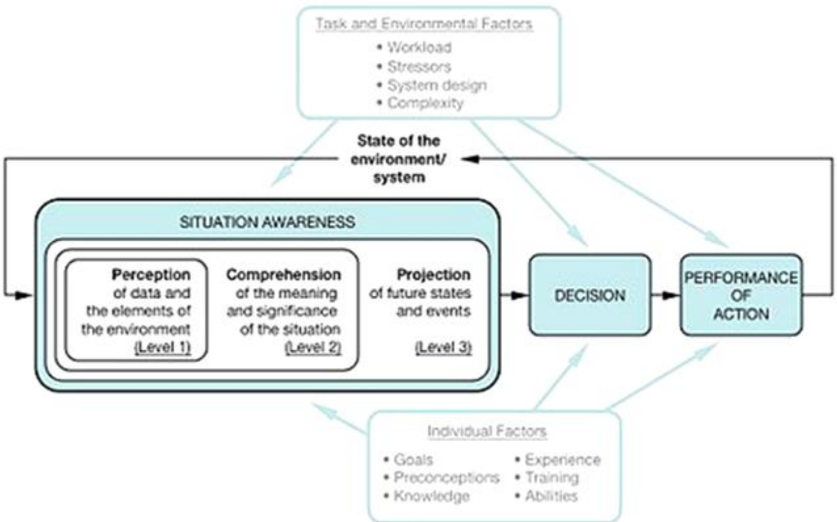

Figure 9 Endsley's Situational Awareness Model

Level 1: Perception

According to the SAM model, the perception of signals is crucial, as the lack of basic perception of fundamental information can lead to an incorrect picture of SA. Perception provides information about the state, attributes, and dynamics of relevant elements in the environment. Perception also includes the classification and integration of multiple pieces of information and provides the basic building blocks for comprehension and projection.

Level 2: Comprehension
Comprehension provides an organized picture of the current situation by defining the meaning of objects/elements and events. Furthermore, comprehension must combine new information with existing information to produce an increasingly complex picture of the situation as it evolves. According to the author, the concept of SA must be considered both in the sense of subjective interpretation (awareness) and in the sense of objective meaning or importance (situation).

Level 3: Projection
The highest level of the SAM model is the ability to predict future events and dynamics, which, according to the model's author, is achieved by operators with the greatest degree of understanding of the current situation. The ability to project from current events and dynamics to anticipate future events enables timely decision-making.
The SAM model depicted in Figure 1 shows situation awareness as a phase separate from the decision-making process and performance. SA is described as an operator's internal cognitive model of the state of the environment. Based on this mental model, the operator makes appropriate decisions to manage the situation. Therefore, SA is considered within the SAM as the primary precursor to the decision-making process. According to the model, situation awareness is not a decision-making process, and the decision-making process is not SA. This distinction has implications for the process of measuring SA.

In the context of critical infrastructure, both linear (e.g., road networks, railways, oil pipelines) and specific (e.g., power plants, industrial plants), the Endsley model is applied to ensure a continuous and in-depth view of the entire system. The peculiarities of these contexts include:

- Wide geographic distribution and fragmentation into multiple components.
- Specific vulnerabilities to natural hazards (floods, earthquakes) and NaTech events (cascading accidents between natural and technological events).
- Need to integrate data ranging from physical sensors to contextual information, ensuring layered and dynamic SA.

8.3. Situational Awareness Factors

Endsley's SAM model, like all other SA models, is fundamentally based on the perception of physical events from an environment, the understanding of their meaning, and the projection of their state in the near future. SA is the result of the processing of perceived information. The level of perception required for an operator to achieve accurate and complete SA is influenced by several factors, such as working memory, attention, goals, and automaticity.
The dynamic aspect of SA - that is, the speed with which information about the current situation changes—further amplifies the criticality of SA with respect to time, as it continually modifies current SA and requires constant reassessment of the projection or prediction of future events. Therefore, time plays an important role in the formulation of SA, regardless of the domain considered. Indeed, one of the critical aspects of SA, also taking into account the distances between the various infrastructure elements and ongoing events, is usually understanding how much time is available until an event occurs or until certain actions need to be taken. Time is crucial in SA models, both during the comprehension phase and during the projection and/or prediction of future events. The dynamic nature of the situation dictates that, as it is constantly evolving, situational awareness must constantly change, rendering it obsolete and therefore inaccurate.
Perceived information can derive from signals received through visual, auditory, tactile, olfactory, or taste receptors. Some of these signals may be very clear and obvious (alarms), while others may be ambiguous or uncertain. A significant challenge, given the increasing use of remote operators, is providing sufficiently clear information through a remote interface that can compensate for signals that can only be directly perceived. It is therefore important that the system, when representing the SA obtained through the perception of sensory information, uses only the necessary information and is important to the operator for understanding the SA, as the operator typically perceives and interprets only a portion of all the available information. The accuracy and completeness of the SA that operators infer from the environment depends on several interdependent factors,

such as working memory, attention span, and goals. In particular, working memory and attention span are limited resources and highly interdependent. The level of attention significantly influences the accuracy and completeness of the SA of a complex environment with multiple competing signals, as it identifies which aspects of the situation will be processed to form the SA, which in turn requires the integration of further information to understand and predict future states. The level of attention, in turn, is affected by the working memory required to process the acquired information. Narrowing attention to certain aspects can lead to superficial or incorrect situational awareness. To reduce the load on working memory, some authors, in addition to introducing the concepts of priority and automaticity, have emphasized the use of active goals as a means of processing information (top-down), as processing can also be data-driven (bottom-up). In goal-driven processing, attention is generalized across the entire environment in accordance with the active goals, and therefore the operator actively searches for the information needed to achieve the goals, while the goals act as a filter in the interpretation of perceived information.

Below is a summary table of the factors and their role in the information processing according to the Endsley model.

Table 5 SA Factors

Factor	Description
Working memory	Limited resources that affect information processing and condition the level of attention.
Attention level	Determines which aspects of the situation are processed to form the SA, influenced by working memory.
Goals	They guide the processing of information from top to bottom; they act as a filter to interpret information.
Automaticity	It helps reduce the load on working memory by promoting automated processes in information processing.

The quality and effectiveness of SA in critical infrastructures is significantly influenced by:

- Data quality and timeliness: Up-to-date, accurate, and complete data are essential for reliable SA.
- Fusion and integration capabilities: The presence of systems that aggregate data from different sources to generate a unified view.
- Reliability of technology platforms: Resilient IT infrastructure and secure communication systems.
- Human and organizational involvement: Operator skills and levels of coordination between agencies and stakeholders.
- System adaptability and scalability: The ability to respond to various scenarios and integrate new information sources.

8.4. Context Awareness

SA in application domains based on human-computer interaction is still an immature concept that can be confused with the concept of Context Awareness (CA), introduced by Schilit in 1994 as a term for ubiquitous computing. The difference between SA and CA lies in the level of abstraction of SA models and the level of granularity and representation of a context.

The concepts of Situation Awareness and Context Awareness are very similar, as both involve making assessments based on sensory information. While SA is aimed at understanding the physical environment, CA leverages contextual information to assess ongoing events. According to A. Dey, context is defined as "any information that can be used to characterize the situation of an entity." An entity is a person, place, or object considered relevant to the interaction between the user and an application. This characterization is used by context-aware computing systems to provide relevant information. Its value depends on the characteristics associated with the application domain within which the Critical Infrastructure is developed. Physical events, generally perceived by devices, are enriched with information regarding spatial and temporal location and the status of monitored objects. This information is typically used to determine the cause of a given situation, achieving Location Awareness (LA) capable of relating ongoing events to objects. However, not all perceptions contribute to situational understanding, as they can infer multiple entities in the environment.

Any additional information would simply seek to provide a more accurate picture of the situation. Instead, SA provides a high-level state of knowledge that explains what an application domain is experiencing at a given moment, resulting from a set of strategic processes.
Contextualization is a fundamental component of SA in critical infrastructures, as it provides the operational context within which events unfold, and risks evolve.

- Geographic contextualization: Includes the precise spatial location of critical infrastructures and their components, mapping the territory, and analyzing geographic vulnerabilities and risks associated with specific areas. Geographic representation allows for the correlation of natural and anthropogenic events with the actual location of the infrastructures, facilitating intervention planning and impact assessment.
- Meteorological contextualization: Integrates information on current and forecasted weather conditions, such as precipitation, temperatures, winds, and extreme events such as storms, floods, or heat waves. This data is essential for anticipating natural hazards and adapting monitoring and response strategies in real time.
- Demographic contextualization: Considers the distribution and characteristics of the population in the areas of interest, including data on population density, social infrastructure, essential services, and human flows. Demographic analysis is crucial for assessing the social impact of events and optimizing evacuation, rescue, and communication operations.

The integrated combination of these contextual elements creates a solid foundation for building predictive models and risk scenarios, improving the ability of critical networks to respond in a coordinated and timely manner to critical events. It also supports the generation of a dynamic Common Operating Picture (COP), expanding shared awareness among all stakeholders involved in managing critical infrastructure.

8.5. Information Fusion for Situational Awareness

Information Fusion refers to the process of integrating data and information originating from multiple heterogeneous sources to produce a consistent, accurate, and useful representation of the operational environment(Figure 10). It allows the system to transform raw data into meaningful knowledge that supports both situational awareness and decision-making.

The fusion process is usually divided into three levels:

- **Low-Level Fusion** focuses on data acquisition and preprocessing. It includes noise reduction, data cleaning, and alignment of measurements coming from sensors or other data streams. The goal is to generate reliable and coherent input for higher analytical layers.
- **Intermediate-Level Fusion** combines preprocessed data to detect relationships, patterns, or anomalies. At this stage, algorithms for event correlation, semantic enrichment, and clustering are typically applied to identify significant behaviors or deviations from normal conditions.
- **High-Level Fusion** integrates the results from the previous layers to generate contextualized information. It supports risk assessment, impact prediction, and the construction of situational pictures that guide operational and strategic decisions.

Through these stages, the system continuously refines the understanding of the monitored environment by correlating heterogeneous inputs - such as sensor data, network logs, video streams, and environmental parameters - it produces a unified and dynamic operational picture that enhances both awareness and responsiveness.

Figure 10 IF Flow

- **Data** consists of homogeneous or heterogeneous observations that are aligned, correlated, and combined within organized and indexed sets.
- **Information** is a set of information that describes the appearance and behavior of the domain being observed.
- **Knowledge** represents the known domain, the knowledge resulting from the process. The knowledge obtained contributes significantly to situation awareness by affecting the following factors:
    - Reduction of ambiguity and uncertainty, leading to improved accuracy of analyses and forecasts.
    - Data completeness. Data fusion also helps obtain a completer and more accurate picture by filling gaps or missing information in individual data sets.
    - Extended coverage in the space-time domain. Both the geographic and temporal dimensions of the information are taken into account, enabling a more complete, dynamic, and timely view of the situation.
    - Greater data robustness. The robustness of the analysis is improved, reducing uncertainty and increasing confidence in the results. By combining multiple sources of information, we can validate the results and identify patterns that might not be evident when analyzing each data set independently. This cross-validation helps identify outliers or anomalies that might otherwise have been overlooked.

Various methods and techniques are used in the Information Fusion process:

- Multidimensional integration: combining data from heterogeneous sources with different temporal, spatial, and semantic characteristics to achieve a unified view.
- Removing redundancies and uncertainty: consolidating information while avoiding duplication and managing incomplete or uncertain data.
- Progressive enrichment: each level of fusion processes the data to produce increasingly meaningful information, moving from raw signals to interpretive models and risk assessments.
- Modularity and scalability: fusion systems must adapt to varying information sources and different levels of detail without losing performance.

The choice of IF technique depends largely on the application context and the type of data available. Often, integrating multiple methods can produce the best results, allowing the advantages of each technique to be exploited. The information fusion technique widely used in the RETURN project is based on integration and progressive enrichment through an overlay process, which consists of the layered superposition of information layers:

- Spatial and temporal overlay: Information is superimposed on geographic maps and timelines, allowing the simultaneous visualization of data relating to the territory, the temporal evolution of events, and their interrelationships.

- Multiple information layers: Each layer represents a homogeneous set of data or analytical results (e.g., infrastructure status, critical events, environmental conditions); the combination of these levels offers an integrated and comprehensive view of the situation.
- Progressive contextual enrichment: The overlay process progressively adds levels of detail and contextual connections, improving the understanding of ongoing dynamics and supporting advanced analyses such as scenario forecasting or the identification of cascading phenomena.
- Dynamic decision support: through the overlay, operators can analyze the interactions between heterogeneous variables in real time, facilitating risk assessment and the planning of timely and effective responses.

8.6. Situational Awareness Model for Resilient Critical Infrastructures

Endsley's original definition of situation awareness as "the perception of elements in the environment within a volume of time and space, the understanding of their meaning, and the projection of their state in the near future," is the most widely accepted. The conceptual model of situation awareness proposes three main components or phases according to a life-cycle process:

- Perception: involves the collection of sensory data such as the state, attributes, and dynamics of the environment.
- Comprehension: uses perceptions and background knowledge about the event to understand the meaning of the data by identifying an event or situation (extracting information from the data).
- Projection: involves the extrapolation of knowledge to identify the future state of the current event.
- Therefore, the main aspect of situation awareness is understanding the future state of the environment from the projection of events in space and time. Perceptions can infer multiple entities in the environment, but not all are responsible for understanding the situation.

8.7. Processing Component for SA Update

The component uses information from the "Asset Analysis" and "Impact Analysis" phases to assess the criticality of each infrastructure element.
The objective is to provide a quantitative and dynamic measure of the network's robustness and vulnerability, identifying strategic assets and supporting the definition of operational priorities in the event of a crisis or infrastructure damage.

8.7.1. Topological Modeling of Critical Infrastructures

Transport and service infrastructures - such as highway and railway networks, bridges, tunnels, and viaducts - are represented as weighted and oriented topological graphs, in which:

- nodes represent intersections, toll booths, stations, interchanges, or logistics hubs;
- arcs represent infrastructure segments (road or railway sections, tunnels, bridges), enriched with geometric and functional attributes (length, type, capacity).

The transformation from physical infrastructure to topological model occurs through a geospatial data processing process that includes noding, snapping, and segment aggregation operations, ensuring the network's connectivity and geometric consistency.
The converted infrastructure becomes a common analytical basis on which all subsequent processing is performed, from criticality assessment to failure simulation and functional resilience calculation.
Topological modeling enables the analysis of the network’s systemic properties—connectivity, redundancy, criticality, and functional vulnerability. These analyses make it possible to understand how the failure of a single component may disrupt service continuity or reduce the system’s overall efficiency. In this perspective, the infrastructure is no longer seen as a set of isolated elements but as an interdependent system whose functionality emerges from the relationships among its components.

8.7.2. Network analysis

Once the topological graph has been constructed, **various centrality and robust indicators** are computed to quantify the systemic role and functional importance of each node and edge.

Centrality is assessed using key metrics: betweenness, eigenvector, and closeness. Each captures a different aspect of a node's role in the network:

Betweenness centrality: measures how many shortest paths pass through a node. A node with high betweenness is critical to the overall flow of the infrastructure; to better understand this type of centrality, it's useful to introduce the concept of shortest paths in a graph. Given two nodes randomly chosen in a graph—say, node A and node B—the shortest path between these two nodes is the sequence of nodes that must be traversed to get from node A to node B so that this sequence has the shortest possible length. The betweenness centrality of a generic node therefore provides a measure of how many shortest paths pass through the chosen node, indicating its influence as a mediator of flows.
Eigenvector centrality: captures not only how many connections a node has, but also how important it's the connected nodes are. A node connected to highly central nodes will have a higher score. Specifically, a node's eigenvector centrality is a measure that captures both local characteristics and those of its neighboring nodes returning a value that is higher as the node in question is connected to nodes that themselves have a high number of connections.
Closeness centrality: measures how "close" a node is to all the others, in terms of shortest path distance. A node with high closeness can reach all other nodes more quickly on average, meaning it is more globally accessible. This metric reflects a node's ability to efficiently interact with the rest of the network and depends on both its direct connections and the connectivity of its surroundings.

These three indicators offer complementary perspectives on the role of assets: betweenness captures the mediation of flows, eigenvectors the structural influence, and closeness the global accessibility. Their combination allows for a comprehensive description of the network's functional topology.
The centrality of a node is linked to the impact its failure can have on other elements of the infrastructure and, consequently, on the entire system. In this sense, there is a direct correlation between the centrality of an asset and its criticality.

In addition to centrality indicators, other measures are used to describe the system's functional robustness, i.e., the network's ability to maintain connectivity and performance in the presence of failures or damage:

- **Global Efficiency (E(G)):** measures how effectively the network connects all pairs of nodes. It is defined as the average of the inverse of the minimum distances between nodes: a high efficiency value indicates a network in which average paths are short, and connectivity is high.
- **Functional Criticality Index (ΔE)**: represents the relative loss of overall efficiency caused by the removal of a single element (node or arc).This indicator quantifies the functional impact of the loss of a component and provides a direct measure of its operational criticality.

These metrics, calculated in the initial state and dynamically recalculated in the event of failures, allow us to:
- identify the elements most susceptible to failure;
- estimate the performance loss at the system level;
- feed the ranking engine for defining intervention priorities.

Graph-theoretic network structural analysis enables the simulations of complex scenarios involving failures, malfunctions, or malicious attacks, allowing the assessment of their impact on network connectivity and overall performance.
Examples of simulated scenarios include:
- Targeted attacks on high-centrality nodes, to represent intentional events such as terrorist or cyber attacks;
- Stochastic failures of edges or nodes, to test resilience against natural events or technical malfunctions;

- Cascading failure models, to analyze domino effects between interdependent components.

Insights from these simulations can guide the design of recovery and redundancy strategies, such as implementing **virtual edges** (temporary alternative connections) or dynamically **redefining logistics routes** to maintain network functionality.

8.7.3. Geospatial Analysis and Hazard Integration

The geospatial analysis component integrates topological information with environmental hazard and structural vulnerability data to assess infrastructure exposure to natural or anthropogenic risks.
Through spatial overlay operations between the infrastructure graph and the hazard layers (e.g., seismic intensity, flood depth, landslide susceptibility), each element is assigned an exposure value (E_e) normalized to [0,1]. This value represents the probability or intensity with which the element is subject to a specific critical event.
When available, vulnerability values (V_e) are also incorporated, either provided by external agencies or derived from structural analyses. Vulnerability describes the asset's propensity to suffer damage given the hazard intensity levels (e.g., the fragility of a bridge or the seismic resistance class of a road section).

Geospatial assessment allows us to simulate critical hazard propagation scenarios using algorithms such as cellular automata, which discretize the territory into cells, each with a state (e.g., "intact," "affected," "propagating"). The transition of cells from one state to another depends both on neighboring cells and on the previously calculated exposure level. These simulations allow us to observe cascading effects, identify critical nodes, and isolate at-risk network segments, providing valuable operational support for planning prevention and protection strategies and prioritizing interventions.

The integration of topological and geospatial information allows us to identify both structurally relevant but protected elements and potentially exposed or vulnerable ones, building a holistic view of network-wide risk.

Composite Criticality Index

The combination of network analysis and geospatial analysis allows for an integrated assessment of the criticality of infrastructure elements, considering both their topological importance within the network and their exposure to natural or man-made risks. Specifically, network analysis measures the centrality of nodes and links, identifying strategic points for connectivity and the overall robustness of the system, while geospatial analysis quantifies the exposure of assets to specific hazards and their structural vulnerability.
Combining these three factors - centrality, exposure, and vulnerability - results in a composite criticality index, which allows for the comparison of heterogeneous assets belonging to different networks and the planning of more effective prevention and recovery interventions. Based on the values of the three main indicators, assets can be classified into different operational categories:

1. **Critical but resilient elements** – high centrality and low exposure: These represent key connectivity hubs, but their geographic location or structural characteristics make them relatively safe with respect to the risks analyzed.
2. **Vulnerable but marginal elements** – low centrality and high exposure: Although susceptible to damage from hazards, their loss has a limited impact on the overall operation of the network.
3. **Critical hotspots** – high centrality, high exposure, and vulnerability: Their compromise can cause severe systemic effects, requiring priority protection actions and timely recovery strategies.

This multidimensional approach allows us not only to generate criticality rankings for individual assets, but also to support preventive planning and post-event management, guiding decisions towards targeted interventions that maximize the resilience of the entire infrastructure.

8.7.4. Early Warning System

The component integrates an advanced Early Warning System, designed for real-time monitoring and proactive management of infrastructure risk.

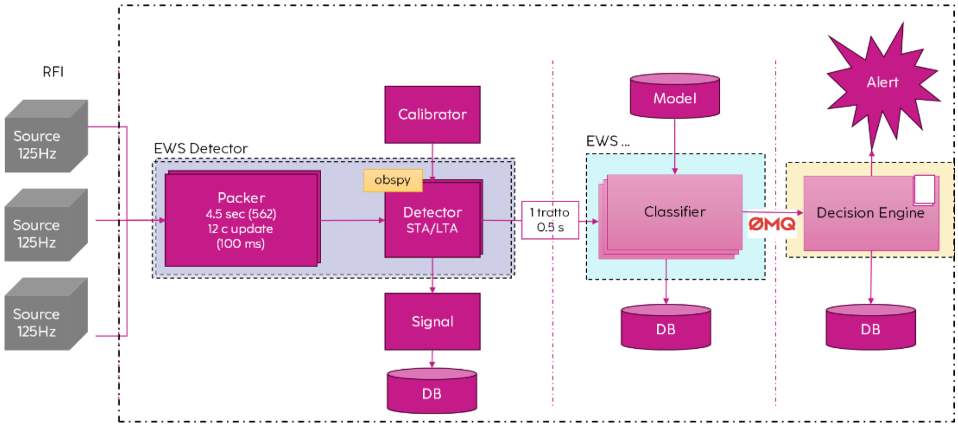

Figure 11 Early Warning System Components

The EWS (Figure 11) is structured as a distributed modular architecture, capable of monitoring signals from network monitoring stations and promptly detecting earthquakes. The main modules that make up the EWS (Figure 11) are:

- Acquisition and pre-processing of seismic signals: data from accelerometers and other environmental sensors are acquired at high frequency (e.g., 125 Hz), filtered, and segmented into moving windows optimized for seismic detection.
- Timely event detection: an STA/LTA algorithm analyzes the signal windows in real-time, identifying activations that indicate the beginning of an event—a portion of the signal that differs from background noise. Immediate detection of the first impulses of events allows the acquisition of critical data from the first 0.5 s of the event, providing sufficient information for preliminary classification and rapid alarm activation.
- Seismic event classification: detected events are sent to a classifier trained to distinguish events into earthquakes, trains, or spurious signals, using temporal and frequency characteristics of the signals. Each classification is accompanied by a quantitative confidence index, essential for the decision engine to establish the validity of the alert.
- Spatial-temporal Decision Engine: centralizes information from all stations, integrating geographic location and temporal propagation of seismic signals. It evaluates the propagation speed against the physical parameters of the terrain and infrastructure network, confirming or rejecting the alert in real-time.
- Automatic recording and calibration: all events are stored in a centralized database, allowing historical analysis and daily calibration of detection parameters through evolutionary algorithms. This ensures dynamic adaptation to operational conditions and maintains high reliability of seismic detection.

The entire system was developed and validated using two months of real accelerometric data acquired from 20 monitoring stations along the Rome–Naples railway line, provided by Rete Ferroviaria Italiana (RFI). This large-scale dataset enabled both algorithmic tuning and performance assessment under real operational conditions, ensuring robustness and scalability of the proposed architecture.

Event Classification

Within the Seismic Early Warning System, the automatic event classifier plays a central role. Its main function is to quickly distinguish between real seismic signals, anthropic vibrations such as passing trains or heavy traffic, and spurious or accidental interference. The goal of the classifier is not only to identify the nature of the signal but also to provide a probabilistic assessment of the event's origin, accompanied by a quantitative confidence index. This allows the system to trigger alerts extremely quickly, within a few tenths of a second from the detector's initial detection, ensuring a timely and reliable response.
Building the training dataset is a fundamental step to ensure the model's effectiveness. The dataset used combines different sources to faithfully represent the main types of events: real seismic signals, acquired from academic datasets such as those provided by the University of Naples (UniNA); anthropic signals and environmental noise, collected from twenty test stations in areas with train traffic.
Each raw signal undergoes careful preprocessing, including noise filtering, normalization, and temporal segmentation. Subsequently, the data are transformed into the frequency domain using the Fast Fourier Transform (FFT), generating the power spectrum. This representation allows the extraction of a set of normalized

numerical features ready for classification.
From the FFT transformation, the main spectral features characterizing each event are derived. Among these, the energy distribution between low and high frequencies is particularly useful to distinguish earthquakes, typically at low frequency, from train or industrial activity signals, often concentrated in higher bands. The spectral slopes indicate the rate at which energy decreases or increases frequency; high values may signal impulsive phenomena such as earthquakes. Finally, analysis of correlations between sensor components allows the separation of real structural events from cyclic or repetitive signals typical of anthropic activities. This multidimensional approach creates a distinctive profile for each type of event, significantly improving the model's ability to discriminate between similar signals of different origins.
To ensure robustness and reliability, various machine learning approaches, both supervised and unsupervised, were explored, with parameter optimization via Grid Search and evaluation through precision, recall, and confusion matrix metrics. Among the models tested we can mention: K-Means Clustering, used for preliminary evaluation of data separability, which showed that clusters are linearly separable in most cases; Gaussian Mixture Model (GMM), a soft clustering model capable of estimating the probability of each signal belonging to a particular class, providing a confidence index useful to the Decision Engine; Logistic Regression, chosen for its interpretability and low computational cost, with excellent performance in terms of accuracy and generalization; and finally, Random Forest, a high-performance model known for noise robustness and the ability to capture nonlinear relationships between features, used as a reference for final validation of results. Evaluation metrics analysis showed high discriminative ability between classes, with overall accuracy above 90% on test datasets, confirming the effectiveness of the approach.
Each classification produced by the system is not limited to a label but is accompanied by additional information essential for data management and spatial-temporal aggregation. Provided are the assigned class (earthquake, train, or spurious event), the prediction confidence, expressed as the probability estimated by the GMM or as the mean of votes from the individual Random Forest trees, and finally timestamps and station metadata, necessary to correlate events detected at different locations and for subsequent statistical or operational analyses. This structured output allows the EWS system not only to generate timely alerts but also to support decisions based on objective and verifiable data, significantly enhancing the overall system safety and reliability.

Spatial-Temporal Decision Engine

The Decision Engine constitutes the highest level of analysis and integration of the system, representing the core of the decision-making logic for alert confirmation or rejection based on data received from monitoring stations. This module receives classifications produced by each station, each of which has already performed local preprocessing and signal analysis.
The main functionalities of the Decision Engine span multiple dimensions:

- Spatial-temporal aggregation of events: the system organizes and compares events detected by different stations based on their geographic location and associated timestamp. This phase allows reconstruction of a dynamic map of ongoing events, facilitating identification of coherent patterns and isolated anomalies. For this purpose, the Decision Engine uses temporal and spatial clustering algorithms, described in detail in Appendices A and B, which show the temporal data structure and the geographic coordinates of the stations, respectively.
- Calculation of apparent propagation velocity: for each pair of successive stations detecting the same event, the system estimates the apparent propagation speed of the phenomenon based on detection time differences and inter-station distance. This calculation is essential to distinguish real signals from local artifacts or noise, as illustrated in the attached flowchart (Appendix C).
- Comparison with physically compatible values: the calculated velocities are compared with physically plausible ranges for different types of phenomena, such as seismic waves, train-induced signals, or other mechanical events. Only propagations within these ranges are considered consistent and therefore candidates for confirming an alert. Appendix D contains tables and references for the limit values used, derived from technical literature and historical experimental data.
- Integration of classifier confidence: the final decision combines the confidence associated with each station's local classifier with the spatial-temporal consistency of the signals. This multi-source probabilistic approach allows weighting both the reliability of a single detection and its consistency with events detected by other stations. Appendix E shows examples of how individual confidence is integrated into the overall alert probability.

Thanks to this methodology, the Decision Engine significantly reduces false alarms, triggering alerts only when

signal consistency is confirmed by physical and statistical criteria. The adoption of a probabilistic, multi-source model ensures that the system does not rely solely on a single station but considers the event in its global dimension, increasing accuracy and reliability of the overall monitoring system.
Integration of the EWS with topological modeling and geospatial information enables rapid and contextualized alert generation, providing operational information for immediate earthquake management and strategic planning for infrastructure network resilience. The system's modularity and scalability allow extension to new types of sensors and critical infrastructures, ensuring complete coverage and timely response in complex seismic scenarios.

8.8. Situational Awareness Components

The Source Data Gathering Framework continuously monitors incoming data flows. Upon detection of an alert or an anomaly message, the framework normalizes and standardizes the data so it can be understood by all RETURN platform components. The relevant information is then forwarded to SA4CI for processing (Figure 12).

The SA4CI module is made up of several components that work together to contextualize the alerts received, enrich them with additional information, update the status of the affected infrastructures, and process the new SA level.

The outputs produced by SA4CI feed the situational awareness dashboards, ensuring a clear, up-to-date, and integrated view of the monitored infrastructures.

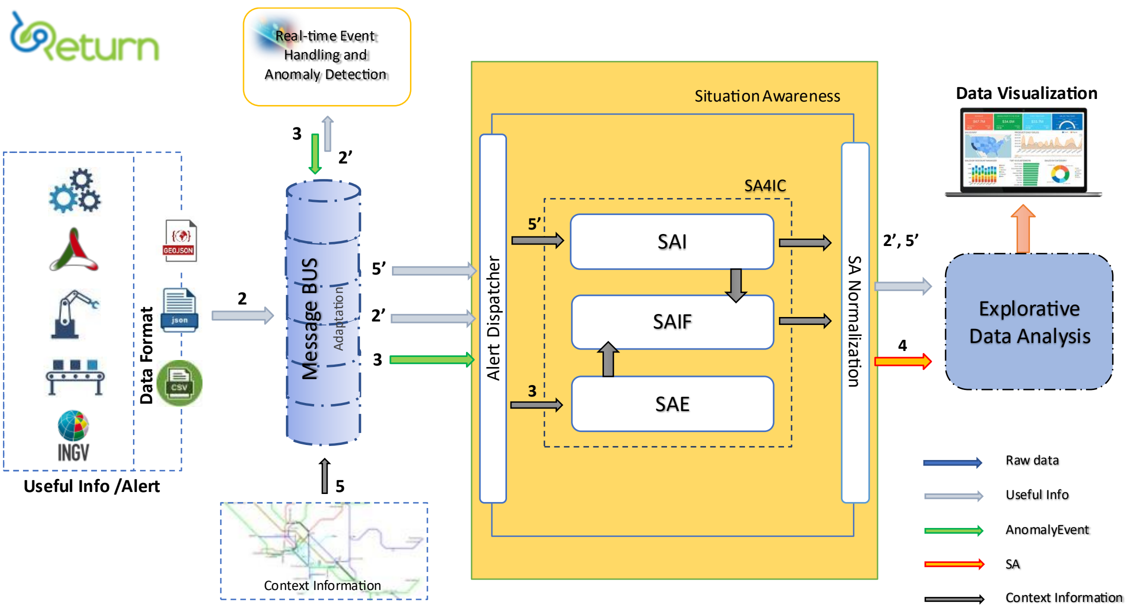

Figure 12 SA4IC Components

- **SAE** (Situation Awareness Events): Component dedicated to updating and managing events.
- **SAI** (Situation Awareness Infrastructure): Component responsible for updating the infrastructure level. It updates the operational status of the monitored infrastructure to ensure that the SA reflects the current operational situation.
- **SAIF** (Situation Awareness Information Fusion): Processing component responsible for assessing the criticality of infrastructure elements in terms of operationality, centrality, and risk exposure. It enhances the SA by providing strategic information to support decision-making and prioritize interventions.

Specifically, the SAI (Situation Awareness Infrastructure) component is responsible for updating the status of infrastructure. It integrates static data, real-time data, and user reports to update the operational status of monitored assets.

Infrastructure-level information is dynamically recalculated and updated in real time with each change in asset status.

The SAE component processes new alerts and anomalies received, contextualizing them and enriching them with contextual information to ensure information consistency within the platform. When the component receives an alert related to a natural hazard, it determines the event's warning level and priority.

The SAIF processes information from SAI and SAE to assess the overall status of infrastructure in terms of operational readiness, criticality, and risk exposure through the application of geoanalytics and network analysis. It analyzes infrastructure networks, identifies the most vulnerable areas, and prioritizes intervention, providing a quantitative basis for risk management and decision-making support. It re-determines the severity level and status of the SA in real time. Every update regarding potential threats or changes in asset status is logged in MongoDB and made available for viewing on dedicated dashboards (e.g., Kibana), ensuring a complete, integrated, and up-to-date representation of the SA.

8.8.1. Functional Recovery Based on Reinforcement Learning

Once the most critical or damaged elements have been identified, the system can initiate a recovery optimization phase through the application of Reinforcement Learning (RL) techniques.

The infrastructure recovery problem is formalized as a Markov Decision Process (MDP), where:

- The state (S_t) represents the current network configuration, indicating which arcs are operational or interrupted, and their efficiency and connectivity values.
- The action (A_t) consists of selecting an arc to be restored at time t.
- The transition (T) describes the evolution of the network state following the restoration of the selected element.
- The reward (R_t) measures the improvement achieved in terms of network efficiency or reduction in overall criticality.

The reinforcement learning algorithm is trained on simulated damage scenarios to learn the optimal arc recovery sequence, maximizing the cumulative reward (i.e., the speed and effectiveness of overall functionality recovery).

In this prototype phase, the reward function is primarily based on efficiency gain (ΔE), but the model is designed to integrate additional parameters such as average recovery times, economic costs, and operational priorities in the future.

This component introduces a data-driven and adaptive approach to post-event management, capable of suggesting more effective recovery strategies than those based on static or heuristic rules, improving the overall resilience of the infrastructure system.

9. Data Visualization (DV) Techniques for SA

The use of information technology is constantly expanding, accompanied by a parallel growth in increasingly sophisticated network attacks targeting both IT and OT systems. To ensure the security and stability of critical infrastructure, the platform continuously monitors a vast stream of data representing key system characteristics. Data Visualization (DV) is an important component for reconstructing and understanding critical infrastructure, as it enables interactive exploration and analysis of large amounts of data and can help operators detect unexpected patterns more efficiently and effectively than traditional text-based representations. As part of the RETURN project, we leveraged the work of critical infrastructure security experts to explore the use of visualization and improve situational awareness in a cyber and physical security environment. From the analysis of the study conducted on SA models, it was found that DV aimed at understanding SA and more generally for security analysis, the representation of contextual data and data related to cyber and physical threats generated by malfunctions or attacks, can provide powerful tools to support exploration and discovery in an effective and timely manner only if based on simple and efficient visualizations.

9.1. Explorative Data Analysis

Exploratory Data Analysis (EDA) is fundamental to data analysis processes, aimed at understanding the structure, relationships, and intrinsic characteristics of a dataset. It facilitates a deeper understanding of complex phenomena, improving risk management and optimizing SA. Unlike confirmatory data analysis (CDA), which starts from predefined hypotheses and verifies their validity, EDA adopts an inductive and exploratory approach. This approach aims to uncover patterns, anomalies, and relationships that are not immediately apparent, without presupposing initial hypotheses. EDA is therefore essential for identifying hidden insights in data that might otherwise be missed with a more rigid analysis. The EDA process develops incrementally and cyclically, alternating phases of visualization, transformation, evaluation, and reflection. Initially, individual variables are explored, followed by a multivariate analysis, with the goal of continually refining the understanding of the underlying phenomena.

The main objectives of EDA include:

- Data cleaning: The detection and correction of errors, missing values, duplicates, or anomalies, ensuring the reliability of the information. Cleaning is crucial to prevent data errors from compromising the accuracy of subsequent models.
- Quality assurance: The assessment of data completeness, consistency, and integrity, ensuring they are suitable for analysis and representation, avoiding bias in the results.
- Statistical synthesis: The production of descriptive measures such as means, medians, variances, percentiles, and distributions for numeric and categorical variables. These summaries provide a comprehensive picture of the characteristics of the dataset.
- Pattern and trend identification: The exploration of relationships between variables, temporal or spatial trends, clusters, and anomalies, to highlight critical aspects in a context, such as the detection of anomalous increases in certain periods that could signal an emerging risk.
- Correlation analysis: The assessment of links and dependencies between variables, to understand complex dynamics and identify potential cause-and-effect relationships. For example, exploring how temperature and humidity can affect agricultural production.
- Selection of relevant variables: Identifying the most significant features for AS. This helps simplify dashboards and reduce information overload, focusing attention on key indicators. Using techniques such as feature selection or PCA (Principal Component Analysis) is essential to reduce dimensionality and improve the interpretability of models.
- Interactive visualization: Using graphical tools (such as histograms, boxplots, scatterplots, heatmaps, time series) to represent data and facilitate its interpretation. Interactive visualizations allow users to

dynamically explore the dataset, highlighting correlations and trends that are difficult to identify in a static table.
- Outlier detection: Identifying anomalous values that could signal critical events or measurement errors. For example, an unexpected spike in an industrial sensor could indicate an impending failure. Outliers are treated with caution, as they can be valuable signals of situations that need to be monitored.
- Exploratory hypothesis formulation: Generating insights and questions that guide further investigations or improve monitoring models. EDA often raises questions that require further exploration and could lead to unexpected discoveries.
- Temporal and spatial consistency verification: Analyzing data evolution over time and space, which allows for the identification of significant variations. An example would be analyzing real-time traffic data to predict areas with increased congestion at certain times.

This process plays a crucial role in decision support and data visualization, serving as a privileged interface between the operator and the system. It transforms the normalized and enriched data from the SAI, SAM, and SAE modules into clear and easily interpretable information, enabling continuous monitoring and proactive emergency management. EDA not only supports real-time decision-making but also facilitates the prediction and management of potentially critical events.

To enable EDA, advanced tools such as Kibana, which allows the creation of interactive dashboards for real-time data visualization, MongoDB Compass, and NODE-RED, which support the aggregation and rapid exploration of datasets, are used. These tools enable quick and intuitive consultation of historical information, improving the accessibility and analysis of historical data to make timely and informed decisions.

9.2. Representation of Situational Awareness

Data Visualization (DV) techniques to support SA have evolved far beyond traditional approaches based on tables or text lists, which proved ineffective at representing complex patterns and relationships. In complex contexts such as critical infrastructure, these tools fail to fully capture dynamics and meaningful connections, while visual representations offer an immediate and in-depth understanding of the data.

More sophisticated visualization techniques are now used to represent SA, including node-link graphs, parallel coordinates, and thematic maps that highlight various properties of the infrastructure and associated events, as well as representing hierarchical relationships between infrastructure elements and data.

The volume of data generated by sensors, both physical and human, is enormous. For this reason, an approach based on multiple dashboards is adopted, each specialized in visualizing specific aspects of the infrastructure and ongoing events. With the ability to switch between an overview and more detailed views, operators can focus on relevant subsets of information, facilitating accurate and targeted awareness.

The visualization system is therefore composed of multiple views, each designed to explore different aspects and perspectives of the infrastructure's status at varying levels of detail.

Visualization techniques for critical infrastructure security are also based on selective attention criteria and information prioritization, essential tools for highlighting the criticality of the situation in terms of status and severity. They synthesize the enormous amount of data generated by acquisition systems, allowing for focus on relevant information.

The approach adopted in this prototype is designed to effectively meet the needs of SA operators, offering clear and functional visualizations. Operators can customize dashboards, select the most appropriate graphs and adapt them to their mental model, thus improving the quality of the decision-making process.

9.3. RETURN Dashboards (ELK)

To meet the configurability, accessibility, scalability, and integration requirements of a data visualization system for representing SA in the RETURN project, we implemented a web-based visualization system to generate operator-configurable dashboards focused on analyzing suspicious activity and building and understanding SA.

The application of data visualization techniques for the RETURN project was achieved by adopting Kibana, a component of the Elastic stack (ELK stack). Elasticsearch, the other key component of the ELK stack, enables reliable and secure data acquisition from any source and in any format, while Kibana allows for real-time search, analysis, and visualization.

Kibana allows for the easy creation of various types of 2D graphs to represent values, trends, and relationships between data. Operators can manually select graphs from all available ones to create their own visualizations. Creating custom views enables the correlation of multiple data sources and exploration at multiple levels of detail, facilitating the representation of an SA that is efficient for understanding and effective for achieving a high level of awareness.

Elasticsearch

Elasticsearch is an open-source, distributed search and analytics engine for all types of data, including textual, numerical, geospatial, structured, and unstructured data. Elasticsearch is based on Apache Lucene, known for its simple REST API, distributed nature, speed, and scalability. Elasticsearch is the core component of the ELK stack, a set of open-source tools for data ingestion, enrichment, storage, analysis, and visualization.

Elasticsearch's speed, scalability, and ability to index many types of content enable its use in numerous use cases.

Raw data flows into Elasticsearch from a variety of sources. Data ingestion is the process by which this raw data is analyzed, normalized, and enriched before being indexed in Elasticsearch. Once indexed in Elasticsearch, users can run complex queries on their data and use aggregations to retrieve complex summaries of their data. From Kibana, users can create powerful visualizations of their data, share dashboards, and manage ELK stacks.

- Elasticsearch is not a relational database; it doesn't allow joins or subqueries. It allows for the storage of denormalized documents with quick and direct access to data, according to the following structure:
- An Index is a collection of documents with similar characteristics. A search query on Elasticsearch never applies to the content itself, but always to the index, where all the contents of all documents are stored.
- A Document is the basic unit of indexable information. Each document is expressed in JSON (JavaScript Object Notation) format. An index can store an indefinite number of documents.
- The set of Fields constitutes the Document.

Information definition occurs through the mapping process. Mapping allows you to define how documents and the fields they contain are stored and indexed. Field data types can be simple (text, keyword, data, long, double, boolean, or ip), object or nested (json), or spatial data (geopoint, geoshape).

The backend components of Elasticsearch are nodes and clusters. A node is a single server that is part of a cluster, stores our data, and participates in the cluster's indexing and search capabilities. A cluster is a collection of one or more nodes that hold all your data together and provide federated indexing and search capabilities. There can be N nodes with the same cluster name. Elasticsearch operates in a distributed environment: with inter-cluster replication, a secondary cluster can act as a hot backup without the need to restart Elasticsearch.

Kibana

Kibana, written in Angular JS, allows you to visualize data in Elasticsearch indexes through a wide range of customizable graphs and dashboards. Kibana used through any browser (localhost:5601) allows for accurate data analysis of correctly indexed data.

Kibana's main functions are roughly represented by the different items in the left menu. Specifically, they are:

- **DevTools**: This environment is used to create and modify data in Elasticsearch, a valid alternative to using Curl for creating queries from the terminal. Kibana's DevTools function allows you to query the Elasticsearch server to obtain information related to nodes, indexes, mappings, etc. Before starting the process of historicizing the data acquired from the RETURN platform, it is necessary to create the appropriate indexes in Elasticsearch using DevTools. When creating the index, it is necessary to specify the type for each attribute.
- **Discover**: This section allows you to explore the index by filtering data and running queries. Within the Discover page, you can interactively explore the data; through it, you have access to every document in every index that meets the requirements of the selected index pattern. You can submit queries, filter search results, and view document data. You can also analyze the number of documents matching the search query and obtain statistics on the value of a given field. If the selected index pattern has been configured to have a time-dependent field, the distribution of documents over time will be displayed via a histogram at the top of the page. Features offered by the Discovery tool:
  - Filtering by date and time
  - Search
  - Saving and loading queries
  - Field filters
- **Management**: In this section, you can modify various advanced Kibana settings and, most importantly, manage index patterns. This section is editable via plug-ins; therefore, in addition to the features natively present in the package, you can add plug-ins such as X-Pack. The Advanced Settings page allows you to directly modify the settings that control Kibana's behavior. For example, you can change the format used to display dates, specify the default index pattern, and set the precision of the displayed decimal values. The Saved Objects option, on the other hand, allows you to manage objects created on Kibana: this will include dashboards, visualizations, and previously saved searches. To use Kibana, you need to choose the Elasticsearch indexes you want to explore by configuring one or more index patterns. An index pattern identifies one or more Elasticsearch indexes you want to explore using Kibana. Kibana will search for index names, retaining those that match the specified pattern. It is important to keep in mind that when defining an index pattern, the indexes that match that pattern must exist in Elasticsearch and, furthermore, must contain data.visualize: through this tool it is possible to create various types of graphs and generate visualizations from queries. Excerpt from the list of possible representation methods:
  - Metric: used to represent the current state of the Situational Picture;
  - Pie chart: to highlight the severity of the infrastructure in percentage terms, or to highlight which hazards and their impact on the infrastructure;
  - Heatmap: to relate the status of events to the affected asset, or the severity to the status of events;
  - Bar chart: required mitigation time per event, or how long each managed situation was in a critical state;
  - Tag cloud: used for an immediate reading of the severity or status of the infrastructure;
  - Table: used to represent in textual form all the information relating to an event or to the infrastructure elements;
  - Tile maps: used to geolocalize data on a map, the map represents the infrastructure assets, differentiated by ID (shape of the symbol), status (color of the symbol), and other data

characteristics. From the map, you can highlight the highest concentration of events (heatmap) within the infrastructure.

- Dashboard: In this environment, you can create dashboards using pre-saved graphs or creating new ones;
- Timelion: This is a time-based data viewer that offers a variety of features on a single screen.

> **ELK stack: Index**

To facilitate understanding, rebuilding the SA using the ELK stack required defining a certain number of elastic indexes, which will be used to create panels or widgets and aggregated for dashboards. The indexes are used by the ELK stack to map the data structure with the data generated by the various components of the RETURN platform. Based on messages from various sources, the SA4CI module will normalize the information based on the elastic indexes. Normalization for representing data and/or information using Kibana's graphical tools will also include alerts, anomaly events, and all the information necessary for rebuilding the SA.

With each SA update, the module uses the Elasticsearch API to update the Elastic Documents. The same operation is performed by the module with each update of the context data generated during the definition and/or update of the infrastructure, and whenever there is a state change in one of the infrastructure elements.

For the RETURN project, the implemented dashboards enable multiple operations, including:

- Aggregate all the data needed to obtain comprehensive information about the infrastructure in a single view.
- Monitor the status of assets and infrastructure elements over time, focusing only on the most important information.
- Monitor the evolution of events related to one or more threats in real time over space and time.
- Reconstruct the status of the situation and facilitate understanding in order to empower operators to make immediate decisions.

These dashboards effectively support SA by integrating configurable elements (maps, lists, graphs, and level indicators) that have been designed to ensure usability, rapid interpretation, and targeted orientation to users' operational needs. Particular attention has been paid to the clarity and relevance of the information displayed. (Figure 13)

Dashboards can be:

- Operational, designed to represent system status in real time and promptly detect malfunctions, failures, anomalies, intentional events, or incidents;
- Strategic, designed to monitor KPIs and organizational metrics to support planning and control activities;
- Analytical, dedicated to exploring data to identify trends, recurring patterns, and other significant findings.

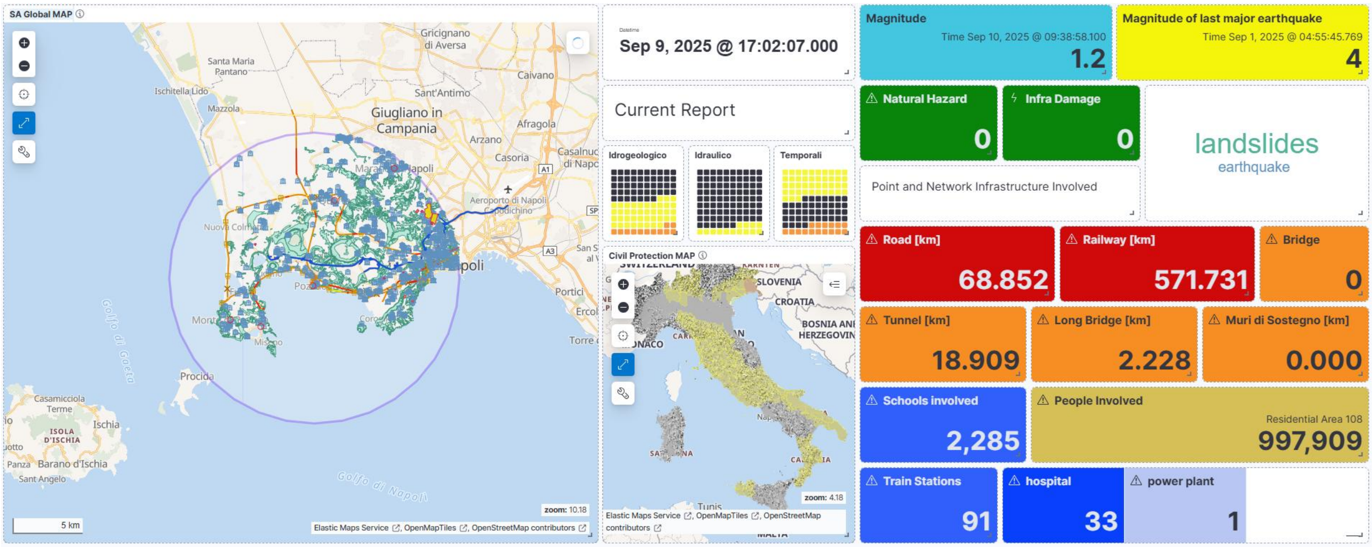

Figure 13 Integrated Dashboard for Situational Awareness Using the ELK Stack

10. Use Cases

10.1. Enhanced dashboard for prioritizing interventions to mitigate risks and improve resilience

In a context characterized by increasing risks related to climate change, unplanned urbanization, and the structural vulnerability of infrastructure, the research presented here focuses on holistic risk reduction and strengthening territorial resilience.

The goal is to develop an integrated approach that combines data analytics, visual analysis, and Territorial Digital Twins (TDTs) to support the decision-making process of policymakers and civil protection authorities, promoting more proactive and evidence-based management.

10.1.1.Methodology and System Architecture

The case study is based on two complementary approaches:

- **Data analysis** – includes systematic processes for processing and interpreting large amounts of heterogeneous data (meteorological, geospatial, infrastructural, social). This analysis allows for the identification of trends, correlations, and precursors of critical conditions, forming the basis for predictive models and risk simulations.
- **Visual analysis** – focuses on interactive data visualization through dynamic dashboards and thematic maps, facilitating exploration and understanding of information even by non-technical users. The approach follows the principles of Nica et al. (2023) and Afzal et al. (2023), enhancing the representation of complex phenomena through visual analytics tools.

The integration of these two components is achieved through a Decision Support System (DSS) designed as an early warning system. The DSS integrates data acquisition, predictive analysis, resilience assessment, and emergency management modules, enabling:

- real-time processing of information flows from sensors, institutional bulletins, and crowdsourced data;
- visual representation of results through interactive decision-making dashboards;
- quantitative risk assessment through the Real-Time Quantitative Risk Analysis (RTQRA) approach, which enables rapid decision-making in critical situations.

10.1.2.Application: Dynamic Assessment of Territorial Resilience

In this application, the system is used to assess the resilience of a coastal area subject to combined flood and landslide risks.

Geospatial and meteorological data are acquired from institutional sources and integrated with local information, such as field observations and traffic data (Figure 14).

The dynamic resilience model develops vulnerability and response capacity indicators, estimating the temporal evolution of the risk.

The results are displayed in the DSS dashboard (Figure 6), which shows intervention priorities and critical areas, allowing decision makers to evaluate different operational strategies.

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Thanks to the implementation of the RTQRA module, the system performs real-time probabilistic analysis of critical event precursors, providing predictive alerts and suggesting emergency management procedures, such as traffic diversions, preventive closures of infrastructure sections, or the deployment of rescue resources.

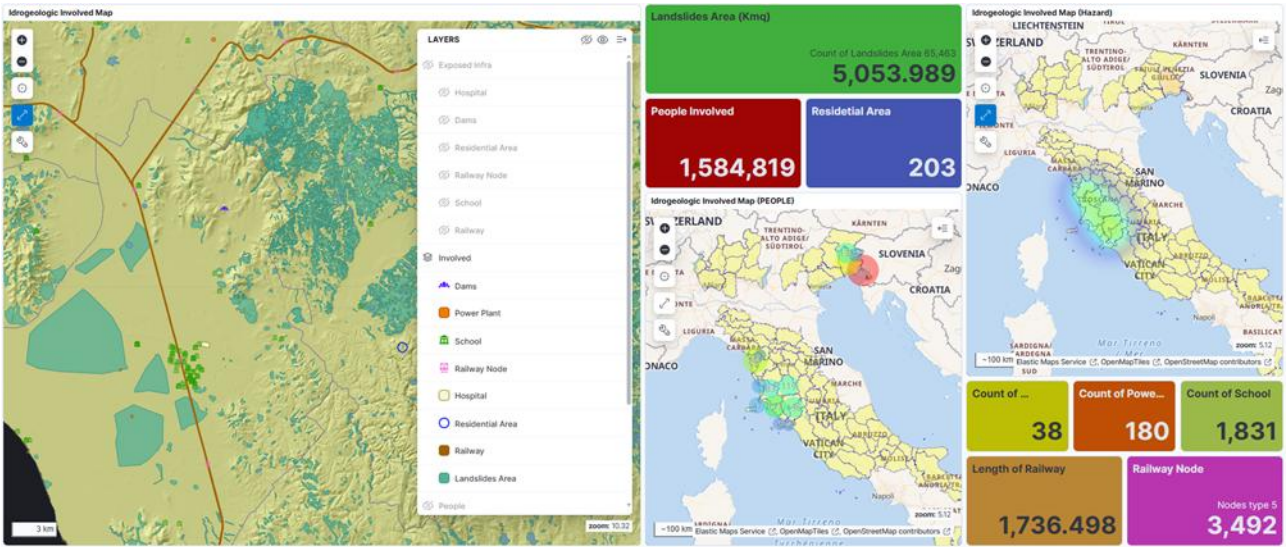


Figure 14 Example of dashboard for prioritizing interventions to mitigate risks

10.1.3.Role of Territorial Digital Twins (TDT)

An innovative element of the case study is the integration of Territorial Digital Twins (Chioni et al., 2023).

These virtual models allow the physical and functional conditions of the territory to be represented and simulated, combining 3D data obtained through photogrammetry and GIS mapping.

The DDTs act as a digital testing environment, allowing risk scenarios and mitigation strategies to be tested before their actual implementation.

Furthermore, their direct connection to the DSS allows the networking of distributed resources (such as sensors, databases, and monitoring systems) and the consistent integration of information from different entities.

10.1.4.Results and Impacts

The integration of data analytics, visual analysis, and DTT has enabled:

- improving the multidimensional understanding of territorial vulnerability;
- optimizing the prioritization of mitigation and maintenance interventions;
- reducing emergency response times, thanks to the automation of the alert process and the use of the RTQRA model;
- promoting participatory governance, through the inclusion of local data and citizen input.

The proposed approach has demonstrated high potential for transfer to other application domains, such as seismic or industrial risk management, where the combination of AI, DSS, and DTT can strengthen the resilience of critical infrastructure and communities.

10.1.5. Conclusions

This case study demonstrates how the synergy between data analysis, visual analysis, and advanced digital technologies represents a decisive step towards holistic risk reduction.

The use of Territorial Digital Twins and a dynamic resilience model integrated into the DSS allows for the shift from a reactive to a proactive and predictive approach, in which decisions are guided by timely, contextual, and visually accessible information.

In this way, the research makes a concrete contribution to improving the systemic resilience of critical infrastructure and the sustainable planning of vulnerable territories.

10.2. Dynamic Mapping of Critical Infrastructures at Risk

10.2.1. Case Study: Seismic Event

Following a high-magnitude seismic event that strikes a region with a high density of critical infrastructure, including transportation networks, hospitals, and energy distribution systems, the platform enters emergency mode, automatically activating the data acquisition and analysis modules.

The data processing module integrates information from institutional seismic bulletins (e.g., INGV or the Civil Protection Department) in real time, updating the geospatial layers relating to macroseismic intensity and potentially damaged areas (Figure 15).

Simultaneously, the orchestration engine coordinates the processing of new inputs, activating routines for recalculating exposure and vulnerability indicators for each infrastructure asset.

Field users—municipal workers, technicians, or citizens—can send direct reports via the platform, indicating damaged infrastructure (e.g., damaged bridges, unusable hospitals, or blocked roads). This crowdsourced data is georeferenced, validated, and integrated into the spatial model, improving the local representation of seismic impact.

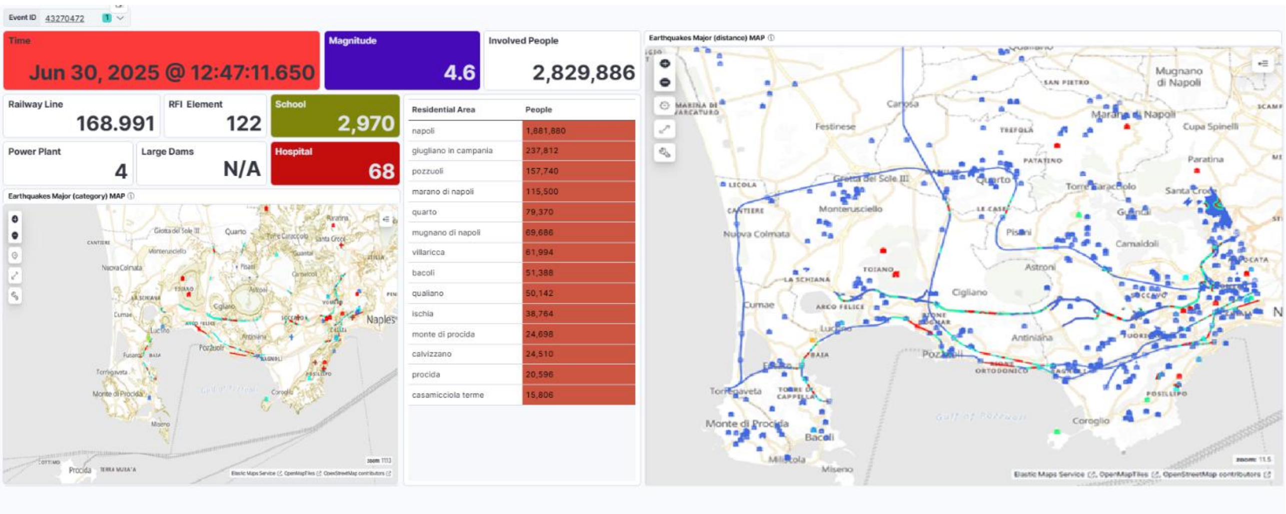


Figure 15 Dashboard for areas most affected by the earthquake, overlaid with critical infrastructure.

The geospatial view allows for a real-time visualization of the areas most affected by the earthquake, overlaid on a map of critical infrastructure. Assets located in the most affected areas are automatically classified as "exposed" and assigned as a high priority for safety assessments. At the same time, the topological representation of the infrastructure network allows for assessment of the propagation effects of the fault: for example, the closure of a bridge can cut off access to a hospital or isolate a city center.

The decision-making dashboard provides a dynamic summary of the situation, highlighting:

- the infrastructure with the greatest topological criticality;
- the most exposed urban areas;
- the population affected;
- the updated status of access routes and strategic nodes.

This scenario demonstrates the system's ability to support operational decisions during the first hours following an earthquake, integrating official data and field information to optimize emergency response planning and resource management.

10.2.2.Case Study: Adverse Weather Conditions

In a second scenario (Figure 16), the system is applied to the management of an extreme weather event characterized by intense and widespread rainfall, with a risk of flooding and landslides in one of the areas reported in official civil protection bulletins.

The data acquisition module collects real-time weather and hydrological alerts issued by the competent authorities, integrating them with digital terrain models, hydrographic data, and historical information on past events. The spatial layers are continuously updated to reflect the dynamics of the event, allowing the identification of areas subject to water accumulation or slope instability.

Platform users can directly report ongoing events, such as flooded roads, landslides, or road closures, by providing images and GPS coordinates. These reports feed into the risk model, allowing the delimitation of the most critical areas to be refined in real time. Geospatial representation highlights infrastructure physically exposed to flooding, such as train stations, underpasses, or power plants, while topological modeling allows for estimating functional impacts: for example, the inaccessibility of a road section could interrupt the connection to a hospital or impede the supply of an industrial area.

The interactive dashboard provides an up-to-date overview of the event, showing:

- the spatial distribution of flooded and landslide-prone areas;
- potentially affected infrastructure and services;
- recommended alternative routes for emergency vehicles;
- risk evolution trends based on forecasting models.

This case study highlights the platform's ability to function as a dynamic decision support system, combining meteorological, geospatial, and network data to assist authorities in the coordinated management of hydrogeological emergencies and the protection of the population and strategic assets.

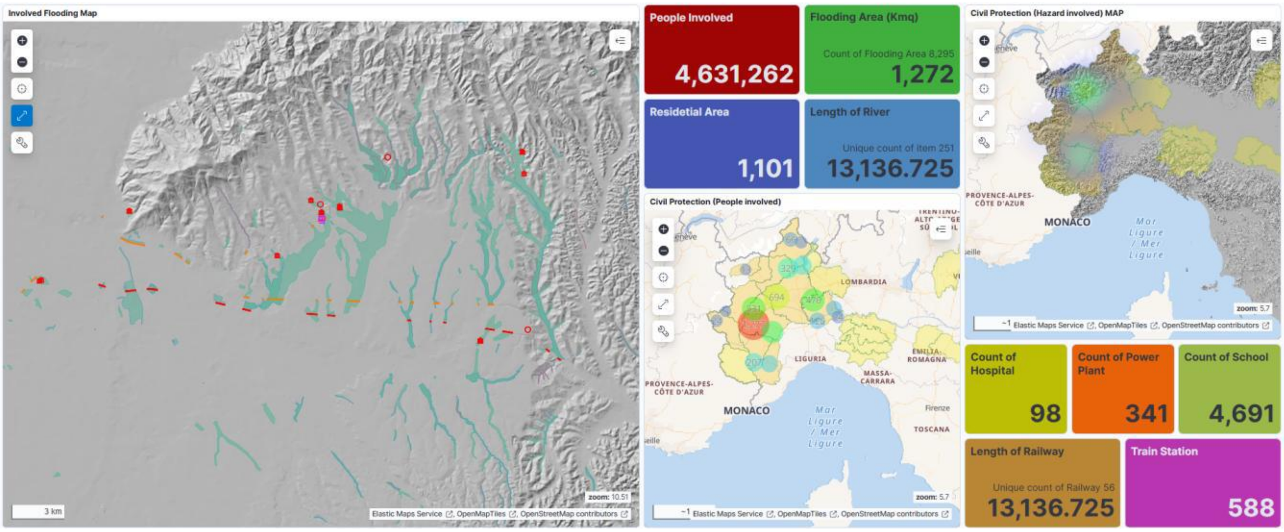


Figure 16 Decision Support Dashboard for Hydrogeological Risk Management

10.2.3.Summary

Through these two use cases - earthquake and adverse weather - the platform demonstrates its adaptability to different risk contexts and its ability to integrate heterogeneous sources to provide timely and actionable information. The combination of geospatial and topological analysis, combined with user participation, enables an evolving representation of risk and systemic vulnerability, improving decision-making readiness and the overall resilience of critical infrastructure.

10.3. Dynamic Risk Analysis for Road Tunnel Safety through Decision Support Systems (DSS)

10.3.1. Rationale and Objectives

Road tunnels represent complex and highly interdependent systems where infrastructure integrity, ventilation, lighting, and safety equipment must function under strict reliability conditions. Given their confined nature, any incident such as fire, collision, or technical failure can rapidly escalate, producing cascading effects on users, equipment, and structural components.
Road tunnels are highly interdependent systems where multiple subsystems for example ventilation, lighting, drainage, and safety installations that must operate in synchrony to ensure resilience and safety. Traditional deterministic risk models often fail to capture the time-dependent evolution of hazards within confined environments (Wang et al., 2021; Gehandler, 2015).
Recent advances demonstrate the relevance of dynamic approaches capable of integrating time-evolving hazard parameters and psychophysiological driver responses in tunnel environments (Niu et al., 2024; Xu et al., 2024). Ntzeremes et al. (2020) propose a risk-based method (PreBack model) to predict the potential severity of fire accidents in road tunnels based on real-time data, with the goal of informing operators about the possible evolution of catastrophic scenarios. Building on this, Ntzeremes & Kirytopoulos (2022) introduce EVADE, a multi-criteria approach to support the selection of fire safety measures in road tunnels, combining regulatory requirements, expert judgement and performance evaluation of different alternatives. Alvear et al. (2013) develop a DSS for road tunnel emergency management, supporting the deployment of emergency services and the control of tunnel systems through a logical workflow that integrates sensor data and standard operating procedures. Abpeykar & Ghatee (2014) design a DSS for incident management in an intelligent tunnel (Tehran Niayesh tunnel), relying on supervised and unsupervised learning algorithms to detect and classify incidents; the system is validated using a 7 traffic simulator. Boletsis & Nilsson (2021) present RiskTUN, a risk-aware DSS that combines a tunnel sensor network, indoor positioning, a mobile app for first responders, key performance indicators for tunnel safety and multi-attribute decision models, providing real-time action suggestions to the control room operators.

Traditional risk analysis methodologies, generally based on static or deterministic assumptions, are not sufficient to capture the time-dependent evolution of critical events in such environments. For this reason, a Dynamic Risk Analysis (DRA) approach has been developed and integrated within the RETURN project prototype so called Decision Support System (DSS) to enable continuous assessment of tunnel safety conditions through real-time data acquisition, event-driven modeling, and predictive analytics.

The objective is to move from a post-event reactive strategy to a proactive and adaptive risk management model capable of supporting operators in decision-making during both normal operation and emergency scenarios.

This chapter presents an integrated framework for the dynamic management of a fire in a road tunnel as a critical infrastructure asset. The framework couples:

- the Situational Awareness platform developed in the RETURN project, including the SA4CI module (with SAE, SAI, SAIF components, the ETL/Service BUS architecture, and the dynamic risk engine), which provides real-time monitoring, fusion, and prioritization of infrastructure risks and supports decision-making at the network scale;

- the DSS (Decision Support System for Safety and Sustainability of Tunnels) which focuses specifically on tunnel-level safety, ventilation control, suppression strategies (e.g. low-pressure water mist), evacuation support, ALARP-based residual risk assessment, and energy continuity through smart/green infrastructure concepts.

10.3.2. Methodological Framework

The proposed framework combines probabilistic inference, Bayesian updating, and real-time data assimilation, consistent with previous dynamic and stochastic approaches applied to tunnel risk evaluation (Wu et al., 2015; Wang Q. et al., 2023).

Decision-support components are developed in accordance with recent ontology-based inference systems proposed for tunnel emergency management (Cui et al., 2024) and data-driven early-warning frameworks (Sun et al., 2024). The DRA approach follows a modular design, integrating:

- Real-time data acquisition from environmental sensors (e.g., temperature, CO/NOx levels, luminance), traffic detectors, CCTV analytics, and safety system status indicators;
- Dynamic modeling modules capable of simulating hazard propagation (fire, smoke, toxic gases) and assessing the evolution of tenability conditions for tunnel users and rescue teams;
- Probabilistic risk updating using Bayesian inference and event correlation to continuously refine likelihoods and consequences as new evidence becomes available;
- Integration with the DSS core, which consolidates all outputs within the *Situational Awareness Dashboard* to display risk levels, critical thresholds, and recommended response actions.

adheres to the structure of ISO 31010 and to ALARP-based quantitative risk assessment principles, adapted for continuous time-series data. The objective of this integration is to shift from traditional static, reactive tunnel emergency plans toward an adaptive, data-driven, and resilient management cycle in which the tunnel is continuously monitored, the evolution of the fire and the associated tenability conditions is predicted in near real time, recommended actions for ventilation, suppression, and evacuation are automatically generated and presented to operators, and these local actions are propagated to the territorial control layer, so that the tunnel is managed as a node within a broader critical road network rather than as an isolated asset..

The framework aligns with the European Directive 2004/54/EC 4 on minimum safety requirements for road tunnels and with its national transposition (Legislative Decree 264/2006 in Italy), which formalizes ALARP-based quantitative risk methodology (Guarascio et al. 2017) and demands that tunnel safety be demonstrated both at design time and throughout operations.

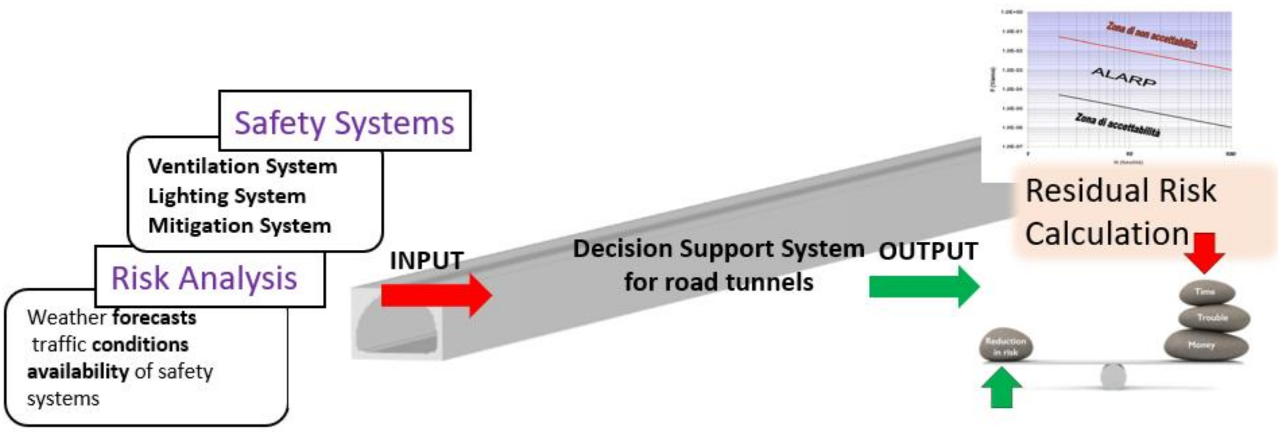


Figure 17 Decision Support System framework – road tunnel application overview

Road tunnels are classified as critical infrastructures because their sudden loss of functionality can disrupt mobility corridors, generate economic and territorial isolation, and directly threaten human life within confined environments. They also act as “single points of failure” in trans-European and national transport networks.

Historically, major tunnel fires, such as Mont Blanc (1999), Tauern (1999), and Gotthard (2001), resulted in multiple fatalities within minutes, exposed significant challenges to self-evacuation, and directly influenced the development of Directive 2004/54/EC. These events underscored the critical importance of quantitative risk analysis for road tunnels.

Despite regulatory progress, two gaps remain:

1. **Static *vs* dynamic management.** Traditional tunnel safety documentation is typically static, built around design scenarios and predefined response plans. While it ensures regulatory compliance, it does not necessarily capture how conditions evolve from one second to the next during an actual event. In reality, fire growth, smoke-layer dynamics, user behavior, and subsystem degradation are all inherently dynamic.

2. **Tunnel as an isolated asset vs tunnel as a system node.** A tunnel fire is not merely a local emergency; it also carries regional implications, including traffic rerouting, emergency-service accessibility, service continuity in adjacent corridors, and potential cascading effects on other infrastructures. Treating the tunnel as a node embedded within a wider network enables more effective prioritization of interventions and optimized recovery strategies under constrained resources.

The integrated framework directly addresses these two gaps. The RETURN Situational Awareness (SA4CI) environment maintains a shared, network-level operational picture of critical infrastructures, constantly updated through data fusion and risk assessment modules (SAE, SAI, SAIF), while the DSS module in this application is focused on tunnel-level safety, operational control, and energy-resilient emergency support of ventilation, lighting, and suppression.

For instance, RETURN identifies, at any given moment, where the highest level of criticality is across the infrastructure network and explains why, while the module of the decision support system translates that insight into immediate operational action: it specifies, whenever the situation changes (for example changing of safety systems conditions, accidents that occurs of maintainability operations, what must be done in that specific tunnel to protect people and stabilize the asset using the available systems and energy.

10.3.1.1 Reference Architectural Framework

The RETURN architecture is built around a modular pipeline: ingestion of heterogeneous data streams, normalization and temporal alignment (ETL), event/context enrichment, infrastructure state update, and fused assessment of criticality. The SA4CI module is structured into three synergistic components:

- ✓ **SAE (Situation Awareness Events):** manages new alerts and anomalies, contextualizes them, and assigns warning levels and priorities.
- ✓ **SAI (Situation Awareness Infrastructure):** updates the status of each monitored infrastructure element (availability, degradations, alarms, etc.) using static data, live sensor data, and operator reports.
- ✓ **SAIF (Situation Awareness Information Fusion):** fuses data from SAE and SAI and quantifies infrastructure criticality in terms of operability, centrality in the network, and exposure to hazards. SAIF applies geoanalytics and network analysis to identify vulnerable elements and to prioritize interventions.

These components continuously refresh the Situational Awareness dashboards (e.g. via ELK/Kibana), meaning that operators at a control room can see, on a shared map/timeline, which assets are threatened, what the evolving risk level is, and what actions are recommended. This allows faster and coordinated decision-making between infrastructure managers and civil protection authorities.

Internally, RETURN relies on an event-driven Service BUS and microservices. Data from sensors, traffic systems, meteorological feeds, and institutional channels (e.g. road operators, civil protection) are ingested through MQTT/REST, normalized, stored, and passed through analysis blocks. This is designed to scale across different hazard types (fire, seismic events, adverse weather, etc.) and different asset classes (tunnels, bridges, viaducts, interchanges).

The DSS system is a tunnel-focused Decision Support System for continuous monitoring of the tunnel infrastructure. It explicitly addresses:

- **Residual risk and ALARP compliance**. DSS dynamically evaluates whether the current tunnel state respects acceptable risk thresholds (as per Directive 2004/54/EC and D.Lgs. 264/2006), not just at design time but during operations, using quantitative risk assessment logic.

- **Active safety subsystems**. These include ventilation (e.g. longitudinal jet fans with variable speed drives and reversible thrust), emergency lighting, acoustic/voice alarm and guidance for users, and fixed firefighting systems such as low-pressure water mist. The system monitors their availability, efficiency and, when possible, commands or recommends specific actuation patterns.

- **Energy resilience**. DSS is designed in the context of a “smart and green tunnel,” where safety systems are supported by renewable generation (e.g. PV, wind, or micro-harvesting along the alignment) and local storage. This is framed not only as an environmental goal but as an operational resilience requirement: even under partial grid loss, the tunnel must maintain life-safety systems long enough for evacuation and event control.

DSS therefore acts as the local joint connection of the real tunnel, combining continuous sensing, predictive modelling (CFD-informed fire and smoke spread estimates, temperature/visibility evolution, etc.), system status, and regulatory acceptability thresholds into actionable guidance for operators.

An example of the automated process is system redundancy, which ensures continued operation even in the presence of a fault. Redundancy actively contributes to overall system reliability. It means that if one component fails, a so-called fault occurrence, other components can continue functioning. System redundancy can be implemented in different ways, generally categorized into two main types:

- active redundancy: all items are performing at the same time;
- standby redundancy: some items are in cold standby or partly standby.

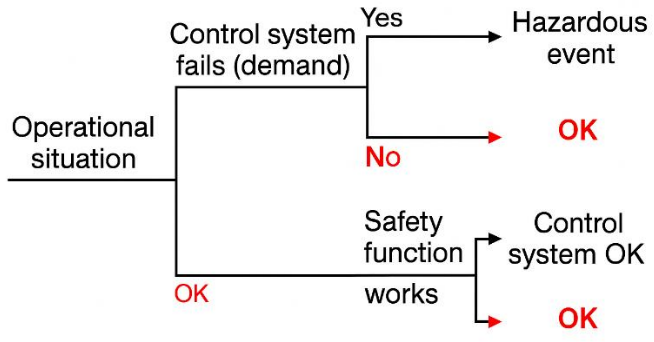


Figure 18 Example of fault of an item in an operational situation (Rausand, 2014)

In the integrated vision proposed here:

- RETURN/SA4CI delivers external and contextual information, including regional traffic rerouting pressures, ongoing weather or seismic hazards, the status of adjacent assets, and the overall prioritization of interventions across the network. This is particularly critical when multiple infrastructures are simultaneously under stress.
- DSS provides RETURN/SA4CI with detailed tunnel intelligence, such as fire location and severity, current tenability zones, recommended ventilation settings, suppression system status, evacuation progress, and remaining energy autonomy of life-safety systems. These insights are then presented through the same situational dashboards that managers use to coordinate emergency services and traffic authorities.

This coupling creates a multi-layered situational picture: tunnel operators can respond rapidly using tunnel-specific tools, while network- or agency-level operators can understand systemic consequences and allocate resources where they are most needed. This process ensures the continuous operation of critical infrastructure.

10.3.1.2 Risk Acceptability – the importance to be compliant within law requirements.

Directive 2004/54/EC defines minimum safety requirements for tunnels in the Trans-European Road Network, including structural and plant measures (ventilation, emergency exits, fire resistance, detection and alarm systems, emergency lighting) and requires that each Member State ensure equivalent levels of safety for users. Italy transposed this directive through Legislative Decree 264/2006, which incorporates a Quantitative Risk Analysis methodology and the ALARP criterion ("As Low As Reasonably Practicable") to assess acceptability of residual risk.

Traditionally, compliance with these requirements is demonstrated through design calculations and periodic audits. However, in tunnels that do not fully satisfy prescriptive measures (for instance, older tunnels with limited emergency exits, or tunnels undergoing conversion from unidirectional to bidirectional flow), compensating safety measures and advanced operational procedures can be adopted — but must be justified on a risk basis.

The integrated DSS framework works with this path in two ways:

1. **dynamic residual risk assessment.** DSS evaluates, in real time, whether the tunnel's operational risk remains within acceptable thresholds, given current conditions (traffic, subsystem availability, energy state). This transforms ALARP from a static design concept into a dynamic verified operational metric.

2. **traceability and auditability**: the RETURN dashboard and data backend generate a structured log of alerts, recommended actions, and operator decisions. Following an event, this log can be used to demonstrate that the response was timely, proportionate, and technically justified. This evidence supports regulatory compliance and contributes to the management and mitigation of liability exposure.

In practice, this means that a tunnel operator can argue that, although a given tunnel might have fewer physical exits than prescriptive requirements suggest, the combined effect of enhanced detection, controlled ventilation, automatic suppression, guided evacuation, and resilient power supply — all managed by the DSS and supervised through dashboards provides an equivalent level of safety and therefore satisfies the spirit of Directive 2004/54/EC and D.Lgs. 264/2006.

10.3.1.3 Validation Basis: Experimental Evidence and Prototype Deployment

The combined approach is not only theoretical but must be integrated in the real design of road tunnel safety systems.

- **Dynamic Risk Assessment pilot** within RETURN. Within the RETURN project, a dynamic risk engine was integrated into the DSS and fed by live tunnel-like sensor data (air temperature, CO concentration, ventilation states, CCTV analytics). During simulated fire scenarios, the risk value can be recalculated according to the
- **Full-scale fire testing and CFD-driven modelling in DSS**. An application includes the design and execution of full-scale fire tests in a real tunnel environment to study the coupling between longitudinal ventilation and low-pressure water mist systems, and to calibrate suppression strategies for both solid and liquid fuel loads. The methodology also includes preliminary controlled burns, instrumentation deployment, thermal/smoke monitoring, and post-test data interpretation to assess ceiling temperatures, smoke propagation, system activation timing, and tenability impacts.

This experimental basis is essential because it bridges the gap between theory and operability: rather than assuming generic design fires, DSS uses empirically informed scenarios to guide ventilation/suppression recommendations and to feed RETURN with accurate projections of risk evolution.

The DSS integrated approach explicitly tries to reduce this cognitive overload by implementing the three stages of Situational Awareness:

1. Perception: automated ingestion and filtering of raw sensor signals (temperature spikes, smoke alarms, fan failures) and CCTV analytics, so the operator does not need to manually scan all sources.

2. Comprehension: the platform contextualizes what those signals mean in terms of tunnel safety and network impact. DSS identifies the type/severity of the event.

3. Projection: the system is capable of simulating how conditions will evolve in the next minutes, highlights zones that will soon become untenable, and proposes specific measures and action to take.

The platform acts as a force multiplier for operators rather than just another screen to monitor. This directly enhances resilience: strengthening operators' ability to understand situations and respond swiftly is one of the most effective ways to reduce casualties, limit damage, and accelerate infrastructure recovery following a critical event.

10.3.2. System Architecture and Data Flow

Integration of the Dynamic Risk Engine within the RETURN DSS follows established architectures for multi-source data fusion and situational awareness (Nirandjan et al., 2024; Zhang et al., 2024). This approach extends the principles demonstrated in DSS platforms for emergency operations in tunnels (Alvear et al., 2013; Capote et al., 2013).

The DSS integrates the dynamic risk engine within the existing RETURN platform Service BUS and ETL framework (Node-RED), allowing for seamless ingestion of data from field sensors and institutional sources (for example ANAS database, Civil Protection, Meteo services).

The processing chain includes:

1. Ingestion layer: acquisition of sensor data and traffic information via MQTT and REST protocols;
2. Transformation layer: normalization and temporal alignment of heterogeneous data streams;
3. Dynamic Risk Engine: real-time computation of probability updates and scenario evolution using rule-based and machine learning algorithms;
4. Visualization layer: representation of results in an interactive dashboard displaying the *Risk Index*, *Trend curves*, *Critical thresholds*, and *Recommended actions*.

The dashboard provides a multi-layered situational picture combining infrastructure topology, equipment status, and environmental parameters, thus enabling immediate identification of abnormal trends (e.g., overheating, smoke accumulation, ventilation failure).

The integrated work is described according to the layer expressed in the following Figure 19:

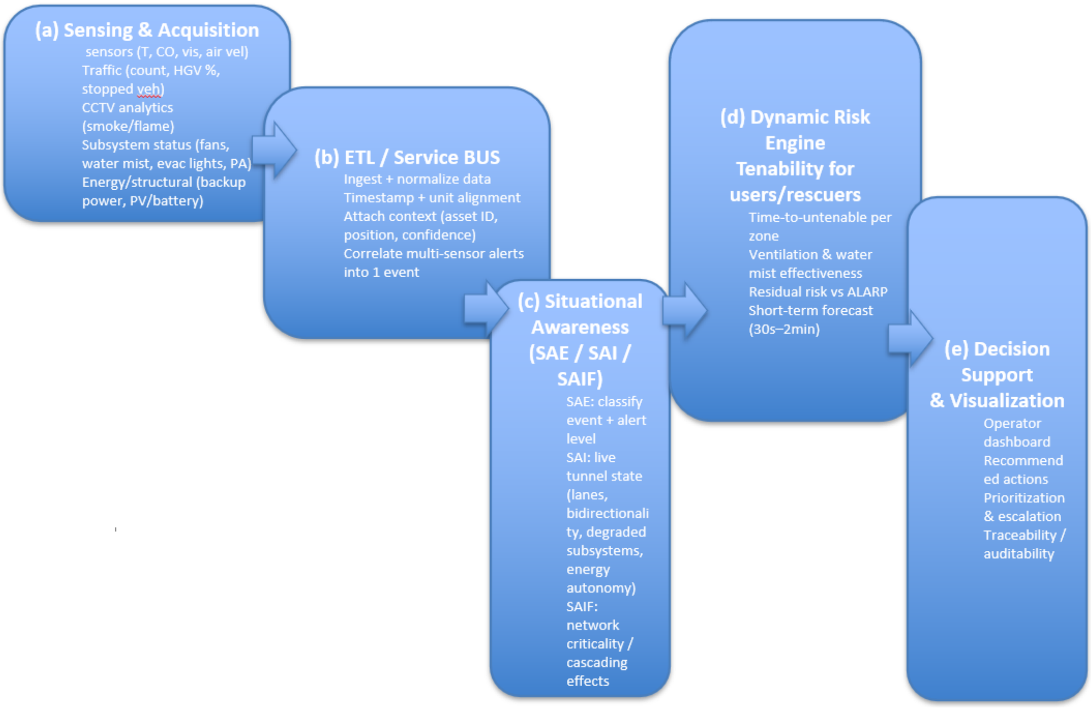


Figure 19 Flow chart of the integrated work – step of the analysis

✓ **(a) Sensing and acquisition layer**

The tunnel environment is continuously monitored via:

- environmental sensors (temperature, CO, visibility/opacity, air velocity),
- traffic sensors (count, heavy vehicle percentage, stopped vehicle detection),
- CCTV analytics (smoke/flame detection, stationary obstacle detection),
- subsystem status (fan on/off and thrust direction, water mist pressure and valve state, evacuation lighting state, PA/voice alarm state),
- structural/energy data (availability of backup power, PV/battery charge levels, ventilation inverter status).

These raw data streams are essential both for rapid alerting and for preparedness, for example, to determine whether the tunnel is currently operating under a configuration that increases vulnerability, such as bidirectional traffic with high HGV density and partially degraded ventilation.

✓ **(b) ETL / Service BUS layer**

Within RETURN, incoming data are ingested via a Service BUS architecture, normalized, including timestamp alignment and unit standardization, and stored for immediate consumption by downstream modules. This layer also enriches the data with contextual metadata, such as asset ID, tunnel location, and confidence scores from each detection algorithm.

For fire management, this means that a spike in temperature at position x, a drop in visibility in the same zone, and a CCTV smoke flag are recognized as a coherent, co-located event rather than three unrelated alerts. This correlation logic is the foundation for fast, reliable event confirmation and for reducing false positives.

✓ **(c) Situational Awareness layer (SAE / SAI / SAIF)**

Once ingested, the data are processed by SA4CI components:

- SAE contextualizes the event (e.g. "high-temperature anomaly consistent with fire," "ventilation failure in a critical node," etc.) and assigns an alert level.
- SAI updates the tunnel's operational state, including degraded subsystems, partially closed lanes, temporary bidirectionality, and energy autonomy estimates. This is crucial because tunnel safety strongly depends on traffic configuration and subsystem availability at that exact moment.
- SAIF fuses these results to assess the criticality of the tunnel not only in absolute terms ("fire ongoing") but also in network terms ("this tunnel is a high-centrality arc whose loss will fragment connectivity"). SAIF's geoanalytics and network analysis let decision-makers assign response priority and anticipate cascading impacts on the mobility network.

✓ **(d) Dynamic Risk Engine / DSS core**

In parallel, DSS evaluates the evolving fire scenario from a tunnel-safety standpoint and estimates:

- tenability for users and rescuers (temperature, smoke layer height, CO/CO_2/FED thresholds),
- time to untenable conditions in each section,
- effectiveness and sufficiency of current ventilation and suppression strategy,
- compliance with ALARP criteria for residual risk.

This step uses predictive models (including CFD-derived curves and full-scale test evidence) to project the near-future state — essentially solving "if we keep this fan pattern and water mist setting, what happens in 30 seconds, 1 minute, 2 minutes?" The RETURN prototype has already demonstrated periodic (e.g. 30 s) risk index updates using live data, dynamically recomputing probability and consequence indicators and re-coloring a tenability map for the tunnel.

✓ **(e) Decision support and visualization**

The fused outputs are then published in two human-facing ways:

1. **DSS dashboard:** local operators see recommended ventilation thrust direction and speed, suppression activation timing, evacuation lighting/voice messages, and safe egress routes for users and responders. The interface highlights which areas are still tenable and for how long.
2. **RETURN dashboard:** regional/national operators (e.g. road authority, civil protection) see the tunnel as an entity in the broader network map, with its current status (fire active / evacuating / stabilized), criticality ranking, and expected recovery trajectory, which supports resource allocation and communication with external stakeholders.

This dual flow of information is crucial for coordinated crisis management: the tunnel control room implements immediate safety actions, while higher-level authorities oversee traffic management, deploy responders, and plan service restoration based on quantifiable situational awareness.

10.3.3. Road Tunnel Safety Scenario

A representative application was carried out on a road tunnel section. The DSS received live data on air temperature, CO concentration, and fan operation states. During a simulated fire scenario, the dynamic model updated the risk index every 30 seconds, incorporating data from the ventilation and CCTV systems. The visualization module generated an evolving map of tenability zones, correlated with evacuation route accessibility.

The DRA approach allowed operators to identify the optimal ventilation mode and to anticipate critical conditions several minutes before threshold exceedance, supporting timely decision-making and effective resource allocation. The dynamic module continuously recalculates probability and consequence indicators every 30 s, similar to stochastic real-time evacuation or fire-propagation models tested in recent tunnel studies (Zhang et al., 2024; Capote et al., 2013; Borghetti et al., 2022).

A specific application of the Decision Support System (DSS), currently being refined, concerns a critical event in road tunnel design: fire. In recent years, fire safety management in tunnels has become closely linked to artificial intelligence. To enhance the DSS's ability to detect various types of fires and promptly initiate emergency procedures, a reference database has been integrated with fire test data, thereby improving its response capabilities.

The process illustrates the entire cycle of managing tunnel safety systems during a fire scenario, highlighting how real-time data collection, transmission, and processing are essential to ensuring the effectiveness of safety measures implemented. The use of full-scale fire tests provides valuable insight into the functionality and resilience of tunnel safety systems, ensuring reliable operation in real emergency situations.

The procedure is divided into several key phases, as illustrated in Figure 20. An essential prerequisite for the decision support system is the integration of a continuous cycle of monitoring and risk analysis. This process consists of interconnected phases, each playing a crucial role in ensuring accurate monitoring and timely responses to emerging risks.

- data monitoring and risk exposure update: the first phase involves monitoring traffic data (in terms of intensity and composition) and providing an updated estimate of the probability of occurrence of initiating events (critical events) in the hazard flow, as well as the current risk exposure. Data is collected and updated in real time, keeping the system aligned with the latest available information.
- predictive analysis: in this phase, models and algorithms are used to estimate risk indicators and predict future risks, enhancing the ability to prevent critical situations.
- real-time reporting: this phase enables continuous monitoring of risk conditions through immediate data processing and transmission. It is important to clarify that "real-time" does not necessarily imply instantaneous detection but refers to the concept of a resilient infrastructure, where time is the system's central variable. In this perspective, the infrastructure is designed to withstand and adapt to unexpected events, ensuring operational continuity even in emergency conditions.
- integrated risk model (multi-hazard analysis): the core of the process is the integrated risk model, which allows for the combination of various risk factors within a single system to achieve a comprehensive and consistent evaluation. This model uses advanced algorithms to automate and optimize risk analysis, thereby improving predictive accuracy and efficiency.

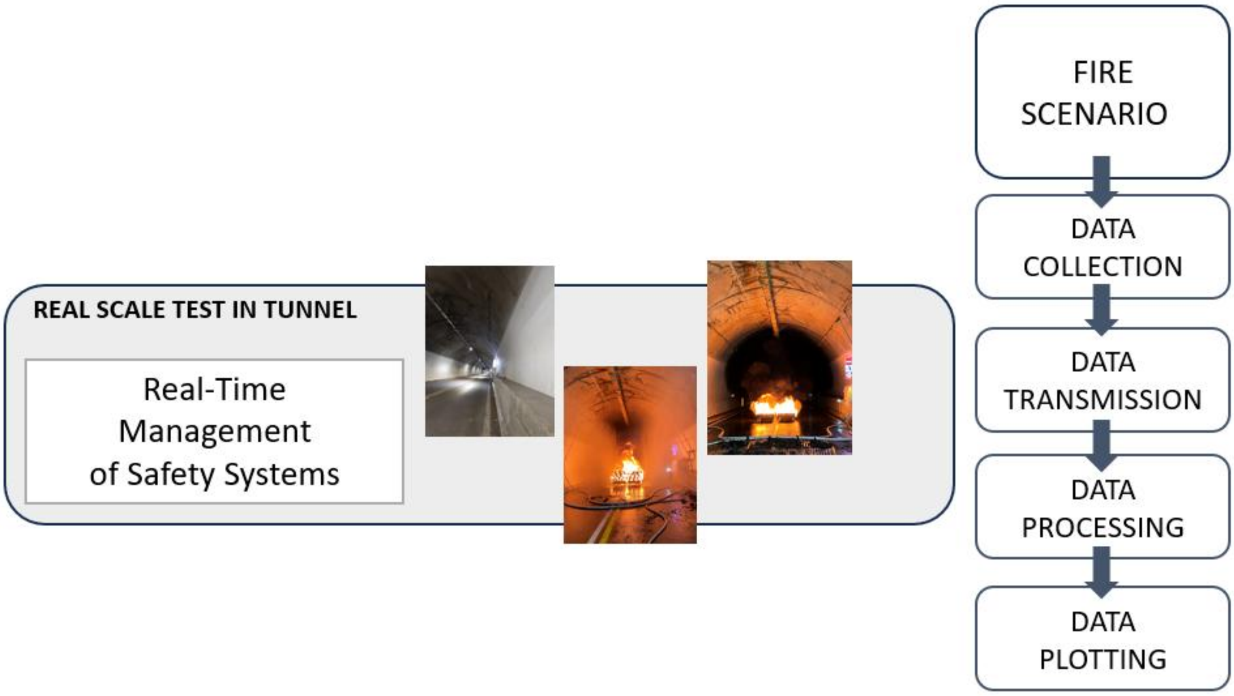


Figure 20 Integrated risk management in case of fire in a tunnel -

Furthermore, to optimize the use of existing data and facilitate the creation of a database for future fire tests, a framework with specific guidelines for data collection during fire tests has been developed, consistent with the DSS input data specifications. Using tunnel tests as an example, data collection should include:

- test parameters based on the tunnel's structural data: available studies document the technical specifications of the tests, such as the scaling factor, correlated to the tunnel's dimensions, construction materials, and site-specific local environmental conditions (ambient temperature, humidity, and wind).
- fire dimensions: information is provided on the fire's location, geometric dimensions, combustible material components (characterization of fire reaction), and the characteristic fire curve.
- sensors: in addition to the arrangement of all sensors and measurement instruments, further details must be provided regarding the type of sensor, measurement range, response time, and data collection frequency or interval.
- video tracking: fire-related phenomena must be documented using recordings from multiple cameras. All video data must include a detailed description of the camera positions, specific environmental information, and operational condition data, as well as a detailed timeline of the main fire processes and critical events, such as ignition, flame spread, ventilation conditions, and suppression activities.
- ventilation strategy: critical velocity for unidirectional tunnels and fixed velocity for bidirectional tunnels.

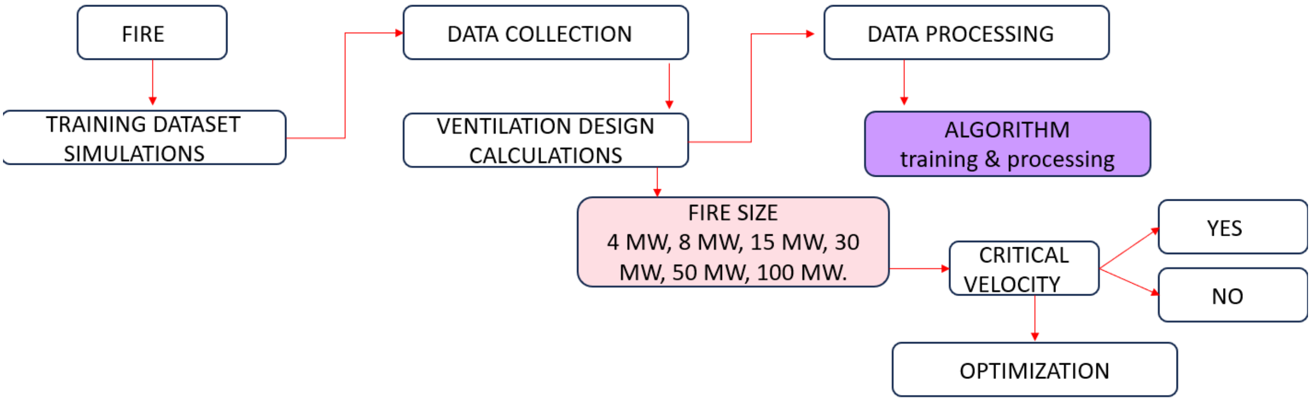


Figure 21 management of ventilation system strategy

The ventilation management system integrates numerous improvements, including the risk analysis system and weather stations, along with an energy consumption forecasting module. The system relies on a digital model of the tunnel, allowing for the simulation of ventilation performance under instantaneous conditions and enabling the evaluation of multiple operational alternatives. The selection of the optimal option is based on criteria of acceptable risk and minimal energy consumption during normal operation, as well as minimized risk during emergency conditions.

The specific output of the DSS for ventilation system management is a setpoint value for air velocity over time, achieved through feedback control of air velocity in the tunnel based on measurements from anemometers installed to ensure representative real-time data acquisition.

In the event of a fire, the system manages a series of scenarios that vary depending on traffic conditions, equipment degradation, fire location, and temperatures detected by sensors. The system selects appropriate measures based on current information to ensure safety conditions.

Regarding the possibility to manage the operation of safety system, an architectural diagram (Figure 21) for tunnel ventilation systems, particularly comparing operational and emergency ventilation scenarios was developed. Ventilation systems are managed during both normal operations and emergency scenarios, taking into account fires and dynamic environmental conditions through the decision support system.

The basic command at level one, referred to as the "ventilation map," is divided into "ordinary ventilation" in green and "emergency ventilation" in red. The various functionalities of the ventilation system are designed to ensure airflow (normal/emergency). On the right side of the representation, a system diagram is provided showing air circulation in the tunnel. This diagram highlights the relationships between various factors:

- "CO / Visibility" (monitored air quality).
- "Critical Conditions" (including safety limits, etc.).

At Level II, referred to as "feedback ventilation," the system is designed to select the two operational modes (operational and emergency) of the ventilation system, with specific functions and thresholds for each mode, following an activation-feedback process with an expansion cycle.

At Level III, referred to as "AI-driven ventilation," a more detailed flow diagram is illustrated, starting with a fire icon (on the left) leading to a decision-making process: the fire event triggers CFD simulations and selects input data available from the data collection phase. The data processing phase provides parameters such as fire size and wind speed and uses algorithms to define critical velocity. The process adapts to unidirectional and bidirectional airflow, leading to a final output box.

The fundamental difference between the three levels of operation implemented in the DSS is as follows:

- Level I focuses on basic operational and emergency modes.
- Level II incorporates feedback cycles and detailed thresholds.
- Level III introduces AI-based management, leveraging simulations and algorithms for advanced control suited to handling more complex conditions.

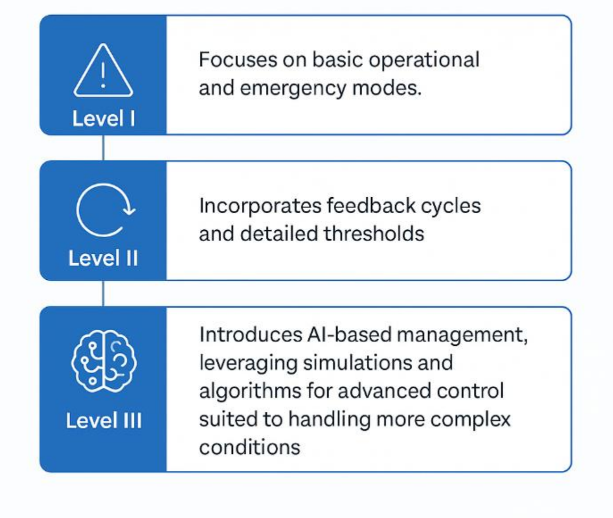


Figure 22 DSS Management of ventilation system in a tunnel - example

As a part of the architectural framework belonging to the DSS, a model was developed within the macro-area concerning accident analysis, specifically focusing on the definition of probability of initial event and historical data analysis.

The model is implemented as an algorithm, capable of performing three fundamental actions required for accident analysis in a tunnel, divided into:

- Chi-square Test (χ^2 Test), which allows for the validation of collected accident data to proceed with the accident analysis;
- Calculation of the Average Daily Traffic (ADT), a key parameter for determining the probability of the initiating event;
- Calculation of the probability of initiating events, which serves as the connection point between the two macro-areas.

The RISK Module of the DSS is integrated, as shown in to ensure the characterization of the pre-event phase, the evolution of the hazard flow, and the estimation of consequent damages.

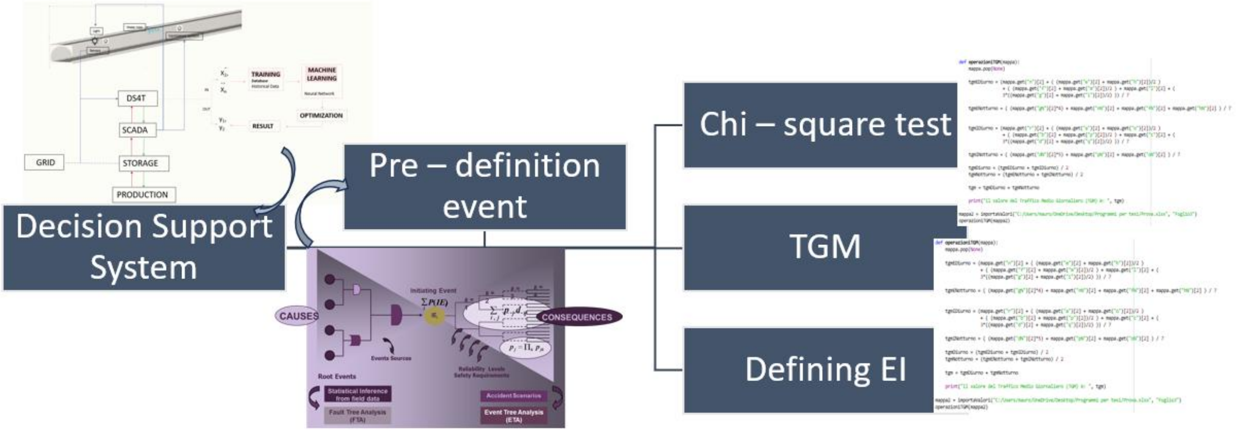


Figure 23 Diagram – extract of calculation of risk module – integrated DSS part

The Decision Support System manages the phase of defining the initiating event, with the ability to interact with the operator by giving an ALERT when boundary conditions change (for example traffic or particularly closing due to maintenance of the tunnel infrastructure).

10.3.3.1 Operational Workflow During a Fire Event

The integrated framework structures the fire event into successive operational phases explained below:

1. **Preparedness** (Pre-event monitoring)

Before a fire starts, the system is already computing exposure. DSS continuously monitors traffic composition (e.g. heavy goods vehicles, hazardous materials), ventilation readiness, evacuation lighting availability, and energy reserves for safety subsystems.

This phase is not passive. If DSS detects that the tunnel is temporarily operating in a higher-risk configuration (for example, reversible/bidirectional traffic during maintenance, reduced number of emergency exits compared to Directive 2004/54/EC thresholds, or partial fan unavailability) it can flag an elevated residual risk state. This feeds SAIF so that the network-level dashboard already “knows” that this tunnel is fragile even before an event starts.

2. **Event detection and validation**

When a fire ignites, multiple sensors and analytics detect abnormal conditions: rapid temperature rise, drop in visibility, smoke detection on cameras, stalled heavy vehicle, etc. These signals are ingested via the ETL layer, synchronized, and contextualized by SAE to confirm that a “fire scenario” is emerging rather than a false alarm. Concurrently, DSS classifies the event type (e.g. heavy goods vehicle fire with potential hydrocarbon pool fire, passenger car fire, secondary asphalt involvement), because the likely heat release rate, smoke yield, and toxic gas production differ significantly. Evidence from full-scale tests and CFD simulations informs this classification and the expected thermal/smoke development curves. The ability to validate the event quickly and accurately reduces delay in activating suppression systems such as low-pressure water mist and in switching ventilation from “normal longitudinal flow for air quality” to “emergency smoke control.”

3. **Projection of fire evolution and tenability**

Once the event is confirmed by feedback the Decision support system acts the dynamic risk module similarly updates a synthetic risk index every time resilience values and boundary conditions changes, combining probability and consequence indicators derived from sensor data, CFD-derived fire curves, and empirical knowledge from fire testing. It then updates the tunnel "risk layer" on the dashboard, visually indicating changing danger zones. This is a direct application of the "projection" level in the classical Situational Awareness model where the system not only recognizes the current state but dynamically updates what the state will be in the near future.

4. Decision support and actuation

Based on the projection, DSS recommends (or, depending on implementation level, triggers with operator supervision) a sequence of actions. These include:

- Ventilation management: adjusting longitudinal ventilation to maintain a unidirectional smoke flow and avoid dangerous back-layering, which would trap users upstream of the fire. Research and tests have shown that choosing the right critical velocity and fan configuration upstream/downstream of the fire controls temperature in the smoke layer and protects evacuation paths.
- Fire extinguisher activation (if there is the possibility to have this equipment in tunnel): water mist systems can sharply reduce upper layer temperatures by cooling hot smoke and suppressing flame growth, provided they are coordinated with ventilation so that droplets remain in the hot layer and evaporation is effective. Full-scale and reduced-scale tests confirm strong interaction between mist characteristics, nozzle orientation, and airflow on fire control and ceiling temperature reduction.
- Emergency lighting and voice guidance: the system can recommend activation of evacuation lighting sequences and PA/voice alarms to direct users toward viable exits. This is essential because self-rescue is often the dominant lifesaving mechanism in early tunnel fire stages, and users' ability to orient in smoke is extremely limited.
- Responder routing: it involves taking into account current tenability (temperature, toxicity), blocked lanes, and ventilation-induced flow. This reduces the pre movement time of evacuees

5. Communication, coordination, and escalation control

This supports:

- rapid communication with traffic management and law enforcement for closures/diversions;
- communication with civil protection about potential cascading impacts (e.g. reduced accessibility of emergency services to downstream communities);
- prioritization of scarce resources (e.g. specialized fire teams, mobile ventilation units) to the infrastructure node with the highest systemic centrality at that moment.

During and after the critical event, recovery planning concept can in principle be applied to schedule the optimal sequence of repairs or temporary measures, in order to restore network functionality as fast as possible. module frames recovery as a Markov Decision Process and learns which "arc to fix next" in order to maximize overall network efficiency gains under constraints. This is particularly relevant after a tunnel fire that damages ventilation, lining, lighting, and safety systems.

10.3.4. Discussion and Impact

Dynamic risk evaluation into a DSS environment enhances situational awareness and supports evidence-based emergency response, in line with current European approaches to tunnel safety management (Gehandler, 2015; Niu et al., 2024; Cui et al., 2024).

This contributes to advancing proactive and adaptive resilience strategies for road infrastructures (Nirandjan et al., 2024).

The integration of dynamic risk analysis into the DSS environment demonstrates tangible benefits in terms of safety management and operational resilience:

- **Real-time awareness**: continuous monitoring of risk evolution improves early warning and response capability;
- **Data-driven decision-making**: the combination of quantitative indicators and predictive models supports evidence-based actions;
- **Scalability and interoperability**: the architecture can be extended to other linear infrastructures (rail tunnels, bridges) within the same RETURN framework;
- **Societal impact**: the system enhances road-user safety and contributes to the sustainability and resilience of transport networks.

One of the key innovations introduced in the DSS is the explicit coupling of safety and sustainability/energy resilience in tunnel management. The smart tunnel controlled and managed by the Decision support system is not only a tunnel that consumes less energy: it is a tunnel that can sustain critical safety subsystems (ventilation, lighting, communication, suppression pumps) but can also optimize the use of energy consumption.

This energy perspective is important in a fire scenario for at least three reasons:

1. Continuity of life-safety systems. For instance, Fans, water mist pumps/compressors, emergency lighting, evacuation signage, and PA systems must remain powered throughout the emergency, even if the main supply is compromised. Embedding renewable sources (e.g. PV near portals, micro wind, energy recovery systems) and local storage (batteries, supercapacitors) gives the tunnel a buffer of autonomous operation.
2. Adaptive load management. The system can, in principle, prioritize loads in real time. For example, if available stored energy is limited, the system can recommend maintaining longitudinal ventilation at a minimum thrust that still prevents back-layering, while briefly dimming non-critical lighting in unaffected zones. This transforms sustainability from a "green add-on" into an operational resilience tool.
3. Regulatory and strategic alignment. The EU sustainability agenda (including SDG 7 on affordable and clean energy) and national smart road initiatives push for renewable integration into transport infrastructure. Embedding that into tunnel fire safety is a way to meet long-term policy targets while directly improving emergency survivability and post-event recovery.

In this view, the tunnel is reframed as a "smart energy node" that uses, stores, and redistributes energy strategically to guarantee safety, not only as a high-consumption liability. This represents a conceptual leap from traditional tunnel design, where energy is treated as an external utility rather than an integrated resilience resource.

10.3.5. Application to case study

The Decision Support Systems for Dynamic Risk Analysis for Road Tunnel Safety previously presented is then applied to a test case.

The application of the dynamic risk analysis modules integrated into the decision support system is composed of additive modules that make it possible to calculate and modify input conditions that vary over time autonomously, and then be reintegrated into the computation of the dynamic risk analysis tool, in order to obtain values of retro-cumulative distributions associated with the different scenarios that characterize the critical event.

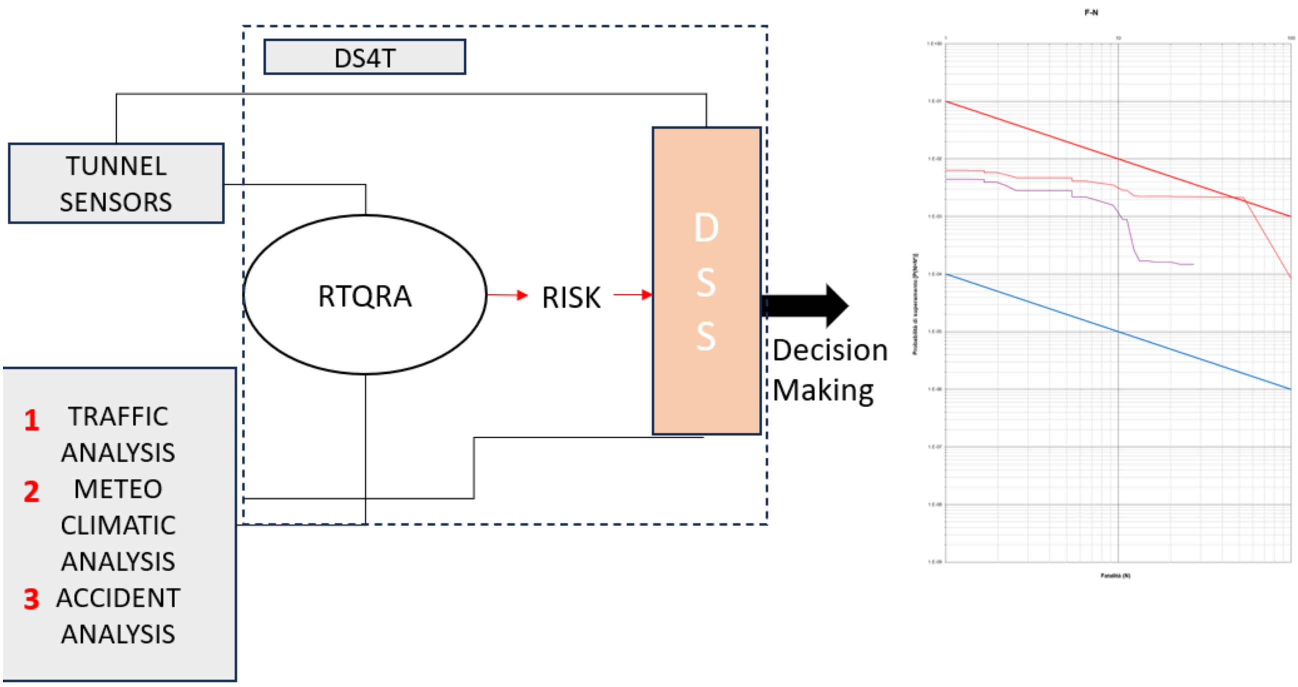


Figure 24 DSS and Dynamic Risk Analysis – modules functioning in a test case

Following the architecture described as in Figure 24 three illustrative examples of input data for the dynamic risk analysis modules are presented.

These refer to:

(1) traffic analysis;

(2) meteorological–climatic analysis;

(3) accident analysis.

Each input type is time-dependent and can be updated within the DSS, allowing the RTQRA module to continuously revise the risk estimates used to support decision making.

Example 1 - Traffic analysis

The first example concerns the traffic analysis module, which provides the main boundary conditions for the generation of vehicle flows and queue patterns within the case-study road tunnel. The input dataset is derived from long-term traffic monitoring on the relevant motorway section and from a dedicated traffic study, which includes both historical series and forecasts up to the year 2040, for example as in a test case in Figure 25.

On the basis of these data, an Average Daily Traffic (ADT) of approximately 21,600–22,000 vehicles/day is obtained for the reference period 2011–2024, with a mean proportion of heavy vehicles of about 21%. Forecasts indicate a progressive growth of the ADT up to 24,296 vehicles/day in 2040, corresponding to 12,148 vehicles/day per lane, while the share of heavy vehicles remains essentially constant at around 21%. The input dataset also specifies the share of vehicles transporting dangerous goods (ADR), estimated at about 1% of the heavy vehicle stream (≈0.2% of total traffic), and the proportion of buses, about 0.6% of total traffic, corresponding to approximately 3–8% of the heavy vehicles.

In addition to average daily volumes, the traffic module requires a description of the temporal distribution of flows over the day, the week and the year. The traffic study shows a predominantly daytime pattern, with higher intensities between approximately 07:00 and 20:00, and moderate seasonal variations associated with periods of increased demand. This information is translated into time-of-day and seasonal factors, which are applied to the ADT to obtain time-resolved traffic demand for the dynamic simulations (e.g. peak vs. off-peak hours, ordinary vs. high-season conditions).

For the purposes of dynamic risk analysis, the traffic input is further enriched with statistics on congested traffic, derived from historical series of queue events on the considered motorway section. provide a characterization of:

- the probability of occurrence of congestion upstream of the tunnel portals;
- the distribution of maximum queue lengths inside the tunnel;
- the distribution of vehicle residence times in the confined space under congested conditions.

These elements are essential because the number of users initially exposed in a given scenario depends not only on the ADT but also on the formation of traffic queues at the time of the initiating event. Consequently, in the dynamic model, the traffic module:

- generates stochastic realizations of traffic demand based on ADT, time-of-day/seasonal factors and vehicle composition;
- simulates or samples queue lengths and positions according to the historical congestion statistics;
- associates each simulated incident with a snapshot of the traffic state (free-flow or congested), from which the number, type and spatial distribution of vehicles inside the tunnel are derived.

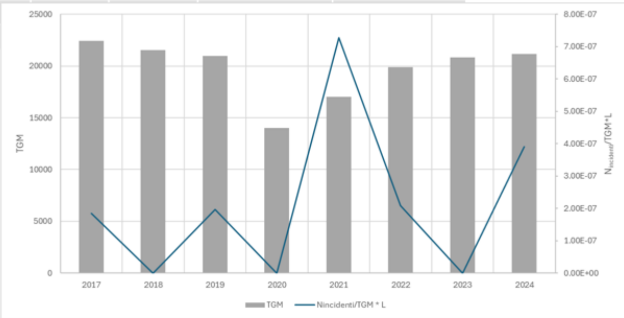
The resulting output of the traffic module, vehicle flows, queue configurations and associated probabilities, is then passed to the accident and consequence modules, which use this information to estimate the exposure of users and the potential number of fatalities for each scenario.

In summary, the traffic input dataset delivered to the dynamic risk modules includes:

- historical and forecast ADT per direction and per lane;
- composition by vehicle category (light vehicles, heavy goods vehicles, buses, ADR vehicles);
- daily, weekly and seasonal profiles of traffic demand;
- indicators of congestion (frequency of congested states, typical queue length, residence time distributions inside the tunnel);
- auxiliary parameters such as average speeds, vehicle occupancies and typical vehicle lengths, used to estimate both travel times and number of occupants in the tunnel at the time of an event.

For example, Figure 25 illustrates the traffic input, including a plot of historical and forecast ADT with the corresponding heavy-vehicle share, derived from the traffic study, alongside a diagram showing the current traffic composition by vehicle type (light vehicles, heavy vehicles, buses, and ADR vehicles). These visuals provide a clear summary of the traffic-related drivers used by the dynamic risk analysis to model vehicle flows and queue configurations within the tunnel.

Year	Event /year	Volume	ADT	Accident rate per 10^8 vehicle Km	Accident 10^8 vehicle*Km
2017	1	8181198	22414	1.84E-07	18.44
2018	0	7866101	21551	0.00E+00	0.00
2019	1	7652017	20964	1.97E-07	19.71
2020	0	5109443	13998	0.00E+00	0.00
2021	3	6215702	17029	7.28E-07	72.80
2022	1	7252664	19870	2.08E-07	20.80
2023					
2024					



Processing

```
def operazioniTGM(mappa):
    mappa.pop(None)

    tgmEDiurno = (mappa.get("n")[2] + ( (mappa.get("e")[2] + mappa.get("h")[2])/2 )
                 + ( (mappa.get("f")[2] + mappa.get("m")[2])/2 ) + mappa.get("l")[2] + (
                 3*((mappa.get("g")[2] + mappa.get("i")[2])/2) )) / 7

    tgmENotturno = ( (mappa.get("gN")[2]*4) + mappa.get("nN")[2] + mappa.get("fN")[2] + mappa.get("hN")[2] ) / 7


    tgmIDiurno = (mappa.get("r")[2] + ( (mappa.get("a")[2] + mappa.get("o")[2])/2 )
                 + ( (mappa.get("b")[2] + mappa.get("p")[2])/2 ) + mappa.get("c")[2] + (
                 3*((mappa.get("d")[2] + mappa.get("q")[2])/2) )) / 7

    tgmINotturno = ( (mappa.get("dN")[2]*5) + mappa.get("pN")[2] + mappa.get("oN")[2] ) / 7

    tgmDiurno = (tgmEDiurno + tgmIDiurno) / 2
    tgmNotturno = (tgmENotturno + tgmINotturno) / 2

    tgm = tgmDiurno + tgmNotturno

    print("Il valore del Traffico Medio Giornaliero (TGM) è: ", tgm)

mappa2 = importaValori("C:/Users/mauro/OneDrive/Desktop/Programmi per tesi/Prova.xlsx", "Foglio3")
operazioniTGM(mappa2)
```

Figure 25 example of traffic analysis in a test case

Example 2 - Meteorological – climatic analysis

The second example refers to the meteorological–climatic analysis module, which defines the environmental boundary conditions affecting natural ventilation and smoke propagation. The input dataset is based on site-specific meteorological measurements collected at a reference station considered representative of the tunnel area.

After analyzing the results concerning temperatures, humidity and other variables and although these variables are relevant for defining the general environmental context, the most critical parameter for tunnel safety is the wind field, as it directly influences the natural longitudinal ventilation in case of fire.

The meteorological input therefore includes:

- frequency distributions of wind speed over predefined classes (e.g. 0–1 m/s, 1–2 m/s, 2–3 m/s, 3–4 m/s, 4–5 m/s, 5–6 m/s, >6 m/s);
- the directional distribution of wind, represented through a wind rose;
- derived distributions of the wind component along the tunnel axis, used to characterize the natural longitudinal airflow.

The analysis shows that the natural ventilation regime is predominantly weak or nearly calm. Conditions with wind speeds below 1 m/s (calm) and between 1–2 m/s (light breeze) are largely prevalent and represent more than 75% of the annual observations. Speeds above 4 m/s occur only in a small fraction of cases (less than about 6%). When the longitudinal component of the wind along the tunnel axis is considered, it is found that approximately 84–85% of the conditions fall within the interval between –1.0 m/s and +1.5 m/s, confirming that the natural longitudinal ventilation is, in most cases, very weak or almost negligible.

For the dynamic risk analysis, these observations are translated into a finite number of ventilation classes, each characterized by:

- a representative longitudinal air velocity at the tunnel portals (e.g. quasi-zero, weak, moderate);

- a probability of occurrence, derived from the measured frequencies of the relevant wind speed and direction classes;
- a qualitative description of the ventilation regime (e.g. quasi-stagnant conditions, longitudinal flow assisting smoke extraction, longitudinal flow opposing extraction).

Each simulated fire and smoke propagation scenario is therefore conditioned not only on the traffic state, but also on the meteorological class. The selected class determines the initial and boundary conditions for the thermo-fluid dynamic simulations (1D or CFD) used to model smoke movement and temperature fields inside the tunnel. Under weak or quasi-stagnant conditions, the model predicts a greater tendency to back-layering and slower removal of smoke, whereas more sustained longitudinal flows can either enhance smoke extraction or, if oriented unfavorably, push smoke towards the evacuation routes.

From the perspective of tenability conditions for users, the meteorological module contributes to quantifying:

- the range of longitudinal velocities to be considered for each scenario;
- the likelihood that smoke layers will remain near the fire region or extend over long distances;
- the variability in available safe egress time (ASET) associated with different natural ventilation states.

Figure 26 illustrates the wind rose displaying the joint distribution of wind direction and speed, which directly supports the definition of ventilation classes and is used as a graphical example of meteorological input.

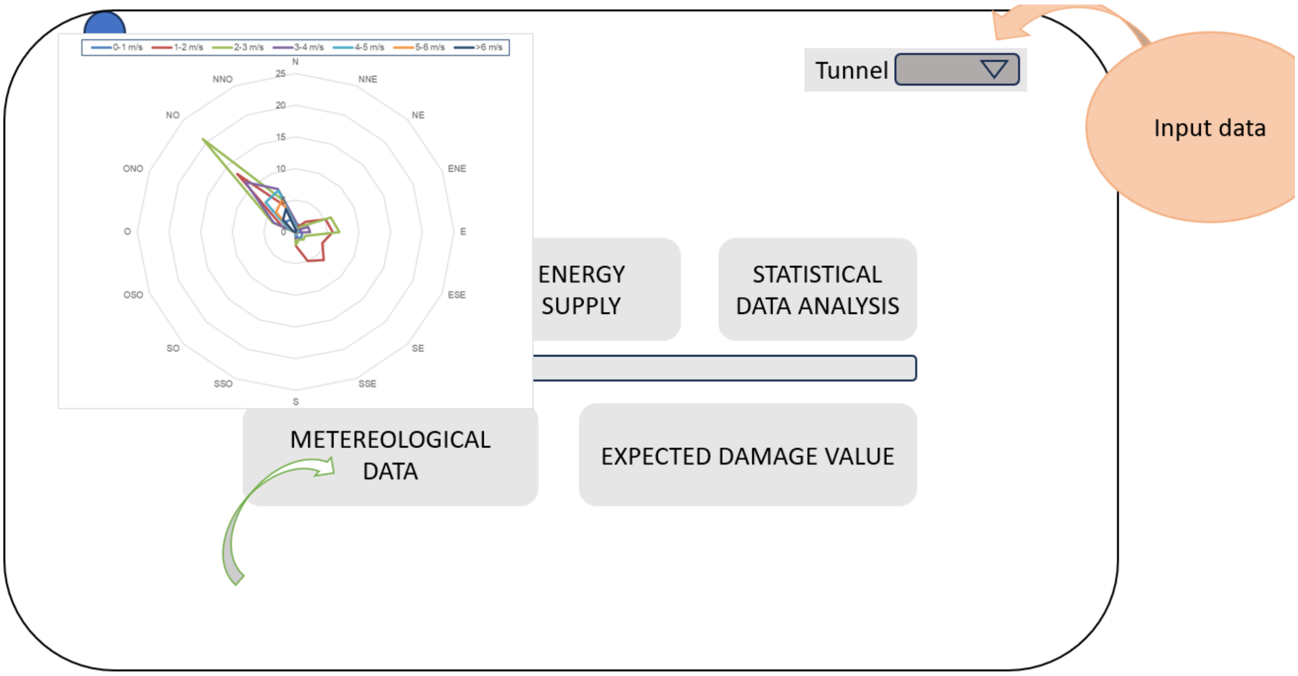


Figure 26 example of the interface of meteorological analysis in a test case.

This provides an immediate visual representation of the meteo-climatic boundary conditions feeding the dynamic risk analysis and clarify the predominance of weak-ventilation situations in the probabilistic framework.

Example 3 - Accident Analysis

The third example concerns the accident and risk analysis module, which supplies the basic frequencies for incident occurrence and the initial probabilities associated with the different hazardous scenarios considered in the Event Tree Analysis. The input dataset is constructed from the multi-year incident time series for the case-study tunnel, using official records provided by the infrastructure operator, and is complemented by a structured assessment of risk factors and tunnel-specific characteristics, as required by the national regulatory framework

The accident dataset includes all recorded traffic incidents in the tunnel over the reference period, with information on date, direction of travel, location along the tunnel, type of accident and severity. Typical event categories comprise collisions between light and heavy vehicles, rear-end collisions in congested traffic, single-vehicle loss-of-control incidents (including motorcycles), and accidents with minor injuries, while no tunnel fires or catastrophic events were observed during the monitoring period The combination of incident counts and traffic exposure (vehicle flows and vehicle-kilometers) allows the derivation of specific accident rates, which are used as baseline frequencies for the dynamic risk analysis and as a starting point for the subsequent decomposition into fire and hazardous material scenarios.

At a first level, the accident process is represented as a rare-event stochastic process, and the empirical yearly counts are used to estimate a mean rate of occurrence and to verify the applicability of a homogeneous Poisson model through standard statistical tests (goodness-of-fit and seasonality checks). The analysis yields a mean specific accident rate of the order of 21.35 incidents per 10^8 vehicle·km, corresponding to about 14.2 incidents per 10^8 vehicles. Once validated, this mean rate is split into sub-rates corresponding to the main scenario families to be represented in the Event Tree, including:

- accidents without fire and without dangerous goods;
- accidents involving heavy vehicles, which are particularly relevant to high-consequence fire scenarios;
- accidents occurring under congested traffic conditions, where the number of exposed users is higher;
- accidents involving vehicles transporting dangerous goods, which may lead to spills of flammable or toxic substances.

Because the monitoring period does not contain any recorded tunnel fires, the fire incident rates are estimated by combining the tunnel-specific accident data with international fire statistics for road tunnels (e.g. PIARC, OECD, UPTUN, NFPA), scaled to the actual traffic composition and volumes of the case study. In this way, consistent fire frequencies per vehicle-kilometer are derived for light and heavy vehicles and then combined according to the observed proportion of vehicle classes. These frequencies, together with the decomposition into accident categories, provide the probabilistic input for the initiating branches of the Event Tree, and are summarized in the input-data summary sheet.

In addition to purely statistical accident data, the accident analysis module is explicitly complemented by a risk factors analysis.

The analysis is then refined through characteristic safety parameters, which include:

- number of lanes per direction and lane width;
- longitudinal gradient and alignment layout (straight/curved, portal configuration);
- fraction of heavy vehicles and presence of dangerous goods;
- extent of traffic congestion (duration of low-speed conditions);
- seasonality of traffic (ratio of maximum monthly ADT to annual mean ADT);
- meteoclimatic conditions at the portals (fog, precipitation, wind).

For each parameter, the guidelines provide limit values beyond which statistically significant changes in the accident rate are observed. When the actual tunnel parameters are compared with these limits, the main anomalies identified for the case study are:

- a fraction of heavy vehicles at the 2040 horizon exceeding the threshold applicable when the transit of dangerous goods is allowed (of the order of ≈ 21–24% of ADT, versus a limit of 15% in presence of ADR traffic);
- a very high frequency of rainy days, corresponding to approximately 37% of the year, significantly above the reference limit of 20%.

These anomalies are incorporated into a negative binomial statistical model relating the accident rate to the characteristic parameters. The model is used to estimate the effective accident rate by applying statistical weights to the different risk factors (structure, traffic, environment, accessibility). In practice, this means that the "baseline" accident rate, derived from generic historical data, is adjusted upwards or downwards according to how the tunnel compares to the limit values of each characteristic parameter.

To synthesize the influence of the various parameters, the methodology introduces a hazard scale based on a set of hazard factors, each of which groups one or more characteristic safety parameters. The main hazard factors considered are:

- Structure (construction type, cross-section, number and width of lanes, alignment);
- Traffic (composition, speed, congestion, seasonality);
- Meteoclimatic conditions (wind, precipitation, fog);
- Accessibility (number and configuration of portals, presence of emergency galleries, availability of alternative routes).

For each factor, a hazard weight is assigned depending on the category into which the tunnel falls (e.g. percentage of heavy vehicles, limit speed, degree of congestion, level of precipitation). The combination of these weights yields an overall vulnerability profile, typically displayed as a bar graph with colored bands corresponding to high hazard (red), attention zone (yellow) and reduced hazard (green).

- tunnel length and use of bores;
- number and width of lanes;
- longitudinal and transversal gradients;
- traffic volume and its temporal distribution;
- likelihood of daily or seasonal queues;
- proportion of heavy vehicles;
- proportion and type of dangerous goods traffic;
- speed-related aspects.

These conditions, combined, lead to the conclusion that the tunnel must be regarded as a tunnel with special characteristics and so following the quantitative risk analysis imposed by law requirements.

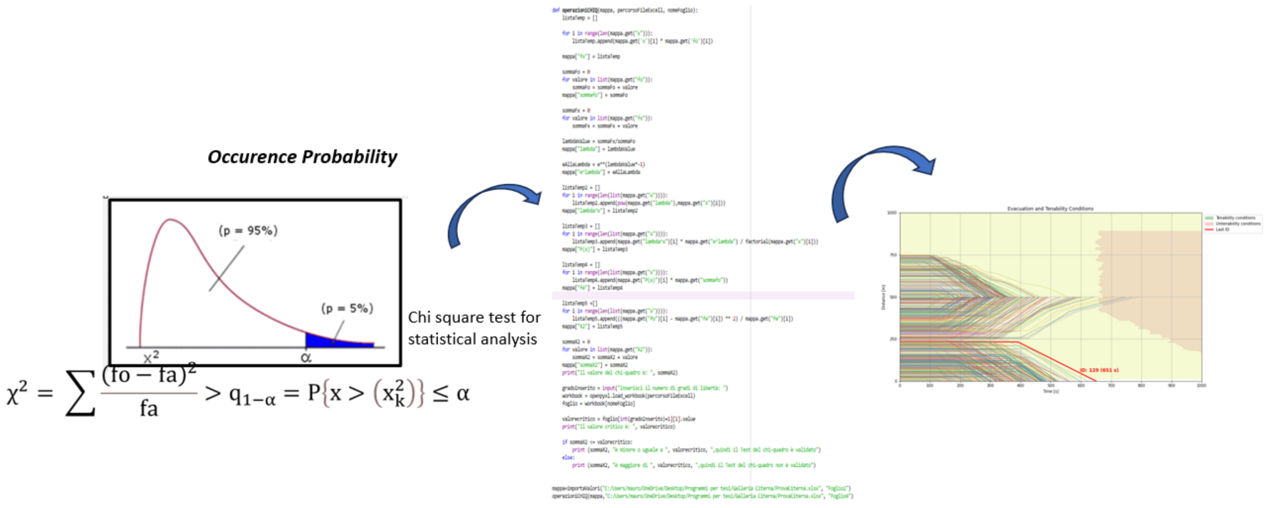


Figure 27 example of accident analysis in a test case

Moreover, a screening is performed using regional databases of major accident: the analysis shows that no establishments subject to major-accident hazard legislation re located in the immediate vicinity of the tunnel, and therefore no additional constraints or domino effects arise from such facilities. Second, a dedicated fluid-dynamic study is carried out to assess the potential mutual interaction between the tunnel and nearby bores located at short distances, both in terms of air-flow patterns and emergency management. The results indicate no significant mutual interaction between the case-study tunnel and the adjacent infrastructure; consequently, the tunnels do not need to be treated as a single continuous system for the purposes of risk analysis and emergency planning.

From the perspective of the dynamic risk model, the information provided by the accident statistics and the risk factor assessment is used in a complementary way:

- the quantitative accident rates and derived fire frequencies provide the numerical values for the initiating events of the Event Tree;
- the classification as a tunnel with special characteristics, the vulnerability profile and the identification of dominant hazard factors (traffic composition, meteoclimatic conditions, speed and cross-section) guide the selection and prioritization of scenarios, the definition of representative fire loads and traffic states, and the evaluation of additional safety measures.

In this way, the accident and risk factor analysis module does not only quantify how often incidents and fires are expected to occur, but also embeds the structural, traffic and environmental specificities of the tunnel into the probabilistic framework, ensuring consistency between the qualitative risk-factor study and the quantitative dynamic risk analysis.

10.3.6. Conclusions and project's impact

The proposed module offers a novel methodological and technological contribution to tunnel safety management. By integrating dynamic risk models with a Decision Support System, it converts real-time data into actionable knowledge, allowing operators to anticipate failures, prioritize interventions, and optimize emergency response.

This approach aligns with European directives on tunnel safety (Directive 2004/54/EC, D.Lgs. 264/2006) and supports the RETURN project for integrated, data-driven resilience of critical infrastructures.

While the integrated vision is powerful, several challenges remain before large-scale operational deployment.

- standardization and interoperability: different tunnels and road authorities use different SCADA/monitoring systems, communication protocols, and naming conventions for sensors and subsystems. The ETL/normalization layer in RETURN addresses this, but widespread adoption will require harmonized interfaces and agreed taxonomies for alarms and subsystem states.
- data quality and reliability: fire management in this framework depends on accurate, fast, and robust sensing. The platform developed and integrated in the decision support system mitigates false positives and false negatives using multi-source correlation.
- operational governance: the decision support system can recommend and take action directly to the functioning of safety systems: fan reversal or mist activation based on predictive models and test data. However, in current practice, many operators and regulators still require human confirmation before actuating high-impact changes. Developing clear governance procedures and training programs is essential.
- integration of sustainability into safety regulation. While the thesis frames renewable energy and storage as resilience enablers for safety systems, most tunnel regulations still treat energy mainly as a cost or an environmental metric, not as a life-safety reserve. There is room (and need) for regulatory evolution so that energy autonomy of critical safety subsystems becomes an explicit performance requirement.

Addressing these aspects will make the integrated system not just a prototype, but an operational standard for smart, sustainable, regulation-compliant tunnel safety management.

11. Conclusions

Technological evolution and the growing complexity of critical infrastructures require increasingly sophisticated data management and situational awareness (SA) systems capable of integrating and interpreting heterogeneous information flow promptly and accurately. The system presented in this document addresses these needs through a modular, scalable, and interoperable architecture, based on consolidated paradigms such as event-driven architecture and the adoption of microservices, while ensuring flexibility, resilience, and robustness. The integration of a Node-RED-based ETL framework simplifies data acquisition, normalization, and transformation into interoperable formats, while information fusion and advanced analytics modules enable a holistic and dynamic view of the state of critical infrastructures. Interactive visualization and exploratory data analysis capabilities support the understanding of complex phenomena and risk management, enabling timely responses to critical events and changes in the operating environment.

The use cases developed concretely demonstrate the system's validity and adaptability. Through earthquake and adverse weather scenarios, the platform demonstrated its ability to integrate data from heterogeneous sources—institutional, sensory, and participatory—providing real-time operational information and evolving risk representations. The combination of geospatial and topological analysis, along with crowdsourced user input, allows for the representation of systemic vulnerability with an unprecedented level of detail and the timeliness of the dataset, improving decision-making readiness and the overall resilience of critical infrastructure. In parallel, the case study on Territorial Digital Twins (TDT) and Decision Support Systems (DSS) demonstrates how the synergy between data analysis, visual analytics, and advanced digital technologies represents a decisive step toward holistic risk reduction. The integration of a dynamic resilience model and the adoption of the Real-Time Quantitative Risk Analysis (RTQRA) paradigm enables a shift from a reactive to a proactive and predictive approach, in which decisions are guided by contextual, timely, and visually accessible information.

In this manner, the research contributes to the enhancement of systemic resilience, operational safety, and sustainable planning in high-risk areas. Overall, the developed system constitutes a substantive advancement toward integrated and predictive risk management, leveraging digital technologies, advanced data analytics, and active stakeholder engagement to strengthen the resilience of critical infrastructures and associated territories

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