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# Secured and Intelligent Massive Machine-to-Machine Communications for 6G (SCION)

## D3.1: SCION Use Case Scenarios

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**ABSTRACT**

This deliverable outlines the set of use cases of SCION to guide research work within the project. This document includes the respective requirements and KPIs for each use case, example scenarios, key benefits and features, and the relationship with the 6G communication technologies. It includes detail information about the three main use cases: industrial network optimization and predictive maintenance, advanced digital twin systems, cyber-physical systems.

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## Executive Summary

This report is the first deliverable of Work Package 3 (WP3) "Cyber-Physical System (CPS) Requirement Analysis and System Architecture Design" and focuses on the SCION 6G use cases requirements and KPIs. This represents the starting point for future work and final implementation. To this aim, this document is organised as follows:

- **Section 1** provides a general introduction to the 6G technology trends from the scope of the SCION project, as well as a motivation for the report.
- **Section 2** describes the use cases that the project will work on. The use cases have been divided in 3 groups:
    - Industrial Network Optimization and Predictive Maintenance
    - Advanced Digital Twin Systems
    - Cyber-Physical Systems

  For each group, a representative use case is selected, showing the main aspects and features of that group. All the representative use cases have a deeper analysis displaying example service scenarios, requirements and KPIs, and key benefits and needs for 6G for those use cases. The KPI analyses in this deliverable are tailored to specific use cases, focusing not only on network KPIs, but also stating the relevance of performance and application-related KPIs, sensing capabilities and other new metrics that need to be considered in designing the new 6G communications.

  Moreover, other use cases have been added to the groups, with a general description and the relationship with the main aspects of the group.
- **Section 3** gives a general conclusion to the document, stating the main benefits of every technology for the use cases presented in the document.

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## Table of Contents

Executive Summary ..... 3
List of Figures ..... 6
List of Tables ..... 7
Abbreviations ..... 8
1 Introduction ..... 9
Objective of the document ..... 10
2 Use Cases (UCs) ..... 11
Group 1: Industrial Network Optimization and Predictive Maintenance ..... 11
UC1: Fault forecasting in industrial networks using machine learning ..... 11
UC2: Wireless network configuration and optimisation based on (network) digital twin in industrial settings ..... 14
UC3: Manufacturing automation enhanced with Machine Learning and semantic communications ..... 16
Group 2: Advanced Digital Twin Systems ..... 20
UC4: Smart cities through massive twinning and real-time data collection ..... 20
UC5: Satellite Communication with digital twin ..... 25
UC6: Massive Digital Twin by leveraging semantic communication ..... 25
UC7: Blockchain Modeling and Digital Twin Optimization: ..... 27
Group 3: Cyber-Physical Systems ..... 30
UC8: Networked cyber-physical systems (representative use case) ..... 30
UC9: Collaborative robots ..... 34
UC10: Network-assisted robotics motion planning ..... 35
3 Use Case Requirements ..... 36
Group 1: Industrial Network Optimization and Predictive Maintenance ..... 36
UC1: Fault forecasting in industrial networks using machine learning ..... 36
UC2: Wireless network configuration and optimisation based on (network) digital twin in industrial settings ..... 38
UC3: Manufacturing automation enhanced with Machine Learning and semantic communications ..... 38
Group 2: Smart Cities communication technologies for Real-Time Data Management ..... 39
UC4: Smart cities through massive twinning and real-time data collection ..... 39
4 Conclusion ..... 40
References ..... 41

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## List of Figures

Figure 1: System diagram for fault forecasting in industrial networks using machine learning. .....13

Figure 2: System diagram for wireless network configuration and optimisation based on (network) digital twin in industrial settings. ..... 16

Figure 3: System diagram for manufacturing automation enhanced with ML and semantic communications. ..... 19

Figure 4 : Smart cities 6G Network system. ..... 21

Figure 5 : Networked cyber-physical systems smart manufacturing example scenario. ..... 32

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## List of Tables

Table 1: Networked cyber-physical systems communication KPIs .....33
Table 2: KPIs for industrial networks .....37

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## Abbreviations

| | |
|---|---|
| **6G** | 6th Generation |
| **UC** | Use Case |
| **TL** | Transfer Learning |
| **E2E** | end-to-end |
| **IoT** | Internet of Things |
| **AI** | Artificial Intelligence |
| **ML** | Machine Learning |
| **Cobots** | Collaborative Robots |
| **MEC** | Multi-Access Edge Computing |
| **ISAC** | Integrated Sensing and Communications |
| **AoI** | Age of Information |
| **AoII** | Age of Incorrect Information |
| **CoCoCoCo** | Communication-Computation-Control-Codesign |
| **KPIs** | Key performance indicators |

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# 1 Introduction

Industrial Network Optimization and Predictive Maintenance are essential applications in Cyber-Physical Systems (CPS), utilizing the sophisticated features of 6G technology. Industrial Network Optimization leverages the ultra-low latency and huge connection of 6G technology to improve network efficiency and dependability. This ensures smooth and accurate communication throughout industrial activities. Optimising this process is essential for making quick decisions and automating tasks, leading to a substantial increase in productivity and a decrease in downtime in industries like manufacturing. Predictive maintenance utilises the improved dependability and fast data transmission of 6G technology to handle equipment malfunctions in CPS proactively. Through the analysis of live data collected from sensors and machines, this method can anticipate possible problems before they worsen, guaranteeing prompt repair and avoiding expensive interruptions. Integrating predictive maintenance in CPS improves the efficiency and resilience of industrial processes. It also enhances the stability and durability of equipment, while complementing the revolutionary capabilities of 6G in enabling intelligent interactions between machines and the physical world.

The CPS have emerged as a critical application domain for 5G technology, bonding the physical and digital worlds to create smarter, more efficient, and responsive environments. These systems, which integrate computation, networking, and physical processes, are pivotal in sectors such as manufacturing, healthcare, and transportation, enhancing automation, precision, and real-time responsiveness. For future 6G communications, CPS are expected to achieve unprecedented levels of performance, characterised by ultra-low latency, massive connectivity, and enhanced reliability [1-3]. The transformative potential of 6G will enable more sophisticated and complex CPS applications, facilitating more seamless and intelligent interactions between machines and the physical world [4].

In addition to CPS, 6G will revolutionise other cutting-edge technologies such as robotics and collaborative robots (Cobots). These technologies represent crucial use cases for 6G, promising to deliver enhanced efficiency, flexibility, and innovation across multiple industries [5-7]. These technologies will benefit from 6G's high data rates and low latency, enabling more precise and synchronised operations, particularly in dynamic and complex environments.

Now the introduction of newer technologies such as satellite communication, Quantum computing and Blockchain technology has opened gates to a whole world of simulation, which can, in turn be used to create smarter Digital twin systems. A Digital twin system refers to computer simulation of all the real-world activities which mimics and even pre-determine actions done in real world. Such a system has huge implications for Traffic management, Anomaly detection, and Safer cities.

sing latest technologies, it is possible to create a smart and advanced digital twin system which is way superior in terms of Security (provided by blockchain), computing power (provided by quantum computing) and speed and accessibility (provided by satellite

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communication). All these technologies can use 6G communications to provide and process algorithms faster making an "Advanced Digital Twin" system.

## Objective of the document

The definition of a new technology starts with the definition of the use cases, requirements and KPIs that the technology aims to meet. To stablish appropriate requirements and KPIs, it is crucial to understand the envisioned applications and the necessary functions to support them. These requirements and KPIs serve as the foundation for the technology's design and eventual implementation.

This deliverable provides a comprehensive set of 6G Use Cases and Requirements that the SCION project will focus their research work on. The use case presented, are based on insights from both industry and academic partners, as well as other relevant European Commision projects. The document provides specific scenarios and applications for the technology, and a consolidated view of 6G use cases and requirements.

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# 2 Use Cases (UCs)

## Group 1: Industrial Network Optimization and Predictive Maintenance

### UC1: Fault forecasting in industrial networks using machine learning

This use case involves the use of a Transfer Learning (TL)–based approach for fault forecasting in industrial settings for both private/public networks. It can ensure better network connectivity so industries can communicate, monitor, and control various machinery, devices, and sensors. In a critical environment of industries with multiple operations, faults can stop the operation of industries, leading to the loss of productivity. These settings will help proactively forecast faults in private/public networks to ensure safer operation without any disruption or reliability. The main motive of this use case is the deployment of Public and Private Networks across different network generations, including 4G, 5G, and beyond, to enhance connectivity and ensure reliability in an industrial context through fault forecasting. This adaptation of the TL-based approach will help resolve the challenges of faults in each network generation. The goal is to optimise the network through optimisation through fault detection, forecasting, and mitigation. The use of TL by adapting pre-trained models to reduce the training cost. This use case can help improve network reliability and response for industrial aspects because of critical operations in terms of production management. It can be deployed for both settings private/public networks in industrial settings.

The TL is a basic technique that gives a fundamental concept of how we train ML and DL models. It provides an efficient shortcut in the realm of ML, allowing us to make the most of the information already gained during the training of one model and apply it to a different but related problem. The basic idea behind TL is that the knowledge learned from one task can be useful for another if there is enough related information between the two tasks. TL can be performed in several ways, including fine-tuning a pre-trained model, using a pre-trained model as a feature extractor, and using a pre-trained model to initialise the weights of a new model.

In today's rapidly evolving industrial landscape, ensuring complex networks' continuous and efficient operation is paramount. Fault forecasting using ML represents a cutting-edge approach to maintaining network reliability and performance. This use case highlights how ML-driven fault forecasting can transform industrial network management, reduce downtime, and enhance operational efficiency. Using ML, private 5G networks dependant industries can transition from reactive to proactive maintenance strategies, resulting in improved efficiency, reduced costs, and enhanced safety.

Age-of-Information (AoI) guarantees the timeliness and freshness of data, which is essential for predictive maintenance and fault forecasting. The AoI is a metric used to assess how fresh the data is at a particular network node. It measures the amount of time that has elapsed since the last update was generated and received. AoI is critical when timely information is required for decision-making processes. AoI contributes to improved forecast accuracy, optimized data transfer, reduced latency, enhanced decision-making, and balanced update

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frequency, all of which lead to more dependable and effective maintenance procedures in industrial networks.

In industrial networks, a fault is typically an abnormal condition or defect at the component, equipment, or subsystem level, which may lead to a failure. It can result from various issues, such as device malfunctions, wire cuts, software errors, or human mistakes. Faults can cause disruptions in the network's operation, leading to inefficiencies or downtime. Some of these failures may result in increased packet loss and introduce additional delays. Packet losses and unwanted additional delay raise the threat to the manufacturing process of the industry, machine-to-machine communication, and the users of the network.

In Industry 4.0 and the Industrial Internet of Things (IIoT), much information and data are generated by network components (e.g., sensors, cameras, robotics arms, etc.) in various environments with different scales. This abundance of data leads to an increasing demand for research on predictive maintenance techniques, which are crucial for the new era of big data and deep learning. These techniques play a vital role in enhancing safety and security by detecting anomalies and faults early, thus preventing potential service downtime problems and ensuring an uninterrupted network operation in industrial settings.

**Benefits and Features:**

- **Proactive Maintenance:** Most traditional maintenance strategies rely on reactive measures, addressing faults only after they occur. The ML-powered fault forecasting shifts the paradigm to a proactive approach that can help resolve network traffic issues, uninterrupted networks, and significant delays and further predicts potential problems before they occur.
- **Data-Driven Insights:** Industrial networks generate significant amounts of data from various sensors, devices, and control systems. ML algorithms can analyse this data to identify patterns and anomalies indicating an impending fault.
- **Enhanced Efficiency:** By predicting faults early, organisations can schedule maintenance activities during planned downtimes, minimising disruption to production. This optimised maintenance scheduling leads to better resource allocation and improves overall efficiency.
- **Reduced Costs:** Predictive maintenance driven by ML reduces the need for emergency repairs and extends the lifespan of network components (e.g., sensors, cameras, robotics arms, etc.). This results in significant cost savings for components and replacement parts, contributing to a more cost-effective operation.
- **Improved Safety:** Early fault detection helps mitigate risks associated with network failures, such as safety hazards and regulatory non-compliance. Organisations can ensure a safer working environment and adhere to industry standards by maintaining network integrity.

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**Example Service Scenario:**

The proposed use case service scenarios consist of fault forecasting and recovery in industrial settings, including public and private networks, using transfer learning (TL). Both wired and wireless networks interconnect numerous machines and devices in the intelligent industry, thereby exchanging valuable information. Reliable and optimal network performance is crucial for achieving effective and ideal communication.

Machine failures and network anomalies severely disrupt the regular operation of intelligent industrial networks (public or private), thereby reducing productivity. To address such issues, fault forecasting and recovery techniques play a significant role. Adapting the TL-based approach will help resolve fault challenges in each network generation. This use case utilises the TL strategy by adapting pre-trained models to reduce training costs.

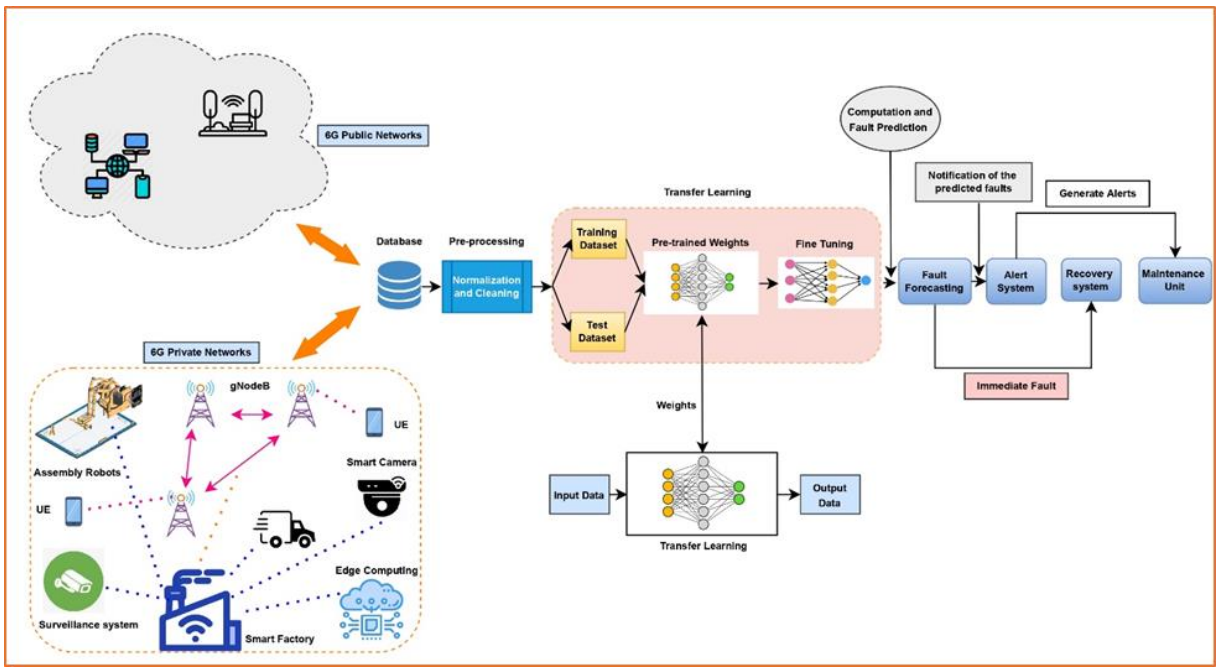



Figure 1: System diagram for fault forecasting in industrial networks using machine learning.

The proposed use-case scenario is depicted in Figure 1. This use case deployment helps explore network assessment, fault forecasting, and recovery in public and private networks. Network assessment analyses real-time industrial data on operational status and network health before forwarding it to a TL-based model. The transfer learning model normalises and cleans the data before processing. To reduce training costs, the TL uses pre-trained models. After fine-tuning, we receive the result, which aids in fault forecasting. Because of the temporal dependency, a forecasting-based model works well with most time-periodic KPI series, such as time-periodic fault detection and fault recovery. On the other hand, a reconstruction-based model (an ML model designed to reconstruct or recreate input data by capturing its necessary features) with an encoder-decoder architecture can deal with spatial dependency. A reconstruction-based model for anomaly detection is a type of ML model that learns the normal patterns of the data and then identifies deviations from those patterns to find anomalies in a dataset. The main concept is that the input data is rebuilt by the model,

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and then it is compared to the original data. The fault recovery process consists of two stages: recovery and maintenance. An automated system responds to predicted faults in the recovery step. This can include adjusting machine operations, rerouting network traffic, or switching to backup systems. The alert system sends information to the maintenance unit to intervene against the faults in the maintenance step.

**Benefits of the use case deployment:**

- Implementing proactive maintenance and network management procedures helps minimise unexpected failures and reduce the resulting delay.
- Cost efficiency is achieved by targeted measures that reduce maintenance and network management expenditures by preventing significant failures.
- Operational efficiency is enhanced by improved machine maintenance and network reliability, leading to increased total production efficiency.
- Transfer learning allows efficient scaling across different machines and network configurations with minimal need for re-training.

Innovative industries may significantly improve their ability to foresee maintenance needs and ensure reliable network connections by utilising the TL in machine learning.

### UC2: Wireless network configuration and optimisation based on (network) digital twin in industrial settings

A digital twin is a virtual representation of a physical entity or system. In wireless networks, a network digital twin is a detailed digital network model that mirrors its real-world counterpart. This includes all network components (routers, switches, access points, etc.), configurations, and dynamic interactions. By integrating digital twin technology with the wireless network, we present the idea of a digital twin wireless network. Through this integration, secure and efficient communication is ensured by transferring real-time data into a digital data space. The proposed solution provides highly dependable wireless communication connectivity on the Internet of Things (IoT) by bridging a physical system with a digital strategy. Network digital twins' fundamental benefit is its capacity to digitally imitate real-world network environments, which enables improved optimisation, predictive maintenance, and monitoring. They can be used, for example, to identify possible failure areas, optimise connection, and simulate network traffic. Additionally, we make use of a multi-agent ML system created especially to maximise network performance and effectively manage resources. This method deals with issues like optimal resource allocation, signal interference, and network congestion. When compared to conventional methods examined in simulation mode, empirical evidence from real-world datasets demonstrates that this methodology improves performance, reduces latency, and improves optimisation. This demonstrates the useful advantages and increases effectiveness of integrating cutting-edge ML techniques with digital twin technology in wireless networks.

With the increasing complexity of industrial networks and the utilisation of wireless technologies like the IoTs inside these environments, optimisation and management of wireless networks are more crucial than ever. A digital twin for network, an exact digital replica of the physical wireless network, offers a sophisticated approach to configuring and optimising industrial networks. This use case explores how leveraging network digital twins can transform wireless network management in industrial settings.

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Using network digital twins for wireless network configuration and optimisation in industrial settings represents a forward-thinking approach to network management. This innovative technology supports the continuous evolution of industrial networks, adapting seamlessly to changing demands and enhancing operational excellence.

**Benefits and Features:**

1. **Accurate Network Simulation:** A network digital twin replicates the physical wireless network's characteristics, allowing for precise simulation of various scenarios. This enables us to identify optimal setups without disrupting actual operations and predict potential changes while implementing new configurations.
2. **Proactive Maintenance:** Digital Twin continuously mirrors the real-time state of the network, and it helps in proactively identifying and addressing issues such as coverage gaps, radio link failures, misconfigurations, and performance bottlenecks. This proactive approach ensures higher network reliability and performance.
3. **Enhanced Optimisation**: The digital twin enables advanced optimisation techniques by simulating different configurations and settings to determine the most effective solutions. This includes optimising network parameters such as transmission power and channel allocation for maximum efficiency.
4. **Cost Savings:** Using a digital twin reduces the need for field trials during network planning and deployment. This saves time and resources and minimises the risks associated with network disruptions and configuration errors.
5. **Scalability and Flexibility:** The digital twin framework supports scalability, allowing for the easy addition of new devices and network expansions. It provides a flexible platform for testing and implementing changes, ensuring the network evolves seamlessly with the industrial environment's growing needs.

**Example Scenario:**

The proposed use case integrates digital twin technology with a wireless network to transfer real-time data to a digital data space, enabling effective and secure communications. The proposed technology is a physical system with a digital approach that offers a reliable, efficient, and optimised industrial network. A digital twin can optimise the design of wireless access points (APs) and network parameters, thereby enhancing the performance of an industrial network. Furthermore, the digital twin uses predictive analytics to foresee network issues and perform maintenance before failures occur.

Figure 2 illustrates the industrial network and its digital twin. The industrial network consists of several types of devices, such as sensors, surveillance cameras, robotic arms, and monitoring systems. We assume that unexpected network issues have been plaguing the factory, leading to production delays and increased maintenance expenses. The digital twin strategy implements a digital replica to address such issues in the actual industrial network.

To build a digital twin, the first step involves gathering data from a real-world industrial setting. This includes information on device configurations, traffic patterns, signal strengths,

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sources of interference, and the actual layout of the industry. The digital twin replicates the network's current state by simulating various network configurations, including access point positioning, channel selection, and adjustment of other parameters. The digital twin analyses the performance of each configuration and adopts the optimal algorithm for the proposed physical network by looking into factors such as wide coverage, minimal delay, high throughput, and reduced interference. Subsequently, we implement the optimised algorithm on the actual network and continuously monitor its performance. To predict future failures, the physical network transfers data to its digital replica in real-time. In conclusion, the real-world dataset shows enhanced efficiency, reduced latency, and an optimised solution is provided in the presence of a digital twin.

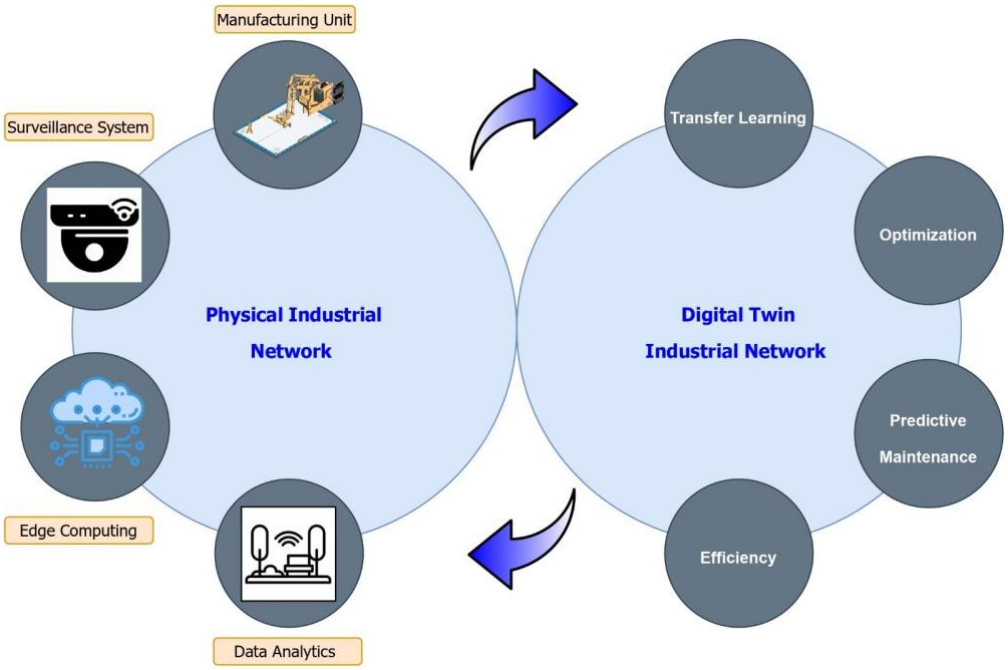



Figure 2: System diagram for wireless network configuration and optimisation based on (network) digital twin in industrial settings.

## UC3: Manufacturing automation enhanced with Machine Learning and semantic communications

Manufacturing automation consists of the use of various control systems, automated machinery, and software technologies to automate production processes in a manufacturing facility. The ultimate goal of manufacturing automation is to increase production capacity and reduce costs. The examples for manufacturing automation applications include the following:

- Robotic Assembly Lines.
- Automated Inspection and Quality Control.
- Additive Manufacturing like 3D printing.
- Automated Guided Vehicles (AGVs).

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- Autonomous Mobile Robots (AMRs).
- Computer Numerical Control (CNC) Machines.

Despite many advantages, Manufacturing Automation comes with its own challenges [3]:

- High Costs and Unrealistic ROIs (Return on Investment)
- Worker Safety
- Integration and Scalability
- Lack of Flexibility
- Staffing Issues
- Cybersecurity

In this use case, the ML algorithms analyse extensive datasets from sensors across manufacturing floors, deciphering patterns for predictive maintenance, resource optimisation, and streamlined workflows. The ML algorithms can be used to analyse both historical and real-time data from the manufacturing process. This data can include machine performance metrics, product quality measurements, and other relevant information. The ML models can predict potential failures, optimise machine settings for improved performance, and identify patterns that human operators might miss.

Semantic Communications is a paradigm in next-generation (NextG) communication networks that focus not only on the accurate transmission of data but also on the meaningful transfer of information. Through semantic communications, machines exchange detailed data, enhancing collaboration and orchestrating processes precisely. Semantic Communications employs Deep Neural Networks (DNNs) at both the sending and receiving ends, aiming to transmit meaningful information relevant to the importance of a specific task. This approach employs multi-task learning, which includes semantic information preservation, source input reconstruction, and integrated sensing and communications. Manufacturing integration with semantic communications heightens efficiency, minimises downtime, and improves product quality. Moreover, it revolutionises decision-making by forecasting demand, anticipating disruptions, and adjusting production schedules based on historical and real-time insights. Interoperability among systems, adaptive manufacturing environments, and optimal resource utilisation are objectives of this use case.

**Benefits and Features:**
Integrating ML and Semantic Communications into manufacturing automation marks a revolutionary step forward, enabling more innovative, efficient, and adaptable production processes. The goal is to improve efficiency, reduce errors, and enhance the production process. This can enable better communication between machines, systems, and human operators in manufacturing. This can lead to more coordinated and efficient operations and easier integration of new machines or systems into production.

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- **Intelligent Decision-Making:** ML algorithms analyze vast amounts of data from manufacturing processes to predict potential issues, optimize production schedules, and improve decision-making. ML-driven control systems adjust operational parameters in real-time based on data insights, ensuring optimal performance and minimizing downtime.
- **Enhanced Process Efficiency:** ML algorithms can detect product defects and anomalies through image recognition and other data analysis techniques, ensuring high quality and reducing waste. ML models optimize raw materials, energy, and other resource usage, saving costs and reducing environmental impact.
- **Context-Aware Information Exchange:** Semantic communications enable machines to understand and interpret the context of the information being exchanged, facilitating more efficient and accurate communication between systems. By leveraging semantic technologies, different systems and devices can seamlessly integrate and interact, enhancing the overall efficiency of the manufacturing process.
- **Scalability and Flexibility:** ML and Semantic Communication frameworks can be scaled to accommodate growing production needs and the introduction of new products and processes. These technologies allow for flexible adaptation to changes in production requirements, market demands, and technological advancements.
- **Overcome Mitigation in industrial networks** due to the exchange of only meaningful data using semantic communications.
- **Mitigation of delays and low maintenance expenditures** by taking timely actions and interpreting data locally.
- **Prompt detection of faults and forecasting** issues helps in proactive maintenance.

**Example Service Scenario:**
The smart manufacturing industries consist of different devices that work together, such as cameras, robotic arms, conveyor belts, and even software, to build automation in the manufacturing process. These manufacturing plants optimise their operations using advanced techniques such as semantic communications and ML. Improving predictive maintenance and industrial network optimisation are the major objectives to minimise delays, increase productivity, and reduce costs. Industrial networks face issues such as bandwidth limitations and frequent delays that affect the synchronisation of machine operations and sensors collecting data. Furthermore, machine or sensor failures in the industrial network cause significant delays and decrease productivity.

We can overcome these issues by integrating TL-based ML and semantic communication to enhance productivity and efficiency. Figure 3 shows how we can optimise the manufacturing automation process into an optimised manufacturing process. Industrial network devices transmit copious amounts of data, which the network uses for control and monitoring functions. In addition, these devices are prone to failures and network delays due to congestion. Figure 3 illustrates how the manufacturing automation unit first collects data from the industrial network, processes it for normalisation and data cleaning, and then applies transfer learning for training and testing. The predictive maintenance unit passes the data to predictive insights, which aim to identify patterns and predict potential failures for

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time series forecasting and anomaly detection. The data is processed through network optimization and semantic communication units for optimization. The network optimization process is responsible for improving the performance, reliability, and efficiency of an industrial network that connects numerous machines and devices within a manufacturing plant. It is crucial for providing seamless communication, lowering latency, and preventing network outages. The fundamental components of network optimization are bandwidth management, latency reduction, fault tolerance, load balancing, and security enhancement. Semantic communication involves understanding the significance of the communicated data, enabling more relevant and context-aware data sharing. In semantic communications, edge computing reduces the need for initial data transmission over the network by processing and interpreting data locally. In conclusion, both predictive maintenances using transfer learning and network optimisation through semantic communications help to ensure an optimised manufacturing automation process in industrial networks.

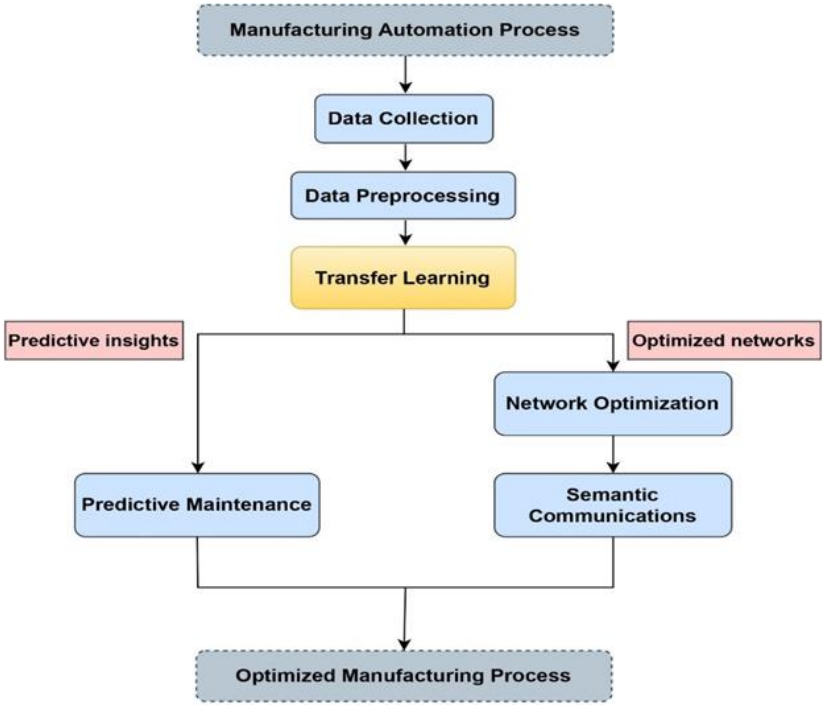



Figure 3: System diagram for manufacturing automation enhanced with ML and semantic communications.

**Performance Metrics:**

The following are some of the noteworthy and general performance metrics for this use case:

**Productivity and Quality Improvement:**

- Overall Equipment Effectiveness (OEE): This metric combines availability, performance, and quality to provide a comprehensive view of productivity.
- Defect Rate: The percentage of products that fail to meet quality standards.
- Yield: The ratio of good units produced to total units started.
- Cycle Time: The time taken to complete one production cycle.

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**Effective Production Systems:**

- Mean Time Between Failures (MTBF): The average time between breakdowns or failures of the production system.
- Mean Time to Repair (MTTR): The average time required to repair the production system after a failure.
- Downtime: The total time the production system is not operational.

**Production Workflow Optimization:**

- Process Cycle Efficiency (PCE): The ratio of value-added time to the total process time.
- Work-In-Progress (WIP): The number of unfinished items in the production process.
- Lead Time: The total time from the start of production to the delivery of the finished product.

**Interpretable Manufacturing Decisions:**

- Decision Accuracy: The percentage of decisions that lead to the desired outcome or improvement in production.
- Decision Time: The time taken to make and implement a decision.
- Compliance Rate: The percentage of decisions that comply with industry standards and regulations.

## Group 2: Advanced Digital Twin Systems

### UC4: Smart cities through massive twinning and real-time data collection

This proposed use case involves deploying satellite communication to accumulate physical world data to generate a Digital twin model by leveraging sematic communication to interpret and act to find suitable recommendations and suggestions for the user using classical and/or quantum algorithms by combining DT and Block Chain (BC) technologies within 6G networks. Therefore, both the physical and digital world would learn and affect each other which later could be seen and controlled using technologies like virtual reality and augmented reality as given in Figure 4. The proposed use case also focuses on creating energy-aware blockchain protocols and efficient data transmission techniques. The creation and adaptation of a digital replica of the real-time data from a city is very challenging and requires both network and processing capabilities that are not currently available. The latency and location accuracy provided by the 6G network is essential for these Quantum-AI applications to create a near real-time replica of the city, thus shaping and changing the current traffic scenario in a city. Other applications include infrastructure monitoring, environmental monitoring, efficient manufacturing lines, emergency response coordination and other fault detections. Blockchain will further enhance security with advanced encryption and decentralized consensus mechanisms, securing sensitive operational data exchanged between DTs and IoT devices.

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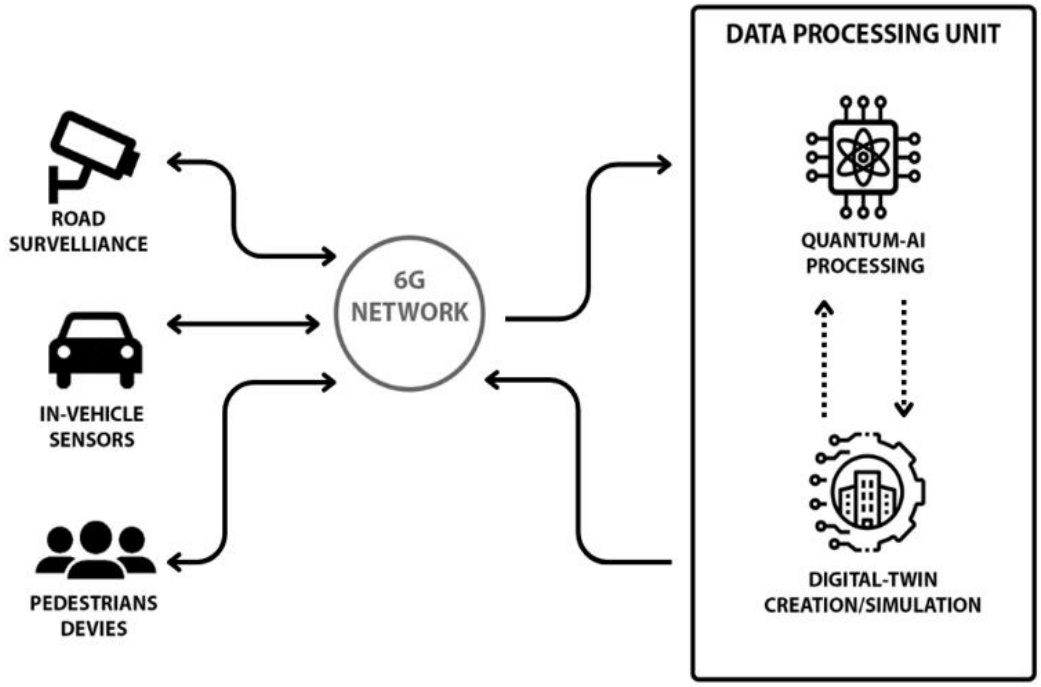



Figure 4 : Smart cities 6G Network system.

**Problems/ Challenges to be solved:**

1. **Data Integration:**

- Heterogeneous Data Sources: Integrating data from various sources such as sensors, cameras, IoT devices, and social media platforms can be complex due to differences in data formats and protocols.
- Real-Time Processing: Ensuring real-time processing and analysis of vast amounts of data to provide actionable insights and timely responses.

2. **Semantic Interpretation:**

- Contextual Understanding: Developing algorithms that can accurately interpret the context of data, including environmental factors, human activities, and dynamic urban conditions.
- Scalability: Ensuring that semantic interpretation mechanisms can scale to handle the increasing volume and variety of data in a growing smart city.

3. **User Privacy:**

- Data Privacy: Implementing robust privacy measures to protect sensitive data collected from citizens, CCTVs while maintaining functionality such as integrating Blockchain.

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- Regulatory Compliance: Ensuring compliance with data protection regulations such as GDPR and CCPA.

**4. System Integration:**

- Interoperability: Ensuring seamless integration and interoperability between different systems and platforms used in the smart city infrastructure.
- Legacy Systems: Integrating new technologies with existing legacy systems without causing disruptions.

**5. Resource Management:**

- Optimization: Efficiently managing and optimizing the use of city resources such as water, energy, and waste based on real-time data and semantic analysis.
- Predictive Maintenance: Using data to predict and prevent infrastructure failures, which requires accurate and timely analysis.

**6. Energy Optimisation:**

- Optimization: The deployment of 6G wireless networks will be characterized by increased network density and higher data transmission rates. This, in turn, leads to higher energy consumption, which can impact the sustainability of the overall system.

**Network Challenges:**

**1. High Data Throughput:**

- Bandwidth Requirements: Ensuring the network can handle high data throughput required for transmitting large volumes of real-time data from various sensors and devices.
- Latency: Achieving ultra-low latency to support real-time applications and services, such as traffic management and emergency response.

**2. Network Reliability:**

- Uptime and Resilience: Ensuring the network is highly reliable with minimal downtime, capable of handling failures and maintaining continuous operation.
- Quality of Service (QoS): Managing network resources to guarantee QoS for critical applications, ensuring consistent performance.

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**3. Edge Computing:**

- Distributed Processing: Implementing edge computing to process data closer to the source, reducing latency and bandwidth usage.
- Coordination: Coordinating between central cloud infrastructure and distributed edge devices to maintain data consistency and accuracy.

**4. Scalability:**

- Network Expansion: Scaling the network infrastructure to accommodate the growing number of connected devices and sensors in a smart city.
- Resource Allocation: Dynamically allocating network resources to handle varying data loads and priorities.

**5. Security:**

- Cybersecurity: Protecting the network from cyber threats, ensuring data integrity and preventing unauthorized access.
- Encryption: Implementing strong encryption methods to secure data transmission across the network.

**Need for 6G**

- Ultra-Low Latency: 6G technology can provide the ultra-low latency required for real-time updates of digital twins.
- High Bandwidth: The high data rates offered by 6G will support the massive amounts of data transmission from numerous sensors and devices in urban areas.
- Enhanced Connectivity: 6G's enhanced connectivity will ensure reliable communication links between satellites, ground stations, urban infrastructure and quantum algorithms to perform best to their abilities as some quantum algorithms are computed on cloud and thus would require high data transmission rate.
- Edge Computing: 6G enables edge computing, allowing data processing closer to the source, which reduces latency and enhances real-time decision-making.

**Techno-Socio-Economical Analysis (Impact)**

- Technological Impact: Accelerates the deployment of advanced smart city solutions, fostering innovation in urban management and digital twin technologies.
- Social Impact: Improves quality of life by enhancing city services, reducing traffic congestion, improving public safety, and enabling efficient resource management by allowing to visualise real-world data on a virtual environment in real time.
- Economic Impact: Drives economic growth by attracting investments in smart city infrastructure, creating jobs, and fostering a data-driven economy and reducing

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operational costs through efficient resource management and minimizing economic losses due to traffic congestion.

**Example Service Scenario:**

- Smart Traffic Management: Real-time data collected from traffic sensors and cameras is transmitted via satellite to update the digital twin of the city's traffic system. The system analyses traffic patterns, predicts congestion, and optimizes traffic light timings using new quantum algorithms along with existing classical algorithms, resulting in reduced congestion, lower emissions, and improved commuter experience.
- Efficient Manufacturing Lines: These smart algorithms can be deployed on a manufacturing line along with smart virtual environment systems that can detect faulty items which can be visualised by a worker working on the manufacturing sites on these smart devices and these data in turn can be used to make the system smarter by feeding into the training set of the existing models. This would reduce the number of personnel required on the manufacturing line along with the reduction in training time.
- Environmental Monitoring: Satellites collect air quality and weather data, updating the digital twin of the city's environmental conditions. The system predicts pollution hotspots, informs citizens, and guides policy decisions for air quality management.
- Emergency Response: During natural disasters, real-time data from various sensors is used to update the digital twin of the affected area. This provides emergency services with accurate situational awareness, enabling efficient resource allocation and faster response times.

**Requirements and KPIs:**

- Bandwidth and Throughput: High bandwidth to support the transmission of large data volumes. (KPI: Data throughput > 10 Gbps.)
- Latency: Ultra-low latency (less than 1 ms) for real-time applications.
- Reliability: 99.999% network reliability to ensure uninterrupted service.
- Data Accuracy: High accuracy in data collection and interpretation to ensure effective decision-making.
- Latency: Ultra-low latency (less than 1 ms) for real-time applications.
- Scalability: Ability to scale the system to accommodate a growing number of sensors and data points.

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## UC5: Satellite Communication with digital twin

This project aims to overcome the disadvantage of low resource usage rate caused by the high mobility of low-earth-orbit satellite and the variation of ground users' requirements. We aim to solve this problem by employing the ability of data collection and system analysis of digital twin.

**Problems/Challenges to be Solved**

- **Data Collection and Transmission**: Collecting and transmitting large volumes of real-time data from various urban sensors and devices across vast areas.

**Need for 6G**

- **Ultra-Low Latency**: 6G technology can provide the ultra-low latency required for real-time updates of digital twins.
- **Enhanced Connectivity**: 6G enhanced connectivity will ensure reliable communication links between satellites, ground stations, and urban infrastructure.

**Techno-Socio-Economical Analysis (Impact)**

- **Social Impact**: Improves quality of life by enhancing city services, reducing traffic congestion, improving public safety, and enabling efficient resource management.

**Example Service Scenario**

- **Smart Traffic Management**: Real-time data collected from traffic sensors and cameras is transmitted via satellite to update the digital twin of the city's traffic system. The system analyses traffic patterns, predicts congestion, and optimises traffic light timings, resulting in reduced congestion, lower emissions, and improved commuter experience.

**Requirements and KPIs**

- **Bandwidth and Throughput**: High bandwidth to support the transmission of large data volumes. Data throughput > 10 Gbps.
- **Latency**: Ultra-low latency for real-time data updates.
- **Reliability**: High reliability and availability of communication links. Network availability > 99.999%.

## UC6: Massive Digital Twin by leveraging semantic communication

This use case aims to revolutionize physical layer design by integrating semantic communication with advanced Multiple Input Multiple Output (MIMO) technologies. By leveraging the interplay between semantic communication and cutting-edge MIMO configurations such as fluid antennas, the project seeks to enhance data transmission

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efficiency, reliability, and context-awareness in next-generation wireless communication systems.

**Problems/Challenges to be Solved:**

- **Semantic Interpretation:** Developing algorithms that can accurately interpret the context of data, including environmental factors, human activities, and dynamic urban conditions.

**Need for 6G:**

- **High Data Throughput:** 6G high data rates support the massive amount of data generated by city-wide sensors.
- **Low Latency:** Essential for real-time applications like traffic management and emergency response.

**Techno-Socio-Economical Analysis (Impact):**

- **Economic Impact:** Reduces operational costs through efficient resource management and minimizes economic losses due to traffic congestion and inefficient infrastructure.

**Example Service Scenario:**

- **Scenario: Smart Traffic Management**
  - Sensors across the city collect data on vehicle movement, traffic density, and road conditions.
  - The data is transmitted in real-time to a central system using a low latency 6G network.
  - Semantic communication interprets the data to identify congestion patterns and predict traffic flow.
  - Traffic signals are adjusted dynamically to optimize traffic flow, and real-time updates are sent to commuters via a mobile app.

**Requirements and KPIs:**

- **Data Accuracy:** High accuracy in data collection and interpretation to ensure effective decision-making.
- **Latency:** Ultra-low latency (less than 1 ms) for real-time applications.
- **Scalability:** Ability to scale the system to accommodate a growing number of sensors and data points.

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### UC7: Blockchain Modeling and Digital Twin Optimization:

This use case aims to develop energy-efficient methodologies that integrate DT and BC technologies within 6G networks, enhanced by machine learning algorithms. The primary focus is on creating energy-aware blockchain protocols and efficient data transmission techniques. Machine learning models, utilizing historical and real-time data from IoT devices, digital twins, and edge nodes. These models will prioritize predictive maintenance, anomaly detection, and optimization of edge computing resources. Machine learning algorithms deployed at the edge will enable real-time data processing and decision-making. Predictive maintenance models will anticipate failures and proactively schedule maintenance, interacting with digital twins to generate schedules and alerts. Anomaly detection algorithms will analyze network traffic and data patterns, issuing real-time alerts for potential issues. Additionally, edge computing resources will be dynamically optimized based on current data processing requirements, ensuring efficient operations and minimal latency. In summary, the integration of DT with Blockchain represents a significant advancement toward sustainable and intelligent energy management systems, with the capability to enhance efficiency, security, and scalability across diverse industrial applications.

**Problems/ Research Challenges to be Solved:**

1. **Energy Optimisation:**
    - The deployment of 6G wireless networks will be characterized by increased network density and higher data transmission rates. This, in turn, leads to higher energy consumption, which can impact the sustainability of the overall system.
2. **Edge Computing Integration**:
    - **Distributed Processing:** Implementing edge computing to process data closer to the source, reducing latency and bandwidth usage. Deploy edge computing nodes to preprocess and analyze data before sending it to central servers, reducing latency and bandwidth usage.
3. **Resource Management:**
    - **Predictive Maintenance:** Predictive maintenance models anticipate failures and proactively schedule maintenance, interacting with digital twins to generate schedules and alerts.
    - **Anomaly detection**: Anomaly detection algorithms will analyze network traffic and data patterns, issuing real-time alerts for potential issues.
4. **Scalability:**
    - **Resource Allocation:** Dynamically allocating network resources to handle varying data loads and priorities.
5. **Blockchain Implementation:**
    - **Encryption and Access Control**: Implement encryption techniques, robust access control mechanisms, and hashing algorithms to secure data transmission and maintain data integrity. Its distributed ledger technology advances transparency and trust among all stakeholders in the DT system,

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supporting scalable management of large-scale energy systems and enhancing operational reliability over time.

- **Decentralized Data Security**: Use blockchain technology to ensure data integrity and security through decentralized consensus mechanisms and smart contracts securing sensitive operational data exchanged between DTs and IoT devices.

6. **Optimize Blockchain Consensus Mechanisms:**
    - To enhance efficiency, scalability, and transaction speed to optimize blockchain consensus mechanisms in 6G wireless networks. This involves exploring energy-efficient consensus algorithms, such as proof-of-stake and proof-of-work and integrating them with 6G networking protocols to ensure low latency and high throughput.
7. **Machine Learning:**
    - Utilizing machine learning algorithms on data from IoT devices, digital twins, and edge nodes can lead to smarter decision-making, predictive maintenance, and overall improved efficiency.

**Example Service Scenarios:**

- **Scenario 1: Smart Manufacturing with Predictive Maintenance**
    - **Objective:** Implement a comprehensive, real-time data analysis and visualization system in smart manufacturing to enhance predictive maintenance, improve operational efficiency, and ensure data security.
- **Scenario 2: Predictive Maintenance for a Manufacturing Line**
    - **Objective:** Reduce unplanned downtime and maintenance costs by implementing predictive maintenance using IoT, edge computing, digital twins, blockchain, and machine learning.

- **Scenario 3: Quality Control and Process Optimization**
    - **Objective:** Enhance product quality and optimize manufacturing processes by integrating real-time data analysis and visualization.
- **Scenario 4: Energy Management and Sustainability**
    - **Objective:** Improve energy efficiency and sustainability in manufacturing operations through real-time monitoring and optimization.

**Requirements and KPIs:**

- **Data Accuracy**: Percentage of data accuracy compared to the actual physical counterpart. This KPI measures the accuracy and reliability of the information provided in the digital twin, ensuring it accurately reflects the physical counterpart.
- **Predictive Analytics:** Percentage of accurate predictions made by the digital twin system. This KPI measures the ability of the digital twin to make accurate predictions of the behavior of the physical system based on historical data.

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- **User Satisfaction:** User feedback score on the effectiveness of Digital Twin in meeting their needs. This KPI evaluates user satisfaction with the functionality and usability of the digital twin system, providing insights into its acceptance and adoption.
- **Cost Savings:** Percentage reduction in physical system maintenance, downtime, and repair costs. This KPI quantifies the financial benefits of using digital twin, including cost savings in maintenance, repairs, and downtime.
- **Transaction Processing Speed:** One of the critical KPIs to measure blockchain in 6G is the transaction processing speed. 6G is expected to offer significantly higher bandwidth and low latency, allowing for faster transaction processing. The KPI for transaction processing speed can be tracked in terms of the number of transactions per second or the average time it takes to complete a transaction.
- **Energy Efficiency:** As 6G becomes increasingly power-intensive, it becomes crucial to evaluate the energy efficiency of blockchain. The KPI for energy efficiency can be measured in terms of the amount of power consumed per transaction or the energy required to sustain the blockchain network. This information helps identify areas for improving energy efficiency and reducing consumption.
- **Security and Privacy:** Security and privacy are paramount in blockchain networks, especially in 6G, where sensitive data will be transmitted and shared. The KPI for security can be tracked in terms of the number of successful attacks or breaches, the number of security incidents reported, or the compliance with industry standards and regulations. Similarly, the KPI for privacy can be monitored regarding the number of privacy breaches, data leaks, or the level of data encryption.
- **Performance Optimization**: Percentage reduction in system downtime due to integrating digital twin and blockchain. This KPI measures the effectiveness of integrating digital twin and blockchain in optimizing system performance by identifying potential issues and recommending corrective actions.
- **User Experience**: User experience is a critical aspect of 6G networks, where seamless connectivity and low latency are paramount. Measuring the user experience, KPI allows us to assess users' satisfaction with their blockchain-based digital twin integration.
- **Resource Efficiency**: Integrating blockchain and digital twins in 6G networks can significantly improve resource efficiency. By leveraging smart contracts on the blockchain, we can automate resource management processes, optimize resource allocation, and reduce energy consumption. Measuring the resource efficiency KPI allows us to evaluate the impact of blockchain and digital twin integration on reducing operational costs and improving resource utilization.

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## Group 3: Cyber-Physical Systems

### UC8: Networked cyber-physical systems (representative use case)

This use case centers aroun3d the integration of networked cyber-physical systems (CPS) in various environments such as industrial manufacturing, logistics, smart living spaces, and infrastructure management. A CPS is defined as a set of embedded physical devices, objects, and equipment that interact with cyberspace through a communication network. These systems include a variety of components such as sensors, actuators, and control systems capable of sensing their environment, communicating with each other, and executing tasks collaboratively. The core objective is to enhance productivity, safety, and efficiency through advanced connectivity and coordination.

In these scenarios, CPS components work together, sharing data and resources in real-time to perform tasks beyond the capability of individual ones. By adopting an application-aware approach for the design of network protocols and architectures, the performance of such systems can be significantly improved. Additionally, machine learning algorithms analyse extensive datasets from sensors, enabling predictive maintenance, resource optimisation, and streamlined workflows.

**Problem(s) to be Solved / Challenges**

- **Ensuring reliable and real-time communication between CPS to facilitate synchronised operations:** CPS components must communicate with each other in real-time to synchronise operations and avoid conflicts. Any latency or failure in communication can lead to performance deterioration or safety hazards. Such as autonomous driving where ultra-low latency is essential to exchange critical information between vehicles in busy roads, or deterministic communication in power grid management to ensure precise synchronisation of control signals. Overcoming these challenges requires robust and low-latency communication protocols that can handle the dynamic nature of CPS networks.
- **Enhancing the safety of human-robot interactions in shared environments:** As CPS applications often operate in environments shared with humans, ensuring safety in the physical environment is paramount. This includes developing advanced sensors and algorithms to detect and respond to human presence and implementing stringent safety protocols to prevent accidents and injuries.
- **Managing the computational and network resources efficiently to support the dynamic and high-throughput requirements of CPS applications:** CPS applications generate vast amounts of data that need to be processed and transmitted in real-time. Efficiently managing these computational and network resources is crucial to maintain system performance at the desired level. This includes optimising how data are processed and transmitted and how bottlenecks can be mitigated through load balancing across the network and computing domains.

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- **Enabling secure and authorised participation of machines and humans in task-solving processes:** CPS are vulnerable to cyberattacks that can disrupt critical operations, such as power distribution in smart grids or control systems in autonomous vehicles, posing risks to human safety and system functionality. Ensuring that only authorised devices and users can access the CPS network is essential to prevent malicious activities. This involves implementing robust security measures such as encryption, authentication, and access control mechanisms to safeguard the integrity and confidentiality of the data.
- **Sustainability and efficient resource usage:** CPSs must be designed with sustainability in mind to minimise their environmental impact. This includes optimising energy consumption, reducing waste, and using resources efficiently. By implementing energy-efficient algorithms and leveraging renewable energy sources, CPS can contribute to sustainable development goals.

**Why is 6G needed?**

The exchange of relevant information among CPS components is essential for cooperation and synchronisation. The evolution of embedded machine-to-machine communication towards subnetworks, along with mechanisms for local reservation of communication resources, serves as key building blocks. Mobile devices may need the capability to request and establish these reservations when local connectivity is necessary.

Current 5G communication fails to meet the latency, reliability, and scalability requirements in demanding scenarios. Increasing the adoption of existing millimeter waves and developing new sub-THz connectivity may be critical in achieving latency targets and managing interference.

6G communications will facilitate the extensive exchange of AI/ML data, including training data, model weights, and AI models. This new AI/ML traffic, with its own new requirements, is characterised by its high volume and complexity, needing 6G's enhanced data throughput and reliability. For example, in smart manufacturing, CPS can leverage 6G to continuously upload sensor data and receive updated AI models for predictive maintenance and optimising machinery performance. Another example is in smart cities, where traffic management systems collect and analyse vast amounts of real-time data from vehicles and infrastructure, deploying AI models to optimise traffic flow and enhance public safety. Federated learning can also be leveraged by enabling edge devices to collaboratively train AI models without sharing raw data, thus preserving privacy and reducing network load.

The integration of sensing and positioning capabilities in the radio interface may assist with collecting data necessary for advanced machine learning applications. Trust management is crucial for safe machine-machine and human-machine interactions and will require reliable, deterministic, and low-latency E2E message transport mechanisms, along with secure sensing results and manipulation-protected positioning.

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**Example service scenario:**

In a smart manufacturing environment, the traditional factory is transformed into a highly automated and efficient ecosystem through the integration of advanced technologies such as IoT, AI, ML, Edge Computing and future 6G communication networks. The goal is to create a flexible and efficient manufacturing ecosystem that can quickly adapt to changing demands and conditions, ensuring minimal downtime and maximising productivity.

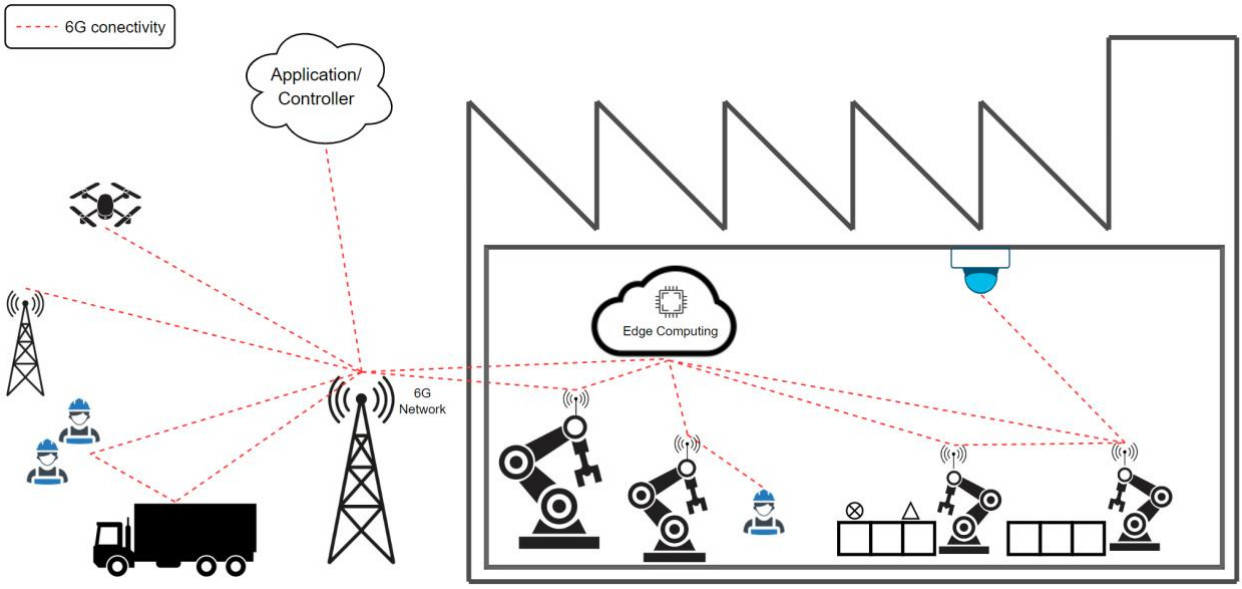



Figure 5 : Networked cyber-physical systems smart manufacturing example scenario.

The network serves as the backbone of smart manufacturing, providing the essential connectivity that enables real-time data exchange and seamless communication between various components of the production process. Specific examples where this will be beneficial include:

- **Predictive maintenance:** Sensors embedded in machinery continuously monitor operational parameters such as temperature, vibration, and energy consumption. Data is transmitted via the network to an edge computing platform for real-time analysis using AI algorithms to predict potential equipment failures.
- **Dynamic resource allocation:** The smart factory dynamically allocates resources such as raw materials, workforce, and production lines based on real-time demand fluctuations and supply chain conditions. Production schedules are adjusted in response to changing requirements.
- **Automated quality control:** Vision systems and sensors integrated into the production line perform real-time inspection of products for defects or deviations from quality standards. AI algorithms analyse the data to identify anomalies and ensure product consistency.
- **Supply Chain Integration:** The smart factory is interconnected with suppliers, logistics providers, and customers through a digital supply chain network. Real-time data exchange enables accurate inventory management, efficient order fulfillment, and seamless coordination across the supply chain.

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**Requirements and KPIs:**

- **Low latency and High Reliability:** Instantaneous data transmission and minimal downtime are crucial for maintaining operational efficiency and responsiveness. The network must offer ultra-low latency and high reliability to enable real-time control, monitoring, and synchronisation of industrial processes.
- **Multi-Access Edge Computing (MEC):** Edge computing enhances operational efficiency by enabling local data processing, AI-driven insights, and responsive control of CPS without overburdening central network resources. Collaborative tasks are characterised by their localised nature, leading to the deployment of subnetworks and MEC systems.
- **Sensing and positioning capabilities:** Precise sensing and positioning through technologies such as ISAC, are crucial for tracking assets, monitoring production processes, and enabling location-aware applications and robot collaboration. On the other hand, introducing AI/ML new traffic and implementing AI/ML processing on edge nodes could significantly improve robot coordination.

Table 1: Networked cyber-physical systems communication KPIs

| Communication KPI | Target Value | Comments/Justification |
|---|---|---|
| Communication service availability | 99.999 9 % to 99.999 999 % | The communication system is in the "available" state as long as the availability criteria for transmitted packets are met. The service is unavailable if the packets received at the target are impaired and/or untimely [16]. |
| Communication service reliability: mean time between failures | ~ 1 month | Mean time between failures states the mean value of how long the communication service is available before it becomes unavailable. Usually, an exponential distribution is assumed [16]. |
| Service bit rate | DL: ≥ 1 Mbit/s<br>UL: > 10 Mbit/s | This is the information rate the communication system aims at providing on average during a given (moving) time window [16]. |
| End-to-end latency | < 16 ms | This parameter indicates the time allotted to the communication system for transmitting a message and the permitted timeliness [16]. |
| Mobility | < 10 km/h | Quasi-static, slow vehicular [16]. |
| Coverage | Up to several km$^2$ | CPS can be closely located (joint tasks) or very widely located (farms and IoT). |
| Positioning accuracy | < 0.1 m (fine)<br>< 1 m (coarse) | Tasks such as environment mapping, robot navigation, and inventory management require precise positioning. In contrast, tasks like robot localisation need less precise, or coarse, positioning [4] |
| Sensing-related capabilities | Y | Network-integrated sensing may complement or replace dedicated sensors. |

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Apart from the communication KPIs shown above, in the networked CPS, the importance of new KPIs such as Age of Information (AoI), Age of Incorrect Information (AoII), and control performance metrics cannot be overstated. These KPIs provide deeper insights into the freshness and accuracy of the information being communicated, which are critical for maintaining system stability and performance. For instance, in systems where real-time data drives decision-making, minimising AoI ensures that the control commands are based on the most current information, thus enhancing the system's responsiveness and efficiency.

The joint modeling of control and communication errors reveals the intricate interplay between packet loss and control performance. Traditional metrics like packet loss rate are now complemented by advanced analyses that consider temporal correlations of packet losses. A negative packet loss correlation, where consecutive packet losses are unlikely, significantly benefits closed-loop control systems by preventing extended periods of information unavailability. This allows for more relaxed yet efficient network requirements [17].

Moreover, the cross-domain modeling of system-level dependability, which integrates Communication-Computation-Control-Codesign (CoCoCoCo), highlights the need for holistic approaches to reliability. Traditional perspectives fail to capture the interdependencies and error propagation across domains. For example, in a case study involving a remote-controlled inverted pendulum, it was demonstrated that the mean time to failure (MTTF) drops from several minutes to a few seconds if the sampling interval increases beyond 0.1 seconds [17]. Such insights emphasise the necessity of coordinated optimisation across all domains to achieve reliable and stable CPS.

### UC9: Collaborative robots

This use case involves collaborative robots, or cobots, which work alongside humans in shared spaces such as factories, hospitals, and homes. Cobots are designed to assist humans in tasks that require precision, strength, or repetitive actions, improving overall productivity and reducing physical strain on human workers. Cobots equipped with real-time communication capabilities and robust safety protocols are essential for operating in close proximity to humans, requiring ultra-low latency for swift responses and seamless coordination.

Cobots interact with humans and other machines using advanced sensors and communication protocols, ensuring safe and efficient operations. They can adapt to various tasks and environments, making them versatile tools in modern workspaces. By harnessing cutting-edge networking technologies and responsive algorithms, cobots navigate dynamic environments with precision, mitigating collision risks and optimising workflow efficiency.

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### UC10: Network-assisted robotics motion planning

Network-assisted robotics motion planning leverages the advanced capabilities of 6G communications to revolutionise robotic operations. This use case aims to enhance the precision and efficiency of robotics motion planning through seamless integration of sensors and real-time data exchange facilitated by 6G networks. By utilising high-resolution sensors like LIDAR and cameras fused with URLLC services provided by 6G, robots can gather detailed environmental data accurately. This data is crucial for enabling robots to adapt their motion planning dynamically in response to real-time changes in their surroundings.

By employing advanced technologies like raytracing for precise environmental mapping and path optimisation, 6G empowers robots to navigate challenging terrains securely and select the most efficient paths autonomously. Ultimately, network-assisted robotics motion planning represents a significant stride towards achieving safer, more agile, and adaptive robotic systems capable of addressing diverse real-world challenges effectively, such as synchronised operations in complex environments like manufacturing floors or disaster response scenarios.

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# 3 Use Case Requirements

## Group 1: Industrial Network Optimization and Predictive Maintenance

### UC1: Fault forecasting in industrial networks using machine learning

**Problem(s)/ Challenge(s) to be Solved:**

- **Cost-Effective Network Management:** Network management is usually costly due to sudden network faults, necessitating unplanned network maintenance. Implementing transfer learning-based proactive maintenance techniques helps reduce computational power costs, directly impacting overall network management expenses. Not only does this minimise costs, but it also extends the lifespan of network components, lowers labor costs, and enhances network management efficiency.
- **Minimising Network Downtime and Disruptions:** Industrial networks are crucial and require uninterrupted private networks due to critical production operations, making maintenance essential. Sudden faults halt the production process and lead to significant network downtime, directly impacting production costs. Deep learning-based approaches, mainly transfer learning-based techniques, help detect faults before they occur, ensuring smoother operations and reducing maintenance costs in industrial settings.
- **Handling Complex and Large-Scale Data:** Industrial network settings involve various connected devices, such as sensors and control systems, which generate large and complex amounts of data. Handling such vast data is challenging. Machine learning approaches can analyse historical data, detect patterns, and identify anomalies, improving fault prediction and overall results.
- **Scalability Across Network Generations:** The environmental settings of industrial networks include various generations, such as 4G, 5G, and beyond. Detecting and managing faults across these diverse networks is challenging. Transfer learning techniques can be applied to diverse network conditions, enabling the detection of faults in different network configurations and technologies. This approach reduces the need for extensive retraining and enhances overall efficiency.

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**Metrics and KPI**

Table 2: KPIs for industrial networks

| KPIs | Range | Justification |
|---|---|---|
| Fault Detection Accuracy [%] | ≥ 95 | It helps uninterrupted connection and reliable operation in industrial settings [19]. |
| Fault Forecast Time Interval [ms] | ≤ 100 | The time interval in the forecast affects the response rate. |
| Pre-trained Models Adaptation [%] | ≤ 10 | The adaptation of pre-trained models affects their reusability [18]. |
| Fault Isolation Time [ms] | ≤ 100 | It helps facilitate faster repairs and reduces downtime. |
| Fault Recovery Time [ms] | ≤ 200 | The rapid recovery of faults is important to resume normal operations. |

**Requirements:**

Table 2 discusses the KPIs for industrial networks, and here are the details of their requirements.

- **Fault Detection Accuracy:** High accuracy is essential for uninterrupted connection and reliable operation in industrial settings. It is important to reduce false positives and negatives.
- **Fault Forecast Time Interval:** The time interval in the forecast affects the response rate, and a rapid forecast can reduce downtime and help maintain productivity in industrial settings.
- **Pre-trained Models Adaptation:** Adapting pre-trained models affects their reusability, and high percentages can reduce the cost and time of training these models.
- **Fault Isolation Time:** The isolation time interval is crucial for identifying the exact fault location and initiating recovery, which helps facilitate faster repairs and reduces downtime.
- **Fault Recovery Time:** The rapid recovery of faults is important to resume normal operations and can save management costs.

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## UC2: Wireless network configuration and optimisation based on (network) digital twin in industrial settings

**Problem(s)/ Challenge(s) to be Solved:**

- **Optimising Throughput and Reducing Latency:** Operating successful industrial networks requires high throughput and low latency. Digital twins can simulate and analyze different network setups to find the best settings. This helps to improve throughput and reduce latency, ensuring the network can handle large amounts of data efficiently and with minimal delay.
- **Optimising Real-Time Network Performance:** Industrial networks, which include devices like sensors, cameras, and robotic systems, need smooth and real-time communication. Traditional network configuration methods can be slow and may struggle to adapt to real-time changes. Digital twin technology provides a flexible solution for optimising network configurations in real-time, ensuring continuous and efficient operations.

## UC3: Manufacturing automation enhanced with Machine Learning and semantic communications

- **Integration of Advanced Technologies:** The system should integrate Artificial Intelligence (AI), IIoT, Cyber-Physical Systems (CPS), Big Data, and Cloud Computing [5].x
- **Semantic AI:** The system should employ Semantic AI, which is a combination of Statistical AI and Symbolic AI technologies. By integrating statistical learning and semantic reasoning, semantic AI enables interpretable manufacturing decisions with augmented intelligence [6].

**Problem(s)/ Challenge(s) to be Solved:**

- **Optimizing Predictive Maintenance:** In industrial networks like smart factories, fault interruptions during automated production significantly impact productivity and increase operational costs. Optimising predictive maintenance is essential for smart manufacturing industries. Machine learning can facilitate the implementation of predictive maintenance, shifting the strategy from reactive to proactive maintenance.
- **Enhancing Network Performance and Reliability:** Bandwidth issues persist in industrial networks, causing frequent latency problems and delays that disrupt the synchronisation of machine operations and sensor data collection. These issues can significantly impact the overall productivity of manufacturing factories. Integrating transfer learning-based machine learning techniques and semantic communication can significantly improve network performance and reliability, ensuring smoother and more efficient operations.

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- **Addressing Data Congestion and Delays**: Industrial work needs a lot of data for all tasks. This complex data can cause congestion and network delays, affecting the entire manufacturing process in industrial networks. Semantic communication and edge computing can help solve these problems by processing and understanding data locally. This reduces the need to send a lot of data over the network, which helps to avoid the congestion.

## Group 2: Smart Cities communication technologies for Real-Time Data Management

### UC4: Smart cities through massive twinning and real-time data collection

In this use case, data load from different sources are needed for the correct configuration and update of the massive Digital twins. Then, the data will be processed and transmitted back following the next flow:

- **Data from In-Vehicle sensors:** Collecting data from the vehicles such as GPS location, speed, number of people inside the vehicle, surrounding vehicles, etc.
- **Data from users:** Collecting data from the handheld devices by the civilians such as mobile phone data, GPS location, movement data (average speed), social media monitoring.
- **Data from other sources:** Collecting data from sources such as traffic lights, CCTVs, road infrastructures, etc.
- **Transmitting data to processing center:** Data from multiple sources will be transmitted over 6G network to a processing center almost in real time as 6G networks provide low latency and higher bandwidth.
- **Quantum-AI algorithm Processing:** These data would then be fed into a Quantum-AI algorithm to process and analyze the data to produce a recommendation or suggestion to the user.
- **Creation of Digital Twin:** All these data would then be used to generate a massive digital twin system along with the newly generated recommendation and the analyzed again to test if the generated recommendation would solve the problem of traffic congestion and/or how it would affect the current traffic situation.
- **Transmitting Suggestion Back to the User:** If the suggestion is useful, it would be transmitted back to the user.

According to this, the most important KPIs for this use case are data accuracy, data rates achievable and peak, connection density and traffic capacity.

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# 4 Conclusion

In conclusion, utilising these cutting-edge technologies for CPS and in industrial settings opens opportunities for more intelligent, effective manufacturing processes, as well as optimising network performance and predictive maintenance. The integration of fault forecasting, digital twin technologies, and improved communication protocols via machine learning and semantic communications illustrates a significant advancement towards the future of industrial automation. Further, an in-depth approach ensures that industrial networks remain resilient, flexible, and capable of meeting the evolving demands of today's industry.

Moreover, the integration of Cyber-Physical Systems (CPSs) with 6G networks represents a transformative advancement in industrial automation and efficiency. The ultra-low latency, high reliability, massive connectivity, and enhanced bandwidth of 6G will empower CPSs to achieve real-time monitoring, dynamic resource management, predictive maintenance, and optimised production processes. Additionally, technologies such as robotics, AI, and IoT will be seamlessly integrated, enabling collaborative robots to enhance precision, provide real-time insights, and extensive sensor networks to ensure precise asset tracking and rapid local data processing through edge computing.

The synergy between 6G and CPSs promises to revolutionise industrial processes, setting new standards for productivity, flexibility, and innovation, and paving the way for unprecedented advancements in operational efficiency and technological integration.

Finally, the use of newer technologies such as satellite communication, Blockchain, and Quantum computing can give rise to Advanced digital twin systems which can process multiple parameter and input fields at the same time to provide precise and reliable predictions to make the city smarter and safer. With the help of 6G, these systems would be able to provide more secure models than our current ones due to the use of faster computing power of quantum computers, satellite communications and blockchain. The foundations laid by this work could lead to a super-reliable and faster simulation of a real-world with many complex parameters and still will be able to mimic a real-life situation which can then help in scenarios such as traffic management.

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