CHALMERS

SensIT – Sensor driven cloud-based strategy for infrastructure management

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Summary

The purpose of this pre-study was to review existing knowledge and define a research roadmap. The pre-study investigates the feasibility of combining Sensors, Machine Learning, Cloud Services and Building Information Modelling to create an integrated system that enables an upgrade of the current infrastructure network through a new generation of *smart* structures. The study focuses on the aspects that are required in order to ensure that such a system could be successfully implemented in practice.

Via workshops and established collaboration, national and international, the project team has generated knowledge and gathered experts from several disciplines, such as data scientists, sensors experts and civil engineers.

The main result of the work is a research roadmap that works as a guideline for Trafikverket in their task to develop and create a new infrastructure management strategy based on emerging technologies and innovative processes.

Preface

The study carried out in this research was funded by Trafikverket according to the project number BBT2013-006 "*SensIT – Sensor driven cloud-based strategy for infrastructure management*". The work was carried out at division of Structural Engineering, Concrete Structures research group during 2017 by Assoc. Prof. Rasmus Rempling, Dr. Ignasi Fernandez Perez and Dr. Carlos Gil Berrocal, as well as Prof. Anders Logg from the Department of Applied Mathematics

Göteborg December 2017

Rasmus Rempling

1 Introduction

1.1 General background

Infrastructure and its role in today's society

Infrastructure can be defined, according to Fulmer [1], as "the physical components of interrelated systems providing commodities and services essential to enable, sustain or enhance societal living conditions". In other words, infrastructures are the fundamental facilities and systems required to support societal activity within a certain region. These are typically comprised by technical structures such as roads, bridges, tunnels, harbours, water supply, electrical grids, telecommunications, etc.

Among the different types of existing infrastructure, the transport infrastructure consisting of mainly roads, bridges and tunnels, is one of the oldest and most crucial elements for society as it embodies the physical platform for the transportation of passengers and goods. The condition of the transport infrastructure has a direct impact on us, both individually and as part of society. We all have experienced the frustration of constantly recurrent traffic jams, which influence our daily trips and represent an enormous accumulating cost for society in terms of traffic delays. According to a report by Trafikanalys Sverige that studied the daily journeys of 1.3 million commuters between Stockholm and Göteborg [2], there are 166 bottlenecks with an average speed of 35% of the allowed one, which renders the current situation as a "traffic stroke" since there is no capacity to improve the traffic flow. After car accidents, one of the most frequent causes for the reduced accessibility of the transport infrastructure and the consequent traffic delays is the performance of inspection operations and the application of maintenance measures to combat ageing of the infrastructure. Consequently, the ageing and deterioration of the transport infrastructure not only poses a very serious issue of public safety but also has a cascading detrimental impact on the nation's economy that negatively affects business productivity, the gross domestic product (GDP) and international competitiveness.

Furthermore, with half of the world's population living in urban areas, according to the World Urbanization Prospects report published by United Nations [3], infrastructures have acquired a new fundamental role since they shape, to a large degree, the environment in which a vast majority of society lives. Therefore, to effectively maintain the performance of the transport infrastructure is of utmost importance for public safety and economic reasons but also to ensure a transition towards a more sustainable built environment.

Current challenges of transport infrastructure management

The transport infrastructure is a vital element of a country but its preservation is not an easy task. In Sweden for instance, there is a total of more than 20 000 bridges (see Fig. 1.1), which represents an enormous challenge for the effective management of the infrastructure. Furthermore, the exposure of these structures to harsh environmental conditions, which may include freeze-thaw cycles, marine environments, de-icing salts or chemical attack among others, may trigger degradation mechanisms that damage the structure and can impair its structural or functional performance, thereby reducing their practical service life. This accelerated degradation of structures poses an additional difficulty for the maintenance of the transport infrastructure, as the requirements on the frequency of inspection and maintenance operations may increase significantly. In fact, inspection and maintenance operations constitute a major part of the recurrent costs of infrastructure, which represent a significant share of the annual budget in developed countries.

According to the OECD database for transport infrastructure investment and maintenance spending [4], in 2015 Sweden invested nearly 3250 million euros in the transport infrastructure including road and railway structures. Approximately two thirds of the total investment (2094 million euros) were used for preservation of the existing transport network with a high percentage of the expenditure devoted to inspection and maintenance operations of deteriorated concrete structures. Moreover, by comparing the yearly investment in the transport infrastructure in Sweden for the last two decades, it can be clearly seen that the investment in maintenance of the transport infrastructure has been increasing steadily over the mentioned period, see Fig. 1.2.

Trafikverkets brobestånd

Antal broar per funktionstyp

Förvaltningsområde	Funktionstyp									
	Vägbro	Jvg bro	Gc-bro	Akvedukt	Faunabro	Lednings-/skyddsbro	Fastighetsdäck	Jvg/väg bro	Bro avstängd för all trafik inkl gc trafik	Total
TRV UHj Byggnadsverk Öppnbara broar	0	14	0	0	0	0	0	0	0	14
TRV UHj Byggnadsverk Öst/Stockholm	76	884	20	0	0	0	2	0	1	983
TRV UHj Byggnadsverk Syd	35	888	22	0	0	0	0	0	0	945
TRV UHj Byggnadsverk Tunnlar	1	0	0	0	0	0	0	0	0	1
TRV UHj Byggnadsverk Väst	61	987	25	0	0	1	3	0	0	1077
TRV UHvä Byggnadsverk Nord/Mitt	5372	0	74	0	4	1	0	3	5	5459
TRV UHvä Byggnadsverk Öppnbara broar	68	0	0	0	0	0	0	0	1	69
TRV UHvä Byggnadsverk Öst/Stockholm	3742	0	36	2	2	0	0	1	0	3783
TRV UHvä Byggnadsverk Stora broar	57	0	0	0	0	0	0	0	0	57
TRV UHvä Byggnadsverk Syd	3312	0	28	0	0	0	0	0	1	3341
TRV UHvä Byggnadsverk Tunnlar	22	0	2	0	0	1	0	0	0	25
TRV UHvä Byggnadsverk Väst	3781	0	56	0	1	0	0	0	1	3839
TRV UHj Byggnadsverk Nord/Mitt	70	1255	24	0	2	1	1	1	34	1388
Total	16597	4028	287	2	9	4	6	5	43	20981

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Figure 1.1. Bridge stock in Sweden from Trafikverket BaTMan data.

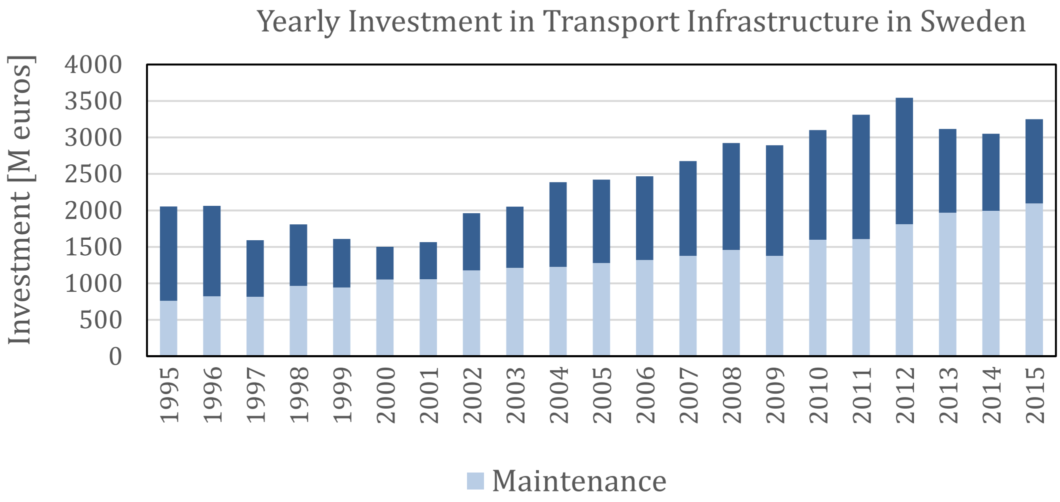

Figure 1.2. Yearly investment in the transport infrastructure in Sweden and the corresponding part dedicated to maintenance, according to data published by OECD [3].

Moreover, several factors are added to the current scenario which contribute to exacerbate the situation. On the one hand, the current bridge stock is comprised, to a large extent, by bridges that were built right after the second world war and therefore are becoming old, see Fig. 1.3. This entails that existing bridges are most likely suffering some sort of degradation process caused by the prolonged exposure to harsh environmental conditions, as previously discussed, resulting in an accelerated ageing of the structure.

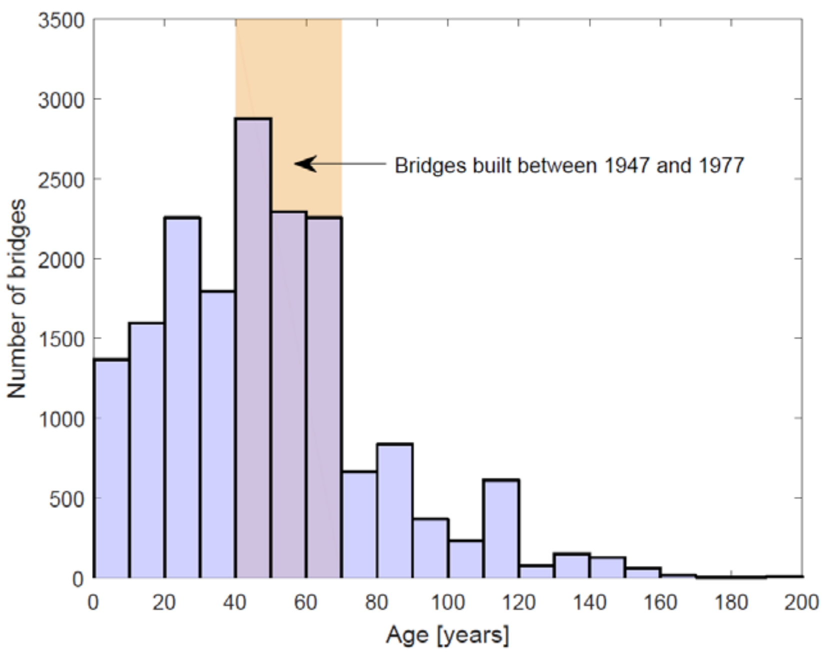

Figure 1.3. Age distribution of 17596 bridges according to information published in BaTMan database.

On the other hand, bridges that were built according to a certain set of regulations and requirements almost 70 years ago, are today expected to withstand a higher level of demands which they were not intended for. As stated by Leander at al. [5], in the recent decades the Swedish railway network has been subjected to an increase of the traffic loads, volume and speed of trains as a result of continuous economic growth. Whereas the road vehicle speed has probably not increased in accordance to the train speeds, an increase of the traffic loads and traffic volume has likely also occurred for road bridges, as suggested by the increase of vehicles per habitant between the years 2005 and 2015, from 514 to 540 vehicles per 1000 habitants [6].

It is, of course, not feasible to re-built the entire bridge stock every time that applicable building regulations are updated nor when the first signs of degradation arise. The reasons include the enormous economic burden that this would suppose for society but also the huge impact that such a drastic measure would have on the environment. In fact, according to a report by the United Nations from 2013, the construction sector is already responsible for more than 40% of the global energy consumption and up to one third of the total carbon dioxide equivalent emissions. Moreover, based on the current trend, it has been estimated that the amount of CO_2 emissions could be nearly doubled by 2050 if no corrective actions are taken.

Consequently, inspection operations and maintenance measures are not only necessary, but they are crucial for the correct development of the transport infrastructure. However, due to the conservative nature of the construction industry relying on traditional methods and lagging behind in innovation compared to other sectors, these activities are today very inefficient.

Using an innovating approach, new management methodologies must be developed based on newly available technologies and new ways of thinking, to deliver smart systems that could minimize the number of interventions in the transport infrastructure. Nevertheless, this change in the paradigm of infrastructure maintenance can only become a reality if all the different sectors pertaining to the civil engineering field, namely industrial actors, public administrations and academia, work together to implement new ways of thinking around the management and maintenance of the current infrastructure.

1.2 Vision, aim and objectives

1.2.1 Vision

The increasing migration of population from the country side to urban areas has made sustainable development an imperative need. This need has become a driving force for innovation and new challenges such as the concept of smart cities and infrastructure, where sensor technology plays a major role. At the same time, technological development is taking society to a new era where an unprecedented type of knowledge will be accessible through the combination of:

- Extensive wireless sensor networks transferring data at high-speed
- Constantly increasing computational power and remote data-storage capacity
- Advanced calculation algorithms and analysis methods
- Computer-aided design and visualization tools

The successful utilization of the aforementioned technologies will enable a whole new range of possibilities such as a sensor driven cloud-based strategy for infrastructure management (SensIT).

Consequently, the vision of SensIT is to implement a novel system for the monitoring of existing and newly built structures to give rise to a new generation of safer, more efficient and more sustainable smart infrastructure: the infrastructure 2.0.

The vision of SensIT is schematically illustrated in Fig. 1.4, where the different parts of the system are shown highlighting various key-concepts.

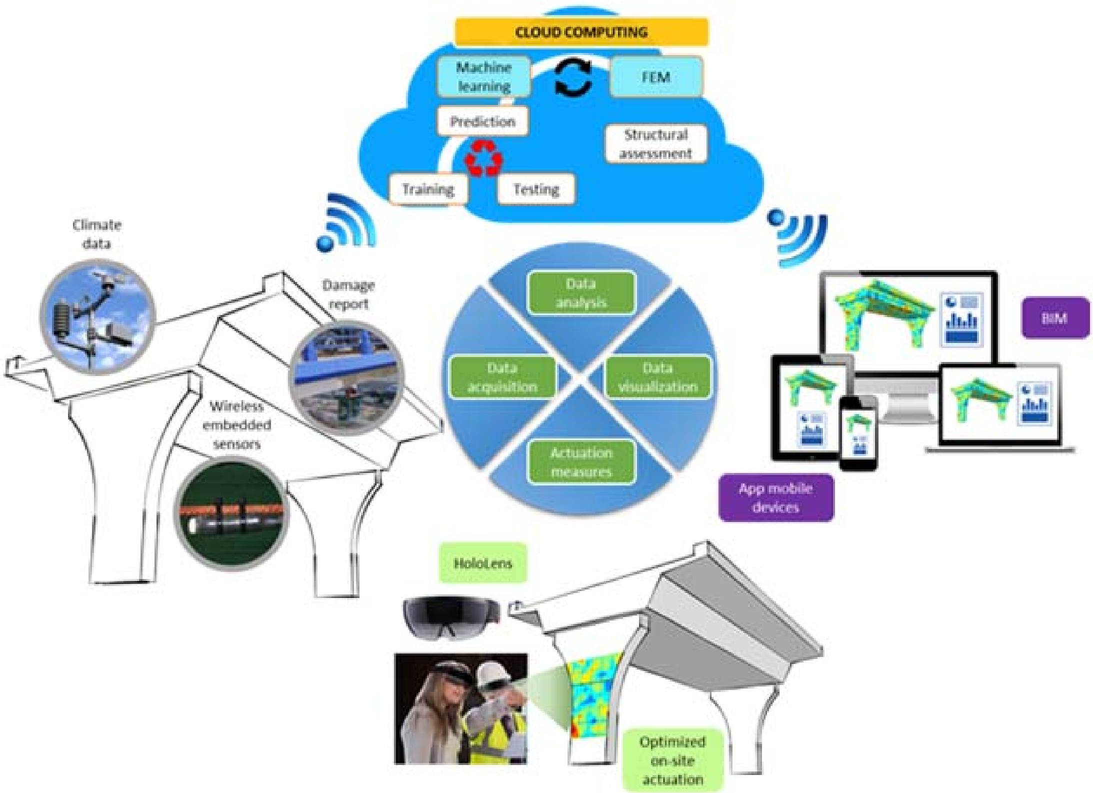

Figure 1.4. Vision of the SensIT monitoring system.

As observed in Fig. 4, once the sensors are placed in the structure a flow of relevant information is immediately generated. This information must be somehow handled in a way the owner/structure manager can understand and interpret. In addition, the volume of generated data can be significantly large so, it is also necessary to translate it into meaningful parameters and variable that can be understood. Consequently, a reduction of the volume data towards an increasing data value is aimed. This unequivocally requires to appeal to the new IT technologies. Cloud computing and machine learning showed to be promising tools in this meaning. By means of intelligent algorithms and subroutines it is possible to translate to brake this huge amount of data to meaningful variables; cloud computing and machine learning. Also, the implementation of advanced finite element models can greatly contribute to help with the interpretation and translation of the obtained data in a faster and optimal manner.

In the last step, it is important to have visual interpretation of the information, so these obtained meaningful variables through the data processing can be clearly read and understood by engineers which need to be able to make proper decisions regarding the possible actuations on the structure. Building Information modelling has stated as suitable platform to fulfil such requirements. By means of the utilization of such platform it is possible to have a transparent real time communication between the user/manager/owner and the structure. Each of the involved agents can make their own decisions and see at the same time their consequences on the structure.

In addition, supported by other technologies such HoloLens it is possible to gather new data form the structure that is not currently being measured. The variables and indicators observed through these technologies allows to the experts to perform high performance and reliable inspections just focusing on the parts of the structures which presents some damage risk or are currently deteriorated. Hence, high quality and optimal decision can be expected. But again, after any actuation, the flow data is still ongoing which means that the direct and futures consequences of any actuation will be monitored and subsequently evaluated to assess its impact and reliability. This will promote in the long run even more optimal and efficient actuation, not just because the actuations can be localized in the most required damaged zones but because it is possible to assess its impact and directly optimize the methods and actuations.

SensIT is based on concepts such as cloud storage and computing, Internet of Things (IoT), physical-digital twins and Building Information Modelling. As shown in Fig. 4, SensIT is divided into four main individual processes, namely Data Acquisition, Data Analysis, Data Visualization and Actuation Measures.

The concept of physical and digital twins is a development of the last 10 years of evolution of Building Information Modelling. What the construction industry is facing today is the potential of connecting the twins by sensors. The connection of twins by sensors and cloud services will be the catalyst for reaching a new generation of safer, more efficient and more sustainable smart infrastructures.

The largest potential of the sensors is believed to be during the management phase of the structure although it is not isolated from the construction- or the design phase. By introducing the need for information in the management phase, both the design and the construction phases can become data driven. In this way we can monitor, make diagnostics and prognoses of our assets and the construction industry can improve the design and construction so that a better product is delivered.

1.2.2 Purpose, Aim and Objectives

The purpose of this pre-study is to review existing knowledge and define a research roadmap. The intention is not to propose a commercialized system, even though a review of "of-the-shelf" systems has been done. We consider that the first step is to show the feasibility of this idea through a so-called *proof-of-concept*. Based on that concept, there is great potential to develop a common commercial system the ownership of which can be shared among the different parties included in the project through a spin-off company.

The main aim of this state-of-the-art report is to investigate the feasibility of combining the aforementioned technologies to create an integrated system that enables an upgrade of the current infrastructure network through a new generation of *smart* structures. The study focuses on the aspects that are required in order to ensure that such a system could be successfully implemented in practice.

The following objectives have been used as a guideline for realising the pre-study:

- Sensors:
  - Which suitable sensor system are available and applicable to existing and new structures?
  - What is the TRL-level of those sensors?
- Data storage:
  - What are the demands and which systems are available today?
- Data processing and analysis:
  - What are the existing methods and which purpose do they serve?
- Visualization:
  - Who is the end-user and how might the user-interface for a system like this be?

1.3 Methodology

The approach has been to identify available key knowledge and experts – international and national – by performing a literature review. The review has been made as a traditional scientific review as well as a review of available information on sites of companies within the sensor industry.

As the project includes experts from the main fields of interest: sensor experts, cloud computing and machine learning experts, contractors and inspectors; a workshop was held early in the pre-study.

Based on the literature review and the workshop, contacts have been taken with international experts in Italy, Canada and Denmark. During this meetings and discussions, collaboration has started and experience has been shared.

1.4 Research significance

The implementation of SensIT would, undoubtedly, result in a series of changes with benefits for the different groups of actors:

Traffic and road administrations:

As the owners and administrators of the transport infrastructure, SensIT would offer a powerful tool to better plan the maintenance operations, thus potentially saving large amounts of money in terms of unnecessary inspections or late detected damage leading to costly repair or replacement measures.

Contractors and/or consultants:

As the operators performing the on-site inspections, SensIT will increase the efficiency of the inspections, by reducing their frequency in time to only when is needed and aiming them at the locations of the infrastructure where damage has been identified.

Infrastructure users:

All users of the transport infrastructure, be it private car owners or trucks belonging to logistics companies, will have access to better maintained structures with a lower affection by inspection and/or maintenance operations.

Society:

SensIT will, overall, result in an extension of the service life of current and new infrastructure, which brings benefits to society in various forms. First, a longer life expectancy of structures yields a lower need of resources for the construction, with a clear positive impact on sustainability. Secondly, thanks to the increased efficiency and effectivity of the maintenance of infrastructure, the value of the taxpayers' money will be increased and national companies will avoid great losses due to traffic delays.

1.5 Outline of the report

The report is a review of existing knowledge and benchmarks the industry technology readiness level within the area of sensors and their application of infrastructure for transports and includes three parts: State-of-the-art review, Assessment of the needs and wishes of the different actors, and finally the scientific road map.

The section of state-of-the art, Chapter 2, deals with the four main pieces of the vision: data acquisitions, storage and management of data, data processing and analysis, and visualization of processed data. As the topics are diverging, a breakdown of the technology readiness levels of the most important elements is done.

Chapter 3 addresses the needs of different actors, is a summary of the workshop held at the beginning of the pre-study.

Chapter 4 outlines the proposed scientific roadmap, which is the main result of this project, and gives a summary of the main tasks to be carried out along the implementation of the roadmap.

Chapter 5 summarizes the main findings of the pre-study and includes the concluding remarks.

2 State-of-the-art review

In this section, the results of a literature study are presented. The literature study is divided into two different parts. The first part gives an overview of what a structural health monitoring system is, what are its main characteristics or desirable properties and a summary of relevant efforts towards the implementation of smart structural health monitoring systems. The second part includes a state-of-the-art review of the enabling technologies included in the different processes comprising the vision of SensIT.

2.1 Structural Health Monitoring (SHM)

Early detection of damage in products, machinery or infrastructure is always beneficial to minimize the economic cost and potential life-risk of an unforeseen failure. However, in order to be able to detect damage at an early stage, well before an eventual failure might occur, some sort of Structural Health Monitoring (SHM) system is required. A SHM system is a technology based on the continuous condition assessment of a structure through the analysis of data acquired on-site by a distributed network of sensors [7].

Although relatively new, this technology is of interest for multiple sectors apart from the Civil Engineering sector, including, the aerospace, aircraft and aviation industry, the defence sector and the energy and mining industry, among others.

An effective SHM system enables the early detection of deficiencies in structural performance and aids engineers and infrastructure owners in making informed decisions, thereby leading to well-planned, timely maintenance operations with minimal disruption to the users and the consequent substantial savings in terms of both money and time [8].

In order to distinguish between different SHM systems, Rytter [9] stablished a nomenclature involving four different categories:

Level 1 The system gives a qualitative indication that damage might be present in the structure (*detection*).

Level 2 The system also provides information about the probable location of the damage (*localization*).

Level 3 The system is able to provide quantitative information about the magnitude of the damage (*assessment*).

Level 4 The system can provide information about the actual safety of the structure based on a certain damage state (*consequence*).

Preferably, a SHM system should be able to autonomously analyze the data to directly provide information about the actual safety of the structure (Level 4), which should then be conveyed in a clear and accessible way to the engineer, thereby enabling timely planning of the maintenance and/or repair operations. Furthermore, a fifth level of SHM systems could be ideally included in the previous list, namely a level in which the system is able to perform predictions about the remaining service-life of the structure (Level 5 - *prognosis*).

If properly implemented, it is believed that these SHM systems can extend the service life of structures by allowing deterioration and/or damage to be identified earlier, thereby allowing relatively minor corrective actions to be taken before the deterioration/damage grows to a state where major actions are required. This may result in enormous economic savings according to De Sitter “Law of Fives”, which states that 1 dollar spent in the design phase is as effective as 5 dollars spent during a maintenance operation and as effective as effective as 25 dollars spent during a replacement operation [10]. In addition, structural health monitoring systems may also help structural designers to learn from previous design mistakes to improve the performance of future structures.

The two main components of a SHM system are the sensors and the software [11]. Today’s most advanced sensors enable the monitoring of a variety of parameters that relate to physical and mechanical changes in the structure as well as the presence and concentration of certain chemical substances, such as: temperature, relative humidity, resistivity, strains, accelerations, chloride ions, pH, etc. Traditionally, an operator was required to the operate the sensors on site. However, using current wireless technology sensors can autonomously send data to a data-acquisition system, which can then be uploaded to a cloud-service, where it can be analysed.

In order to analyse the data, a suitable software needs to be implemented to extract the relevant information. Conventional signal processing techniques such as the Fourier Transform, the Discrete Fourier Transform or Wavelet functions, have been often combined with Finite Element analyses (FEA) to identify damage in bridges from acceleration measurements. More recently, a new approached has been proposed where Machine Learning algorithms are implemented to identify and predict damage occurrences in structures [12]. The combined use of wireless technology, more powerful computers able to solve large complex problems in less time and new more efficient algorithms indicates that SHM systems have a great potential for growth and development.

Over the years the philosophies of the maintenance methodologies applied in different fields have evolved to minimize the negative impacts of unanticipated system failures. Originally, run-to-failure approaches to engineering system maintenance were used. This approach entails that a system is operated until some critical component fails causing a global disruption of the system. Subsequently, the critical component is replaced and the system is restarted [12]. The advantageous side of this procedure is that it does not require of any investment in monitoring systems. However, this approach can be extremely costly as the system failure occurs without previous warning. Obviously, this approach is totally unacceptable when life-safety is at risk.

A newer and more sophisticated maintenance approach, widely used today, is the known as time-based maintenance. This approach involves that critical components are inspected or replaced at predefined times or use intervals independently on their condition. A classic example of time-based maintenance is the scheduled service operations that car owners must undergo, which may include changes of the oil and filters after the car is driven a certain distance or at some prescribed time interval. This maintenance operation is performed regardless of the condition of the components. Time-based maintenance is a more proactive approach than run-to-failure and it has made complex engineering systems such as commercial aircraft extremely safe.

One of the major challenges with the maintenance of the current civil engineering infrastructure is the large size of the structures to be maintained and the stochastic nature of certain deterioration mechanisms such as corrosion, cyclic freeze-thaw, alkali-silica reaction, etc. which depend on the randomness of the material properties and position of local defects.

Consequently, the time-based maintenance approach is hardly applicable to civil engineering structures as previously defined. Instead, a time-based inspection philosophy is usually adopted, where an operator performs an inspection of the structure periodically, irrespective of its current structural condition, and subsequently its conditions is evaluated. One of the shortcomings of the current approach is that inspections are time-consuming, labor intensive and they often create traffic disruptions. Even more important is the fact that current structural inspections are, in a primary stage, based solely on human visual assessment which means they are limited and strongly dependent on the operator's experience. Furthermore, inspections rely on journal records and photographs as documentation material of the inspection, which results in a slow processing of the data and hence deferred evaluation of the structure.

SHM systems will enable a shift of the current time-based inspection approaches towards condition-based maintenance approaches. The concept of condition-based maintenance is that a sensing system implemented within the structure monitors the structural response and notifies the operator when damage or degradation is detected. This approach is more proactive than the aforementioned and it involves two main potential advantages: (i) the organizations responsible for maintaining the infrastructure will reduce maintenance cost by only conducting maintenance when and where it is needed and (ii) damage can be detected earlier thereby preventing further deterioration of the structures. The trade-off derived from implementing such system is that a more sophisticated monitoring hardware will be required to be deployed in the structure, with the associated increase of the initial investment cost and more sophisticated data analysis procedures to extract relevant information from the measured data will need to be developed.

2.2 Enabling technologies

Digitalization, especially regarding the construction site, will change the image of an industry that is lagging behind thereby increasing the attractiveness of the construction sector in terms of recruitment. Fortunately, an understanding of the potential of digitization in the construction industry, as well as particular examples showing how digitization should be implemented, can be realized in practice.

Today, a lot of digital technologies are available and more are under development. With a systematic approach to digitization, based on its four technology areas (automation, digital interfaces, connectivity and data), there is a great potential for streamlining value chains in community construction. A major global study [REF] has shown that the construction site's work productivity can increase by 50% where an important ingredient is cloud-based virtual "air traffic controller", to coordinate building actors based on real-time data. The same study also estimates that digitization within construction can lead to a total productivity increase of about 15%, as well as creating the right conditions for improved design and collaboration, which not only contributes to better work environment and security, but also adds further productivity improvements. In Sweden and abroad, players are based on new business models or modern industrial production, either at the factory or at the construction site, these are also an important part for improved productivity.

Sensor networks and embedded system could be used to register the status of production activities and track movements and position of personnel, machinery, materials and components at the construction site. Applications can touch, for example, strength and moisture content in cast concrete structures, work environment monitoring, tracking of RFID tagged components in warehouses or buildings. The collected data also forms the basis for (BIG) data analyses with artificial intelligence (AI) methods for adaptive production management and experience rehabilitation of completed construction projects. These and many other technologies will enable a technical revolution in many fields and their development is steady, as shown in Fig. 2.1, illustrating the hype cycle of emerging technologies in 2012 and 2017 [13].

As observed, technologies like sensor networks and cloud computing, which were considered as emerging technologies in 2012, are today a reality, at least in many fields. Other technologies such as the IoT and augmented reality have evolved and are today closer to reach the plateau of productivity. Finally, new emerging technologies such as the concept of Digital Twin, have been introduced more recently and are still in an early stage of development.

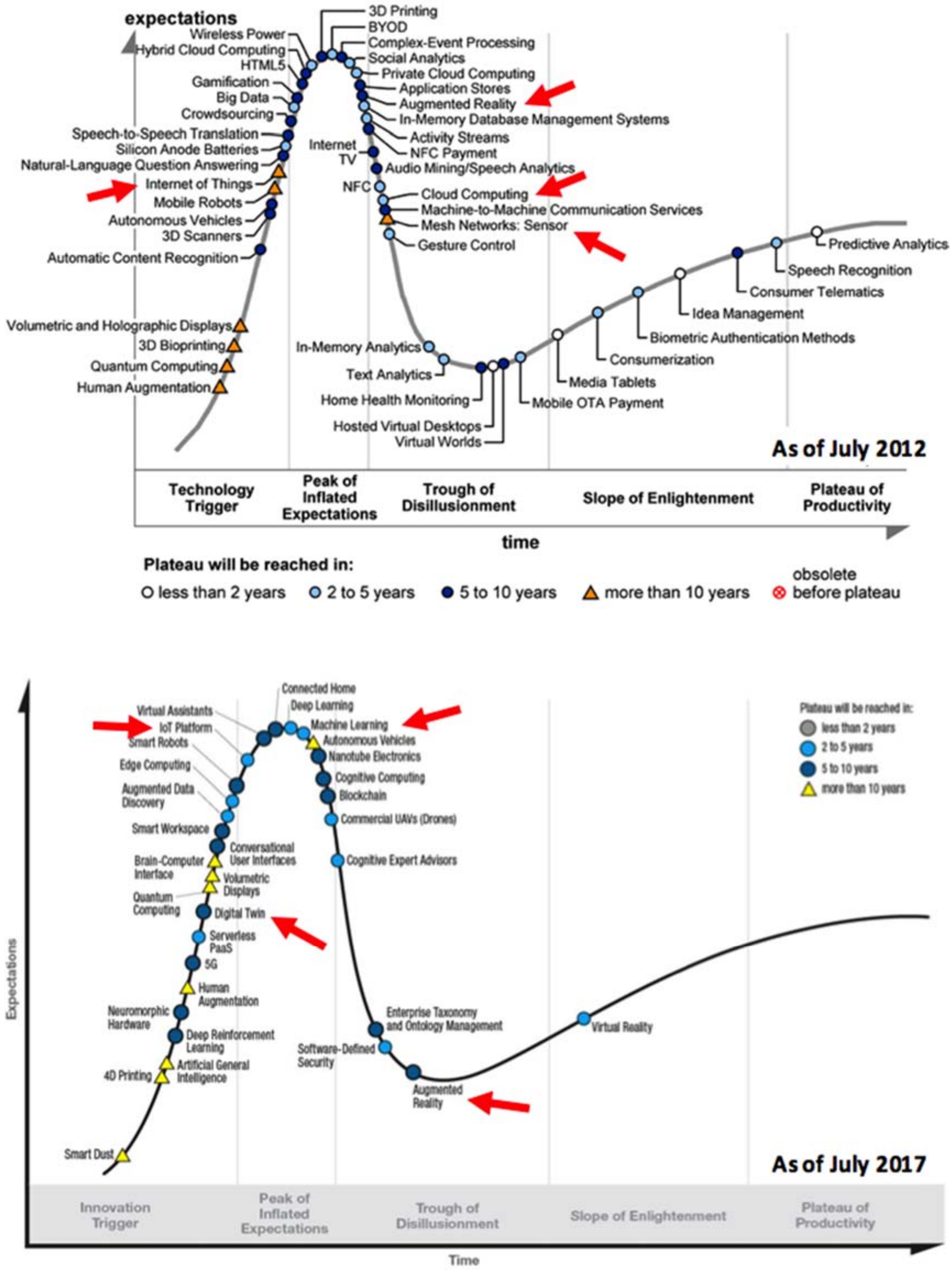

Figure 2.1 Hype Cycle of Emerging Technologies, July 2012 (up) and July 2017 (down). Source (www.gartner.com) [13]

In the vision of SensIT, data must undergo a four step process according to:

1. Retrieval → 2. Management → 3. Analysis → 4. Visualization

In the retrieval phase, data is acquired from the structure either from existing databases or through a sensor network deployed in the structure. These data must be transferred and stored in a cloud service platform where it can be accessed for its processing and analysis. The analysis of the data includes the implementation of machine learning algorithms, with all the corresponding data pre-processing, and integration into finite element analyses (FEA) with updated data. Finally, the results from the data analysis must be presented in a clear and understandable way to convey the most important information quickly and effectively. In the following sections, a state-of-the-art review of the different enabling technologies involved in the previous four process is presented.

2.2.1 Data acquisition

Data from sensors

As discussed in Section 2.1, one of the main problems of the current procedure to carry out inspection and maintenance operations in the transport infrastructure is the time-consuming tasks and disrupting nature of the operations which result in traffic interruptions and great costs for society. By implementing a structural health monitoring system relying on a distributed network of sensors to collect and send data regarding the real-time state of the structure, more objective and time decisions could be made regarding the actuation methods to be applied on structures without the need of causing disruption to the users of the infrastructure. Therefore, sensors are critical elements in the structural health monitoring system, which must be chosen adequately to serve the intended purpose under the expected conditions and for a certain time span.

Before introducing different kinds of sensors, some definitions describing certain characteristics of a sensor are introduced:

Wired and wireless sensors

One of the main reasons why structural health monitoring system have not been yet implemented is that traditionally sensors were wired, i.e. a physical connection between the probe and the acquisition system in the form of a wire, cable or lead was require to collect the data and/or to power the sensor. This fact, naturally hindered the deployment of large network sensors due to both economical and practical reasons.

However, wireless technology has been applied in many fields today, including in sensor technology, which has push forward again the idea of structural health monitoring systems. A wireless sensors is able to collect and send data to the acquisition system without the need of a physical connection. The negative side of the wireless sensors is that in many cases that implied including an antenna and a battery, which may increase the size of the sensors. Nevertheless, great advances has been made in the field of Micro Electro-Mechanical Sensors (MEMS), which have achieved to incorporate all the necessary components in devices featuring dimensions similar to a coin [14].

Embeddable and external sensors

Another important quality to consider regarding sensors is their relative position within the structure. Most monitoring handheld equipment is based on techniques that measure the properties of the concrete from surface measurements. However, for sensors that remain at the same location during long periods, it might not be desirable to have them externally placed, since they can be damaged by external agents. Moreover, for certain properties of the concrete, it might be more effective to perform the measurements inside the concrete, e.g. near the reinforcement. On the other hand, the casting process and the high alkaline environment in the concrete are factors that might damage the sensors. Furthermore, in thick structures, wireless sensors might have difficulties to send data at long distances due to signal attenuation in the material.

Active and passive

Sensors can be classified as either active or passive. Active sensors are those that actively collect and send data to the acquisition system at a certain time interval without the need of any external stimulus. Active sensors must be powered, generally using an internal battery, which makes them more expensive, larger in size and limits their life span to the battery life. However, they usually possess internal memory and data can be both send and received by the sensor, which can be used for instance to change the reading frequency of the sensor. Passive sensors, on the other hand, are sensors that remain dormant in the structure until the operator uses a reader or interrogator, to send a signal that activates the sensor and transmits the data. The main advantage of passive sensors is that they are usually smaller than active ones and they do not consume energy while the sensor is not being activated.

Measured Properties

The most common type of sensors used in SHM application include sensors that measure kinematic quantities, such as displacements, strains and accelerations, dynamic quantities, such as vibrations and forces and environmental quantities, such as temperature or relative humidity (RH). Some of this sensors, like strain gauges or temperature and RH sensors, are today commercially available for reinforced concrete applications.

However, several research projects and technical reviews have shown that conventional sensors present a series of problems that make it difficult to perform stable and reliable readings in the long term. Many sensors can be easily affected by changes in external factors such as temperature, humidity, cable length, magnetic or electric fields, etc. For instance, most of the conventionally used corrosion monitoring systems for reinforced concrete structures rely on embeddable probes which can be affected by electromagnetic interference (EMI) caused by the proximity of electromagnetic field sources such as power lines, radio transmitters, cell phones. Other sensors need to be powered, which requires the use of batteries, thus limiting the service life of the sensors. Nevertheless, the common problems that are often encountered with conventional sensors today will most likely be overcome in the future as new sensing technologies are developed for bridge monitoring and other large structure applications.

In the following, a review of some commercially available sensors specifically developed for concrete applications are presented. Moreover, two examples of novel sensor applications, currently under development, which are planned to be used in the present project and that possess great potential for the long-term monitoring of reinforced concrete structures are also described.

<u>Temperature sensors:</u>

There are several commercially available wireless temperature sensors relying on Bluetooth or RFID signals, with relatively small sizes, which provide reading frequencies of about 2 to 4 readings per hour, for a period of up to 5 years. These sensors are commonly used to correlate the internal temperature development in the concrete due to hydration heat to the strength development, which can optimize the construction process. Consequently, they are out of the box solutions, which are easy to install and start using, which in some cases offer the corresponding software for mobile devices.

Figure 2.2. Commercially available wireless embeddable temperature sensors for concrete structures, [15–17]**.**

Relative humidity sensors:

Giatec Scientific has a Bluetooth based embeddable sensor that can measure both temperature and relative humidity inside the concrete, with a reading frequency of 1 reading every 8 hours, it has an expected battery life of at least two years. Another type of relative humidity sensor has been recently commercialized by *Invisense*, consisting of passive sticker-like sensors that can be glued to a surface and activated using an external interrogator. They have been designed to detect leakage in wall elements but they may be potentially useful in concrete applications too.

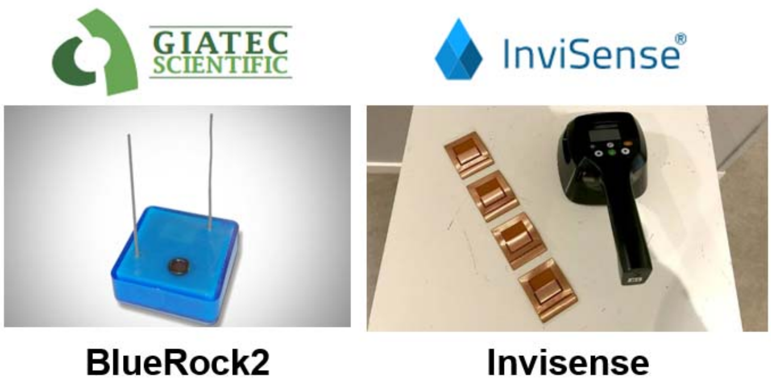

Figure 2.3. Commercially available wireless embeddable relative humidity snesors for concrete structures, [18,19]

Further types of relative humidity and temperature sensors exist, which were not specifically designed for concrete applications but have been tested in concrete. In particular, *Sensirion* and *Maxim integrated* offer each a micro electro-mechanical sensor the size of which is below 20 mm. The latter claims to have a durability of at least 10 years. However, both need to be powered and due to their small size, wiring is required.

Figure 2.4. Commercially available MEMS for temperature and relative humidity monitoring, [20,21]

pH sensors:

Currently there are no available pH sensors specifically developed for concrete applications, although some prototypes has been tested in the literature. The most common way to measure the pH of concrete is by using pH meters, which are applied on the surface of the concrete. These are simple to use handheld devices the specifications of which claim to work between a wide range of pH with resolutions of 0.01pH units. Unfortunately, these devices are not intended for frequent pH monitoring and therefore they are not suitable for structural health monitoring systems. On the other hand, wireless pH meters have recently appeared for laboratory applications, which may open a new path towards the development of wireless pH sensors.

Figure 2.5. Commercially available pH meters for concrete, [22,23]**.**

Chloride-ion sensors:

Currently used techniques to determine the concentration of chloride ions in concrete are commonly destructive techniques in which a core is drilled out of the concrete structure and powder samples are chemically analyzed through potentiodynamic titration. Nevertheless, several attempts to develop chloride ion sensors have been documented, where the concentration of chlorides is related to either a change in electrical potential or a change in concrete conductivity.

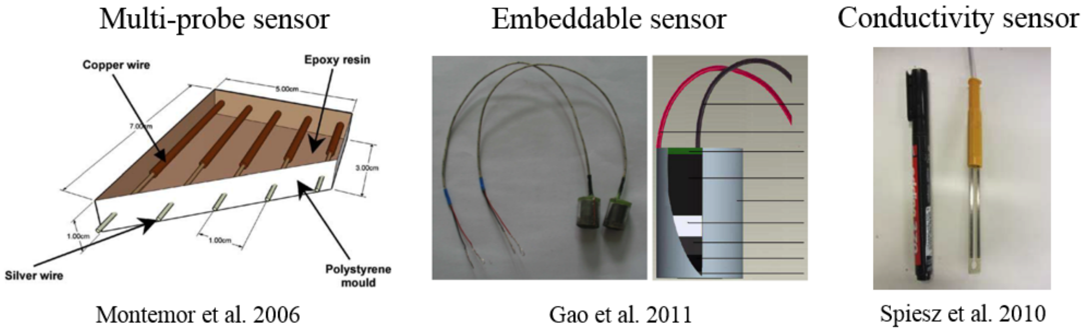

Figure 2.6. Experimental sensors for chloride ion activity monitoring in cementitious materials, [24–27]**.**

Corrosion sensors:

All of the above described sensors are focused on the measurement of concrete properties. However, one of the main degradation processes in concrete structures is the corrosion of steel reinforcement. Currently used sensors for corrosion monitoring are based on the determination of the probability of corrosion or the risk for corrosion initiation. This sensors are wired and they rely on the measurement of potential differences, either between a reference electrode and the reinforcement or between a set of working and counter electrodes. Although single measurements with this type of sensors are difficult to interpret, the evolution of the measurements over time can provide insightful information about the corrosion state of the structure.

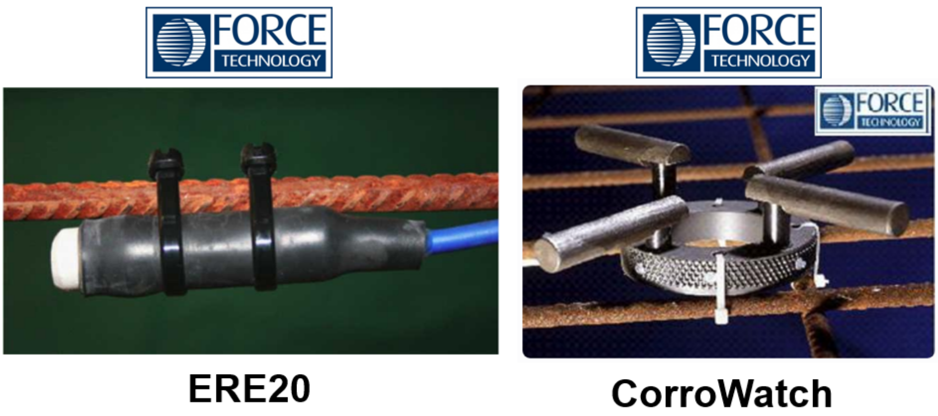

Figure 2.7. Commercially available probes for monitoring of reinforcement corrosion in concrete structures, [28,29]**.**

Smart cement-based sensors:

This type of sensors comprise a new family of multi-functional smart materials with piezoresistive properties that has recently emerged and are able to detect strain/stress changes in the structure. Made of a (nano)-reinforced cement composite, this type of sensors exhibit structural capability, enabling them to be integrated as a part or total component of a structure and are 100% compatible with the highly alkaline environment of the concrete, having the potential to surpass the service life of the parent concrete structure. The down side is that this type of sensors are wired and require external power.

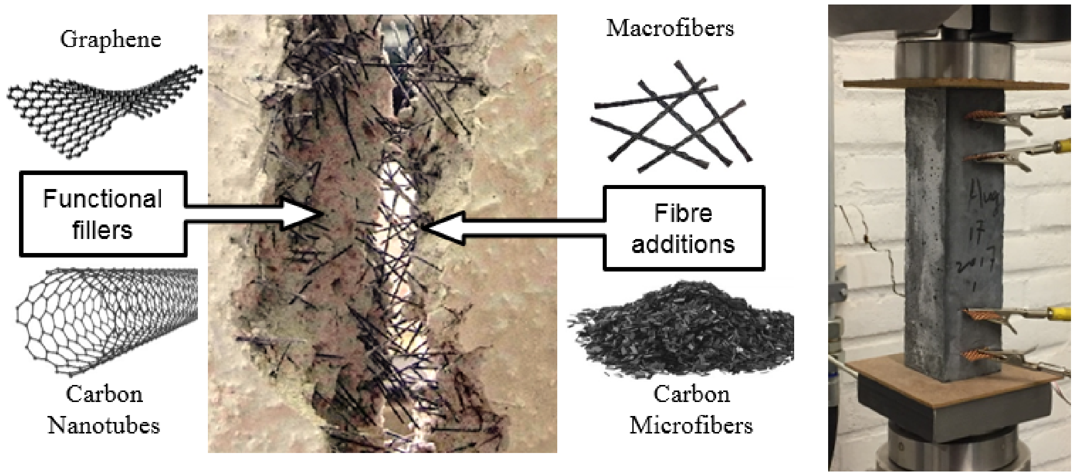

Figure 2.8. Principle and sample of smart cement-based sensors, [30–33]

<u>Polymeric Optical Fiber (POF):</u>

These sensors are a novel optic fiber sensors system develop by SHUTE sensing solutions, which enables real-time monitoring of strain, humidity and temperature in several points along an optical fiber. SHUTE's patented technology is based on a micro-structured POF inscribed with laser induced Fiber Bragg Gratings. The main advantage with respect to conventional strain sensors and other optic fiber sensors is their great flexibility, high sensitivity to both strain and stress and its large deformation capacity (up to 6%). This kind of sensors allow for distributed measurement of strains and although they are wired sensors, they have the advantage that the sensor is the wire itself. The main disadvantage is that the reading acquisition system is currently pricey.

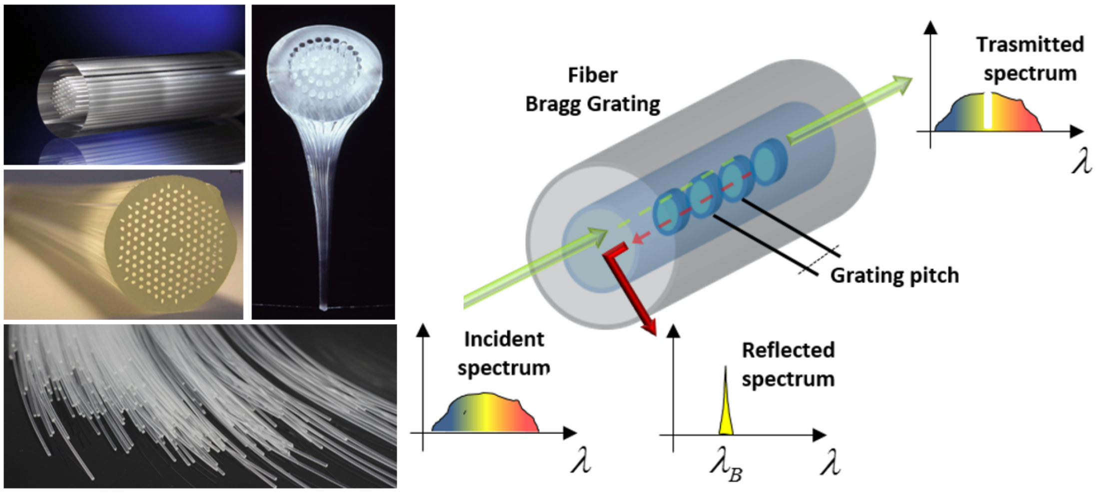

Figure 2.9. Example of polymeric optical fiber and working principle, [34,35].

Furthermore, in the course of the project, the POF sensor is expected to be further developed to measure other parameters relevant for the monitoring of reinforcement corrosion, such as the pH of the concrete pore liquid or the concentration of chloride ions.

2.2.2 Storage and management of measured data (BIG DATA)

Today, data are generated at a faster rate than ever before. As an example, every minute, 300 hours of video are uploaded to YouTube and according to Radicati group [36] an average of 269 billion emails were sent every day in 2017. To have a better feeling of the incredible amount of information that today’s society creates, Fig. 2.10 shows an infographic that summarizes the contribution of the websites with the greatest data traffic worldwide whereas in the following website [37] it is possible to check, in real-time, what happens in one second on the internet. Moreover, the capacity of generating data is readily available to the general public. For instant, today, most people living in a developed country own mobile phone devices which are outfitted with high-resolution camera, GPS and accelerometer, etc.

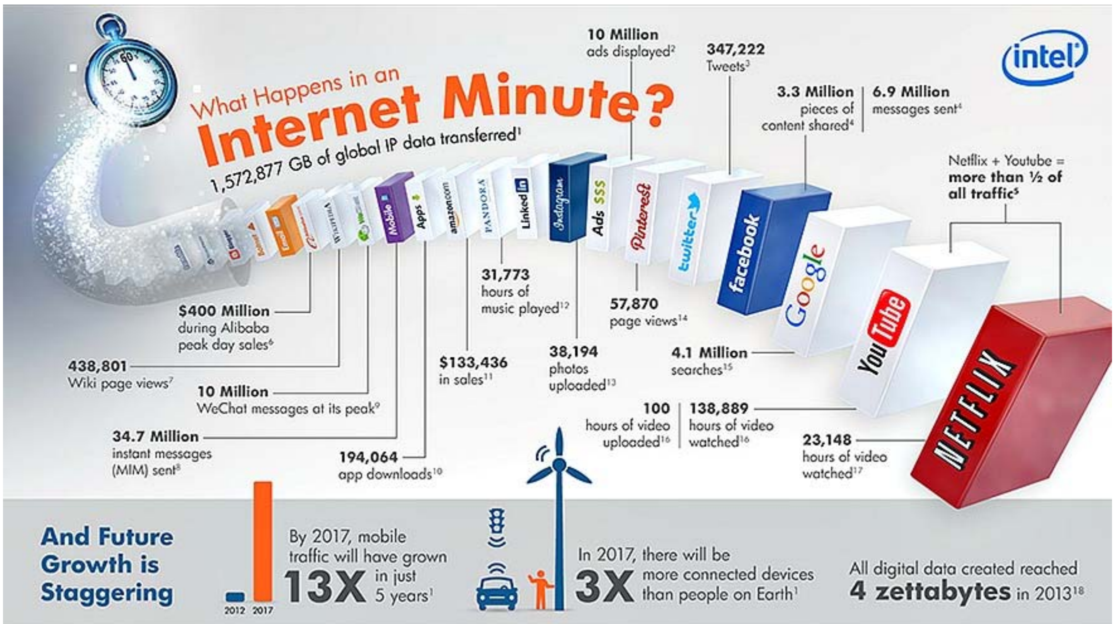

Figure 2.10. Infographic showing what happens in an internet minute, source [www.intel.com].

To deal with such an astonishing amount of data, which easily surpasses the storage capacity of any modern computer, a series of cloud-based platforms have arisen to provide a wide range of services for users with the only requirement of an internet connection. These platforms are referred to as PaaS (Platform as a Service) and can be defined as a cloud computing model in which a third-party provider delivers hardware and software tools (usually those needed for application development) which can be accessed anywhere via a web browser. One of the main advantages of a PaaS providers is that they host the hardware and software on its own infrastructure, thereby freeing users from having to install in-house hardware and software to develop or run new applications. In the following, a summary of some the available PaaS providers is included:

Microsoft Azure

Microsoft Azure [38], formerly known as Windows Azure, is Microsoft's public cloud computing platform. It provides infrastructure as a service (IaaS), Platform as a service (PaaS) and also Software as a service (SaaS) and a wide range of cloud services, including those for compute, analytics, storage and networking. Users can pick and choose from these services to develop and scale new applications, or run existing applications, in the public cloud. Microsoft's data center is located in 34 different regions around the world, where each region is redundant in itself.

Google App Engine (Google Cloud Platform)

Google App Engine [39] is a Platform as a Service (PaaS) product that provides Web app developers and enterprises with access to Google's scalable hosting and tier 1 Internet service. Google App Engine provides more infrastructure than other scalable hosting services and eliminates some system administration and developmental tasks to make it easier to write scalable applications. On the other hand, the App Engine requires apps to be written in Java or Python, store data in Google Big Table and use the Google query language.

Amazon Web Services

Amazon Web Services [40] is a comprehensive, evolving cloud computing platform provided by Amazon. It provides a mix of infrastructure as a service (IaaS), platform as a service (PaaS) and packaged software as a service (SaaS) offerings. More than 100 services comprise the Amazon Web Services portfolio, including those for compute, databases, infrastructure management, application development and security. These services include but are not limited to: computing, storage, database, management, monitoring, security, etc.

2.2.3 Data processing and analysis

Figure. 2.11. The DIKW model for knowledge management and data value extraction

A relevant aspect when data is obtained from the structure is to be able to describe relevant parameters which has some sense for the engineers and owners of the infrastructures. A single measurement only gives a voltage or an intensity for instance, hence it is of major interest to be able to move from this meaningless values to meaningful quantities, or in other words, from voltage/current to strain/stresses and so on. This step can be described as understanding the data, i.e. value relevance and purpose is given to the data. However, in the same way this information, which now has meaning, has to be transformed to knowledge. Discrete points measure along the structure, can give no relevant information about the structural performance, subsequent processing of the information is necessary, transforming discrete points into actual knowledge of the structural performance. This step is done by introducing believes, theory, personal experience, etc. Last but not least, an important step represents the jump from this knowledge to actual expertise, which at the same time transform the data as a decision making tool for the condition assessment, structure safety, structure health and so on. This information enrichment requires of experience, training and education, to provide additional meaning to the measured data.

Then, it is necessary to define a thorough strategy which will enable the utilisation of the measured data into an actual relevant tool. In addition, the same process followed in the opposite direction will enable the attainment of new data which is actually not measured. Once at the top of the data processing, the same approach can be applied in the opposite direction to break down and understand local areas of the structure, which may be damaged or affected by anomalous behaviour. Therefore, by transferring this expertise to new and existing data it is possible to minimize the impact of the actuation on the structure in case of necessity, with the subsequent saving of resources both economical and natural.

SensIT can be understood then as a closed process in which everything starts by the deployment of sensors in a smart way along the structure and ends with new data which comes from the transformation process of the original data into information, knowledge and expertise.

Machine Learning

The term Machine Learning (ML) refers to a field of computer science coming from the broader field of artificial intelligence, in which computers gain the ability to learn and make predictions from fed input data. Machine learning is sometimes referred to as Statistical Pattern Recognition (SPR) and according to the definition provided by Wikipedia machine learning "*explores the study and construction of algorithms that can learn from and make predictions on data, where such algorithms overcome following strictly static program instructions by making data-driven predictions or decisions, through building a model from sample inputs*" [41].

Machine Learning is currently being used in many existing fields of research to develop countless applications, some of which are fully operational in everyday situations such as spam filters or face recognition systems in our phone and computer devices. Other areas in which machine learning is also being applied is game theory, stock market prediction, market segmentation, customized user recommendation, among many other applications. Further applications are currently being investigated, such as text and image recognition, which can be applied to, e.g. self-driving cars and navigation systems in general. A long, yet not comprehensive, list of different existing applications for machine learning can be checked at [42].

In the field of structural health monitoring, machine learning is not exactly new either. In broad terms, two main approaches to damage identification exist. Model-driven methods establish a high-fidelity physical model of the structure, usually by finite element analysis (FEA), and then establish a comparable measure between the model and the acquired data from the real structure. If the model created represents the normal state of a structure or system (i.e. undamaged condition), any deviations from the model response may indicate that the structure has deviated from healthy condition and thus damage is inferred. Data-driven approaches also establish a model, but this is usually a statistical representation of the system, e.g. a probability density function of the normal condition. Deviations from normality are then signalled by measured data appearing in regions of very low density.

Two well-known examples of successful application of machine learning in structural health monitoring date forty years back. Already in the late 1970's and early 1980's, a model-driven machine learning approach was used to detect damage in off-shore oil platforms. At that time, available data was limited and many parts of the structure were not accessible. Therefore, model-driven methods were developed to calculated the resonance frequencies of the structures under multiple numerically simulated damage scenarios which were afterwards compared to the real measured resonance frequencies of the structure [12].

Another important area of early implementation of data-driven algorithms in structural health monitoring can be found in the aerospace and aviation industry. In particular, the Health and Usage Monitoring System (HUMS) deployed in rotorcraft is a clear example of data-driven approach. Due to the constant rotor speed of the engines during the flying regime, a stable vibration spectrum is created along the power transmission system. By detecting deviations from that constant spectrum, faulty engines as well as changes due to deterioration of the components could be effectively detected [12].

In civil engineering, there are also examples of machine learning applications since the early 1980's, particularly for vibration-based damage assessment of steel bridges, see e.g. [43–52]. However, civil engineering structures due to their large size and one-of-a-kind nature, present multiple challenges which hindered the development of effective and generic machine learning algorithms for structural health monitoring.

According to Worden et al. [53], a general statistical pattern recognition paradigm for structural health monitoring systems is integrated by four main parts or procedures, as shown in Table 2.1.

Table 2.1 Parts of a Structural Health Monitoring system, from Worden et al. [53]**.**

1. Operational Evaluation	➔	**2.** Data Acquisition, Normalization and Cleansing	➔	**3.** Feature Extraction and Data Compression	➔	**4.** Statistical model Development
- Life-safety and economic justifications to perform SHM; - Definition of damage to be detected; - Operational and Environmental conditions; - Data Acquisition limitations.		- Type and amount of data to be collected; - Periodicity in data acquisition; - Data normalization procedures; - Sources of variability.		- Selection of the best features of the data from damage detection; - Statistical distribution of the features; - Data condensation.		- Damage or not damaged; - Damage location; - Damage extension; - Damage Type; - Remaining useful life of the structure; - Incorrect diagnosis of damage (FP and FN).

Procedures 1 to 3 can be regarded as pre-requisites that are necessary for a successful implementation of a machine learning algorithm. However, when it comes to classification of the different types of machine learning algorithm, they can be commonly sub-divided into two main groups, namely *Supervised Learning* algorithms and *Unsupervised Learning* algorithms.

The main difference between supervised and unsupervised learning is that for the former, the labels of a certain amount of data belonging to different classes, often referred to as the *training set*, are known whereas for the latter no classes are a priori identified. Regression and classification problems are clear examples of algorithms that fall within supervised learning whereas clustering is a typical example of unsupervised learning where intrinsic relationships between the data in the training set are found. Fig. 2.6 [54] illustrates a classification of the most commonly used machine learning algorithms. Note that some of them, such as Neural Networks (NN), are used for both supervised and unsupervised learning.

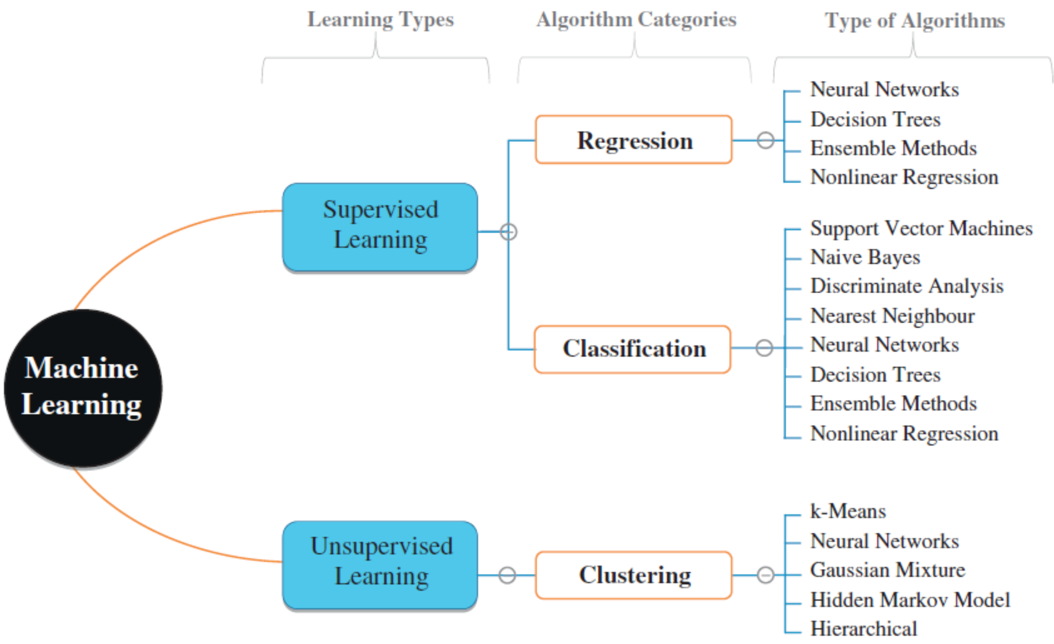

Figure 2.12. Machine learning types and commonly adopted algorithms, from Taffese and Sistonen [54]**.**

2.2.4 Visualization of processed data in BIM and physical environment

Building Information Modelling (BIM) is a process intended to help managing complexities and improve the performance of projects during their construction phase and service life. By combining 3D visualization of buildings with integrated data, BIM facilitates users the tasks of identifying and correcting design errors, optimizing the construction process, including as-built modifications, etc. The rapid development of BIM in the construction industry to handle and visualize measurement data opens up for many new possibilities, such as the real-time structural assessment of buildings and infrastructure.

Today, a variety of BIM software is available, both commercial and free, open-source software. The advantages of commercial software, e.g. Revit, are a more user-friendly and intuitive interface and compatibility with other related software, compared to free BIM software which may require some programming skills. Conversely, open-source software, e.g. freecad, usually provide a much greater flexibility and have large communities of users behind that provide free support and examples.

Perhaps, one of the major technical challenges within the proposed project is to find a suitable interface that enables the integration of real-time measured data with the 3D design model. A very promising solution to this technical challenge is provided by

Autodesk FORGE [55], a connected developer cloud platform comprised of web services, and technical resources that enables the development of customized and scalable solutions to solve design, engineering, and manufacturing challenges. To date, Forge is one of the only platforms as a service (PaaS) that offers SaaS (Software as a Service) for BIM, manufacturing, computer aided design, product lifecycle management, among others.

The main components of Autodesk Forge include:

Viewer displays 2D and 3D design files including basic VR (virtual reality) and associated data from more than 50 file formats. It allows users to share design information via web browsers and create tailored customer experiences for project dashboards, cost estimations, bills of materials, and schedule views. Viewer also leverages information from other applications.

Model Derivative API represents and shares design files in different formats, prepares them for online viewing, and extracts geometry and object property data. Design data can be quickly and easily integrated with other systems such as enterprise resource planning, product lifecycle management, cost estimating, and scheduling.

Design Automation API runs AutoCAD as an engine in the cloud. Use it as a drawing generation engine for web applications or convert thousands of DWG files to PDF files in batch.

Data Management API manages files across A360, Fusion 360, and BIM 360 Docs, as well as Forge's native Object Storage Service. Use a unified interface to upload/download data files from different Autodesk products and web services. Access project- and file-level data for integrating with other enterprise or project systems.

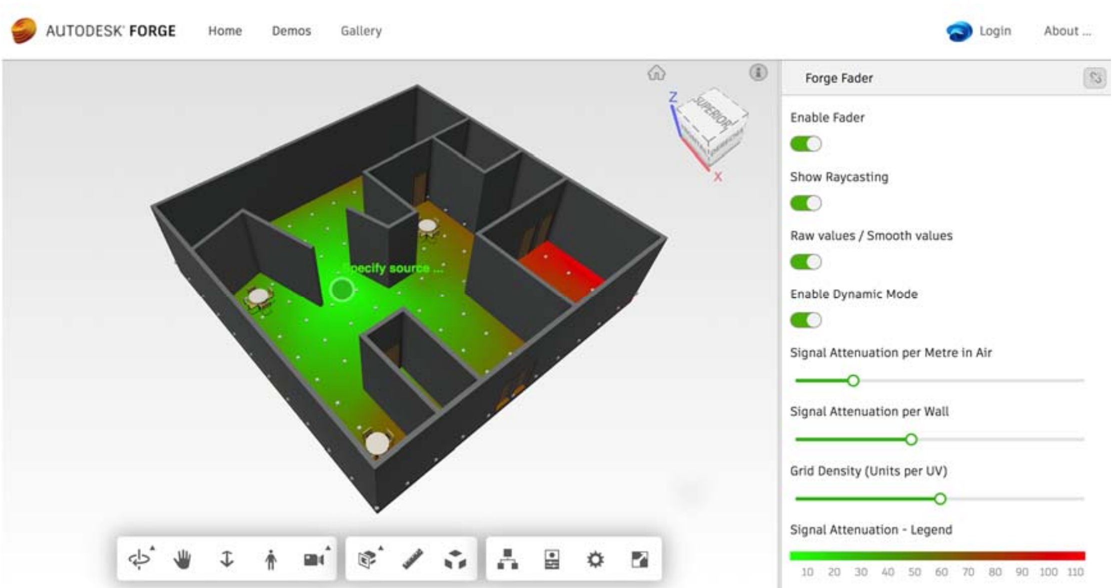

Figure 2.13. Screenshot of Autodesk Forge web-based BIM model with interactive data visualization

2.3 Technology Readiness Level (TRL) of the systems investigated

The technology readiness level is a method used to evaluate the technological maturity of a certain technology element within system and it examines the technology requirements and demonstrated technological capabilities of the element. TRL is based on a 9 level scale as shown in Fig. 2.14, which ranges from the observation of basic principles on the lowest level to commercialization of a final product on the top of the scale.

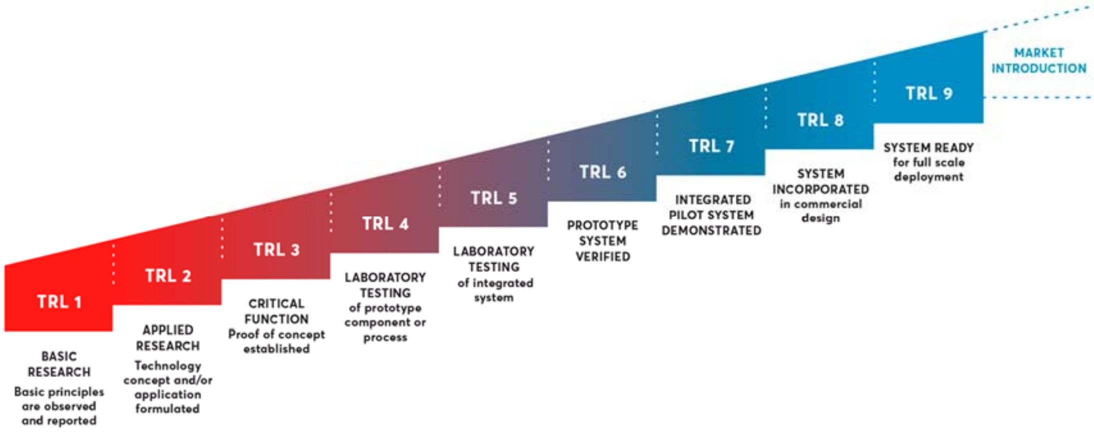

Figure 2.14. Technology Readiness Level (TRL) scale, from [www.brigaid.eu].

SensIT involves the combination of a wide range of technologies to demonstrate the feasibility of an innovative monitoring system for real-time assessment of structures. However, the various elements involved in the system feature very different degrees of technological maturity as illustrated by their positions in the TRL scale shown in Fig. 2.15

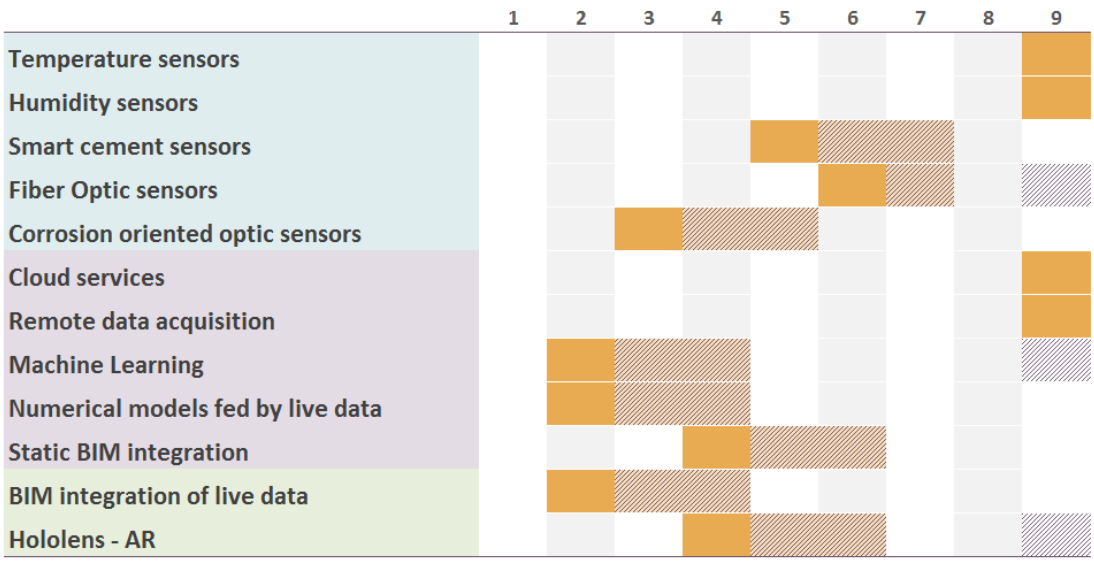

Figure 2.15 Position of various sensors, services and models in the TRL scale. Solid fill indicates current level within the structural health monitoring field, yellow hatch indicates the expected development during the project and purple hatch indicates the highest readiness level within any field.

For instance, some temperature and relative humidity sensors, as well as cloud services or remote acquisition systems are commercially available with a variety of available "out-of-the-box" solutions. Other sensors, such as the smart cementitious sensors, have already been developed but their effectiveness has only been shown in a limited number of small laboratory tests. Another category of technologies, like machine learning applications or the Hololens, are readily available for certain purposes but their applicability has not yet been demonstrated in this field.

3 Assessment of the needs and wishes from different actors and stakeholders

3.1 Workshop

In March 2017, a workshop was held outside Gothenburg. The purpose of the workshop was to discuss the potential of Internet of things and its application on the infrastructure sector. A secondary purpose of the workshop was to identify hindrances and technology readiness of the components of a future implementation in the area of responsibility of Trafikverket. At the workshop, academics, contractors, consultants and researchers participated from Microsoft, Chalmers, NCC, WSP and Trafikverket.

The identified components of a future implementation: sensors, machine learning and maintenance process of infrastructure were the starting point of the discussions.

Chalmers started by presenting a review of available sensors on the market. It was obvious that the available sensors focused on building application such as moisture problems, occupancy and energy monitoring. In the sector of infrastructure, such as bridges, the sensor industry has focused on the concrete casting process – assessing the strength development of concrete by measuring temperature.

WSP gave an interesting view on how the process of inspections is performed today. Each bridge is inspected every sixth year by visual inspections. The inspector takes photos of flaws and defects of the structure. In some special cases, special equipment such has cranes and other type of equipment used for accessing areas that are difficult to visually inspect. From the inspections a report is written and the structure is classified. This report is used by Trafikverket in order to plan the maintenance and if needed do repairs.

Microsoft presented machine learning in theory and practicality, as well as cloud computing and storage of data. Their Azure suite has the components to store and analyze, as well as visualize data in different forms. It was clear that there are obstacles to overcome for using machine learning on a maintenance process of a bridge, more precisely the gather and structure of the data. Sensors could solve some of the problems, but not all. An important aspect that was concluded is how the sensors can help the inspector in the process. One main aspect is that machine learning together with sensors would homogenies the reporting resulting in less subjective reports of defects.

Chalmers also presented the use of HoloLens as a technique for assisting the inspector at site with information from BaTman projected on the structure by augmented reality. The technique is semi-mature in the sense that it is today possible to load a building information model into the HoloLens and project the model based on the room boundary, but it is not at the moment possible to do the same in an outdoor environment.

The vision presented in this report was the main outcome of the workshop and served as a basis for the work done in this pre-study.

4 Scientific road-map

In Fig. 4.1, a schematic illustration of the scientific road-map defined for the SensIT project is presented.

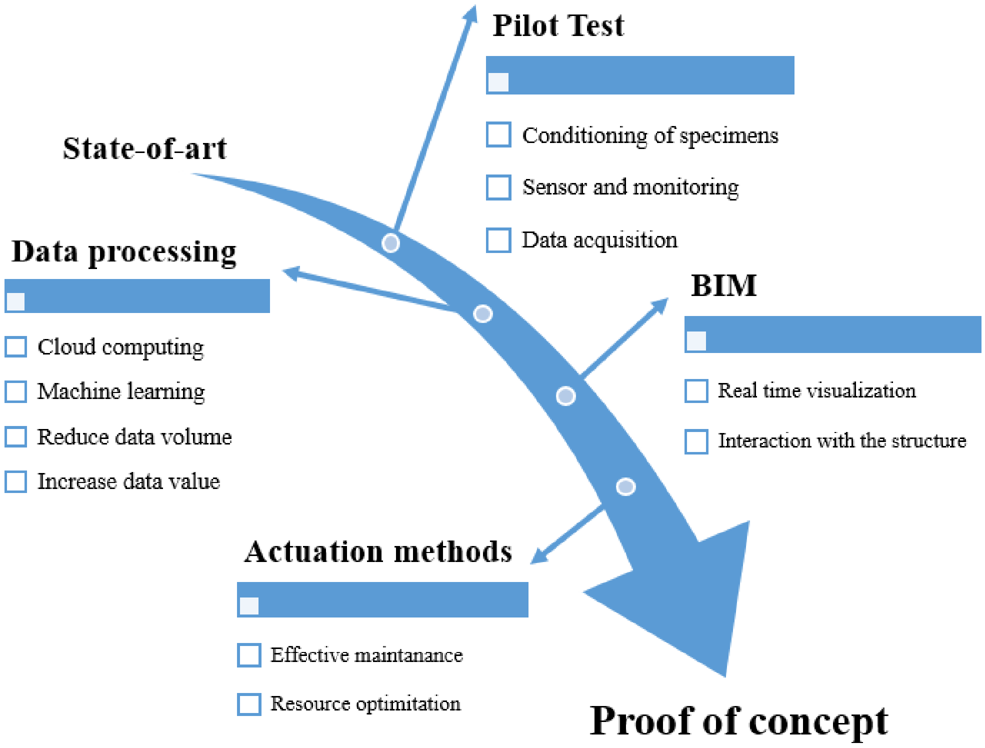

Figure 4.1 Road-map of the SensIT project

4.1 Preliminary experiments for the road-map

As a preliminary experiment for the pilot tests included in the road-map, two different sets of smart cementitious sensors were tested under cyclic compressive strains. The smart cementitious sensors were manufactures at two different universitities, namely the University of Toronto (Canada) and Università degli Studi di Perugia (Italy). The sensors manufactured in Canada were prisms with dimensions 40x40x160 mm (Fig. 4.2a) whereas the sensors from Italy were prisms featuring dimensions 60x50x40 mm (Fig. 4.2b).

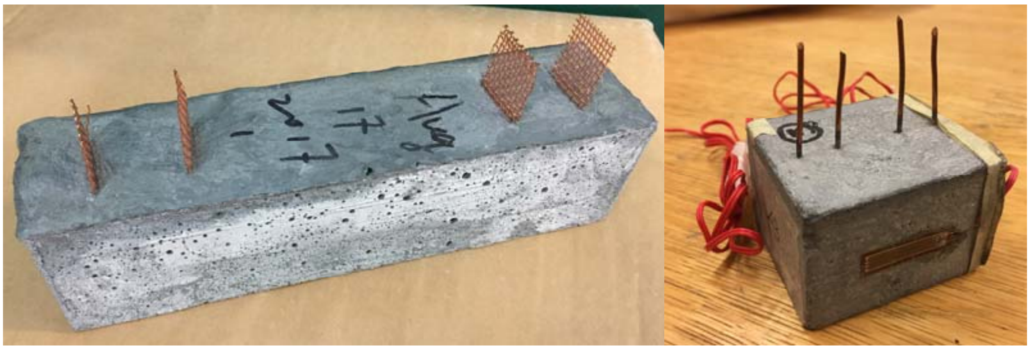

Figure 4.2 Smart Cementitious Sensors from University of Toronto (a) and from University of Perugia (b).

The sensors were tested under load control with a triangular load variation between a minimum load of 5 kN and a peak load of 25 kN. Strain gauges were glued on the sides of the specimen to characterize the strain measurements obtained from the sensors. Regarding the electrical settings, the sensors were outfitted with a 4-electrode setup consisting in copper mesh or copper leads, thorugh which a constant DC current of 500 uA was supplied to the exterior pair of electrodes with an external power source while potential drop (voltage) was measured across the inner electrode pair. The results of one of the sensors from each batch are presented in Fig. 4.3 and Fig. 4.4.

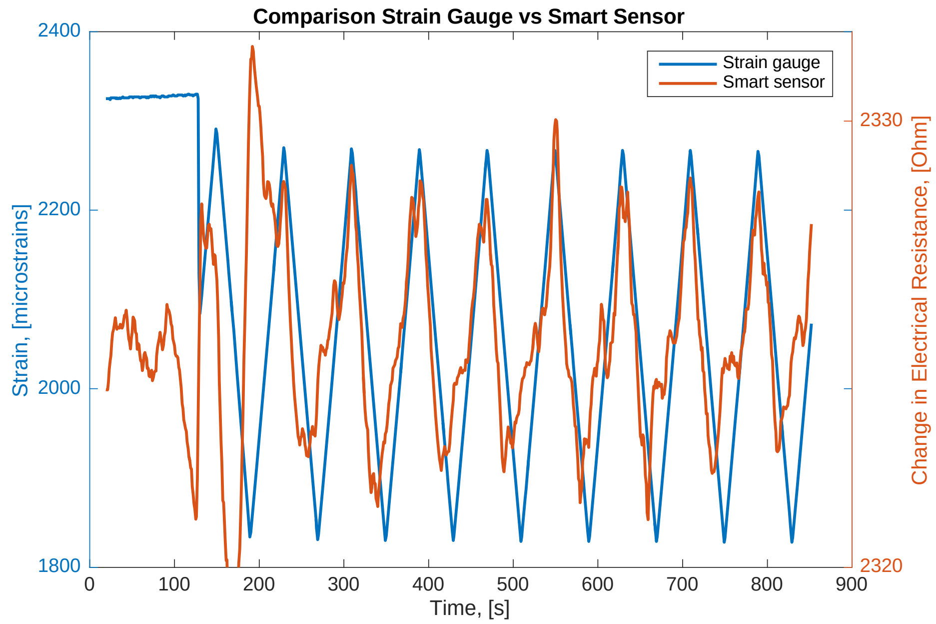

Fig. 4.3 Test results of one of the smart cement sensors from University of Toronto.

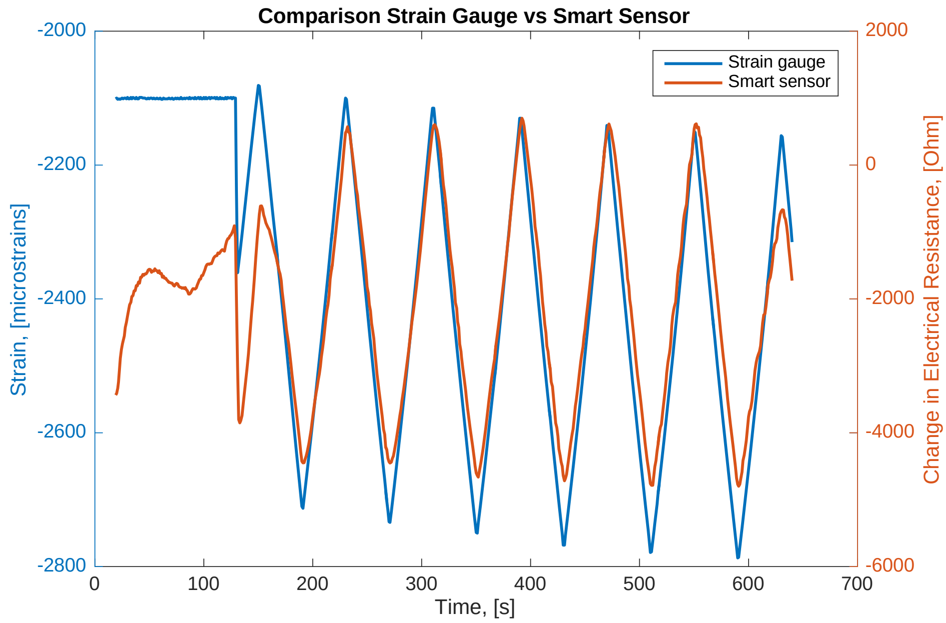

Figure 4.4 Test results of one of the smart cement sensors from University of Perugia.

As observed in Fig. 4.3 and Fig. 4.4 both sensors show a superior strain sensitivity which correlates quite nicely with the results obtained from strain gauges. The sensors from Toronto, however, suffered from a more scattered signal with significant noise compared to the ones from Perugia. An important finding from the tests is that this type of sensors are not well suited for DC current measurements as the transient response of the voltage tends to drift with time, which needs to be corrected afterwards. Moreover, it was observed that during the first loading cycles the readings from the specimens were somewhat irregular. It follows that a pre-conditioning of the prisms seems necessary to enable the self-sensing properties of the cementitious sensors.

Despite the minor shortcomings mentioned, the results seem very promising, specially bearing in mind that this kind of sensors are far superior in terms of durability compared to conventional strain gauges and they are 100% compatible with the concrete environment.

4.2 Pilot Test - 3 feasibility studies

Three different feasibility studies are planned to test the viability of the SensIT. These studies comprise:

- The SensIT Hackathon 2018

The SensIT Hackathon 2018 comes as the natural continuation of the previous workshop carried out in 2017 and will consist in a 48-hour event held during the first half of 2018 that will bring together experts from different technological sectors involved in the development of the SensIT project. During this event, the main objective will be to promote collaborative development of the members towards the implementation of an initial prototype. The aim is to test the SensIt idea using simple laboratory test specimens and readily available sensors, to send data to a cloud service platform, perform straightforward analysis and visualize the results in a web-based BIM model in real-time.

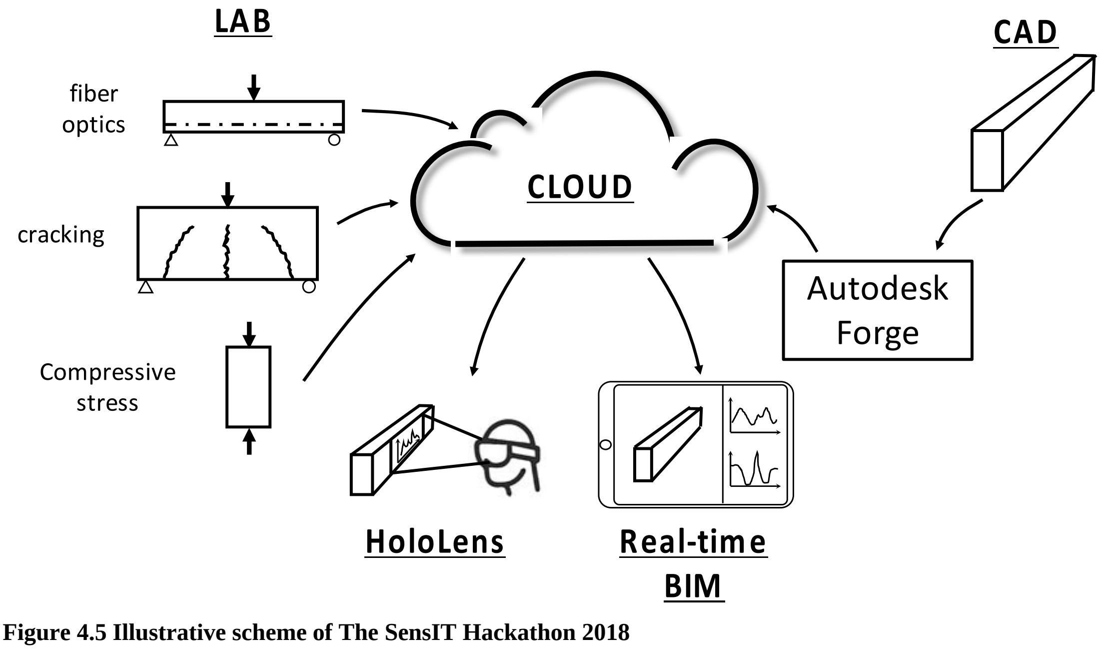

Figure 4.5 Illustrative scheme of The SensIT Hackathon 2018

- Hönöverket is a research wind power plant on the island Hönö outside Gothenburg. The plant will be renovated and moved a short distance. As part of the renovation and moving of the plant, a new foundation will be casted. This pre-study has made it possible to investigate and plan for the deployment of sensors in the ground and the foundation of the plant.

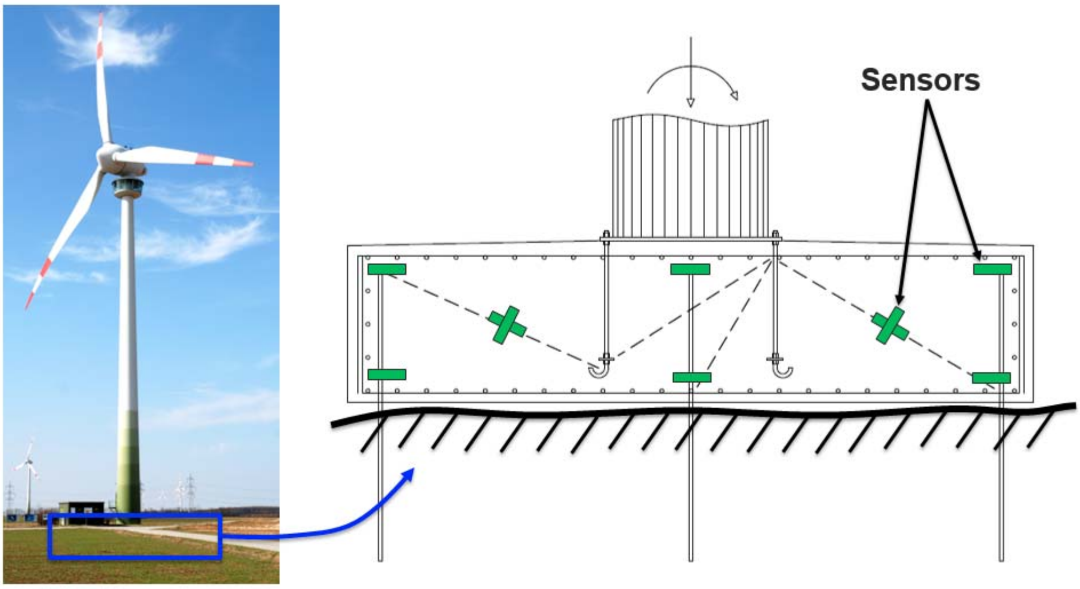

Figure 4.6 Wind turbine (source : https://commons.wikimedia.org) and sketch of the foundation with potential placement of sensors for long-term monitoring of strain

- Long-term laboratory experiments

Real scale concrete specimens will be cast emulating elements commonly affected by deterioration of existing structures. The specimens will be instrumented to be able to acquire relevant data to assess the structural behavior and deterioration state. The type, amount and position of the sensors will be carefully studied along the different task of the present WP.

4.2.1 Literature review

A critical literature review of different existing, novel and experimental sensors will be done; sensors regarding its TRL development will be scouted and carefully spotted during this literature review, which will be utilized in the following tasks of the WP.

The potential of the different possible data acquired by the sensors and how this data can be translated to structural performance and service life prediction. This review will particularly be focused on the different existing examples of using sensor in small scale specimens and how it can its implementation can be scaled up to real size elements.

This task will set the basis for the development of the project and will help to make a significant step forward in the current state of the art.

4.2.2 Design of the beam and study of sensors deployment

This task consists in the design of the structural elements to be tested during the project execution. The specimens will be designed according to the needs and requirements of the infrastructures' stakeholders; hence the outcome and applicability of the results can be maximized and extended to real/existing structures.

The second part of the task consists in the study of the sensors deployment. The different sensors used in the project must be placed carefully to maximize their efficiency and get reliable data which leads to accurate and reliable assessment of the structural behavior and performance. The implementation of sensors in a structure has been largely done during the last years. However, the sensors have usually been placed trying to get information and to monitor explicit parameters in some specific parts of a damaged structure, most probably due to a known phenomenon. In consequence, the sensor deployment results are limited in number and scope, and can hardly be extended to the whole structure. In this project the sensor deployment will be done prior to any damage to measure and assess the overall structural performance, which require different thinking when arranging them. Hence the knowledge obtained in the previous task will be very relevant here.

4.2.3 Placing of the sensors and testing

This task will focus on the casting of the specimens and the formal execution of the experimental study.

At this point a clear picture of the expected data from the placed sensors will be given, consequently the focus will be set to infer different type of disturbances to the beams which will allow to describe different structural behavior when compared to sound beams. In this project two different type of disturbance are planned: first different type of loading conditions combining unload specimens, static loaded beams and cyclic loaded beams, which represents common loading situations. Second, actively damage the structure by means of impressed corrosion of the steel reinforcement, which will be applied along the desired bars. Corrosion is chosen here because it represents one of the most common deterioration situations in existing structures.

In Fig 4.7 a description of the specimens as well as the desired combination between the loading conditions and corrosion damage to which they will be submitted is described.

To broaden the scope and extensibility of the project to real life applications, two sets of beams will be cast and inferred with similar conditions. However, in one group of beams the sensors will be placed in beforehand of casting whilst in the second set of beams the sensor will be placed after some loading/corrosion has happened. By doing this, it will be possible to determine in which extend the proposed method and sensor deployment can be implemented in the design of new structures but in existing structures as well. Hence, it is possible to investigate a real upgrade of the current technology for existing structures and not only for newly build ones. This might be of major interest for the owners of infrastructure facilities.

In addition, at the end of the experimental study, the beams will be loaded to failure by monotonic loading. This will be very helpful to assess the residual structural capacity of the structure under specific damage conditions; valuable data for prognosis and assessment of service life.

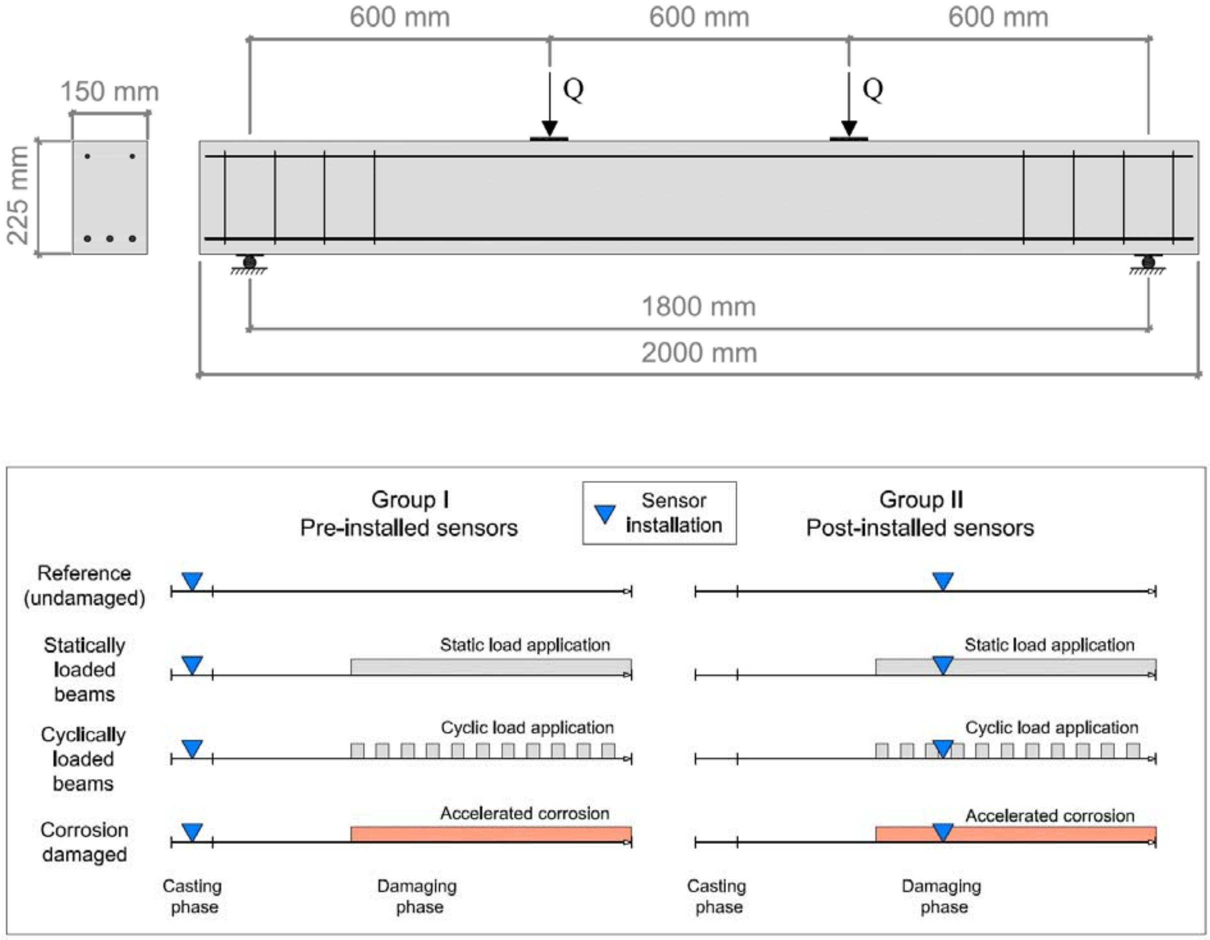

Figure 4.7 Preliminary beam geometry for laboratory tests and schematic summary of the experimental plan.

4.3 Data processing

4.3.1 Task 3.1 Remote data acquisition – cloud services (L1, L2)

One of the goals of the project is to bring the health monitoring concept to a new level. Consequently, this task will focus on the management of the acquired data during the experimental program. A big challenge in the current state of the art is how to move from the simple measurements, usually volts, to structural parameter and structural performance and all of this in an automated and reliable way. So, at the end of this task it will be possible to give relevant information about the actual existence of damage in the structure and moreover where this damaged is produced. To do that existing services provided by Microsoft, partner in the project, will be used.

4.3.2 Task 3.2 Machine learning/Numerical analysis (L3, L4)

Once it is identified the presence of damage in the structure it is necessary then to be able to quantify it and predict the remaining capacity and service life of the structure. Hence, this task will focus on the utilization of new technologies based again on cloud services, i.e. machine learning, supported by numerical analysis to answer the different questions. So, when the data is available on the cloud the different technologies and techniques used in the task will give an assessment of the actual structural state and consequently will be the base for numerical analysis which will allow to predict the remaining service life. In addition, the utilization of machine learning will set the basis for the automation in the prediction of the structural damage. In this task the prediction algorithms provided in the machine learning service will be retrofit with relevant data and teach to be able to predict damage in different scenarios.

4.3.3 Task 3.3 Accessible user interface/ BIM integration

In the last task of the current WP the focus will be put on the visualization of the obtained data. It is important to give to the practicing engineers understandable data, so by providing accessible user interface or BIM integration the data obtained by the different sensors can be represented in a set of structural parameters that the engineer will be able to understand and more importantly use in their assessments and analysis of the structural behavior.

4.4 Real time coupling (Pilot demonstration)

The aim of this work package is not to offer an end-user method or technique but to show the potential of the work developed in the core of the project (WP1, WP2 and WP3) in advanced applications. In other words, it is intended with the development of the present work package to show extended capabilities of the methods developed in the project for future applications which may be of interest for the different actors in play.

4.4.1 Task 4.1 Real time BIM visualization

In WP3 is detailed the integration of the sensor data in BIM models. In this task, it is intended to show a pilot demonstration how this integration can be done in real time. This implies monitoring of a structure in real time which allows to study the actual structural behavior and performance under a specific set of real conditions. Possible interesting applications of this implementation could be the study of the structural behavior during a loading test capacity, an extraordinary event, traffic jam over a bridge, extraordinary snowfall, an accident, etc. and dispose of real time information for fast and reliable assessment.

4.4.2 Task 4.2 Microsoft HoloLens: augmented reality

In this task, a step forward in the current utilization of top of the line technologies, like augmented reality, will be conducted. The utilization of augmented reality is widely utilized in many other fields by means of smartphones or other devices like HoloLens. In this project, it is proposed to bring the capabilities of this technology to the construction field. After the implementation in this pilot demonstration it would be possible to have a visual representation of the measured damage through the sensors in terms of structural parameters along the service life of the structure. So, it will be showed the potential of such applications connected with the structural monitoring for instance when it comes to inspections. By utilizing such technologies, the inspectors can really focus on the parts of the bridge which actually has been affected by damage by means of interpretation of collected data.

5 Concluding remarks

5.1 Conclusions

The purpose of this pre-study was to review existing knowledge and define a research roadmap. The pre-study investigates the feasibility of combining Sensors, Machine Learning, Cloud Services and Building Information Modelling to create an integrated system that enables an upgrade of the current infrastructure network through a new generation of *smart* structures. The study focuses on the aspects that are required in order to ensure that such a system could be successfully implemented in practice.

Via workshops and established collaboration, national and international, the project team has generated knowledge and gather experts from several disciplines, such as data scientists, sensors experts and civil engineers.

The main result of the work is a research roadmap that works as a guideline for Trafikverket in their task to develop and create a new management process based on modern tools and processes.

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