Holistic Approach to Smart Factory

Cristina Monsone

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Cristina Monsone[1]

[1] Széchenyi István University, Győr , Egyetem tér 1, 9026, Hungary
monsone.cristina@sze.hu

Abstract.

This article presents the key elements of the digitalization of a system, industrial and non, providing a new holistic formulation for Industry 4.0, I4.0, and a concept base of a new API system in the field of Digital Twin for industrial integrated smart solutions based on Internet of Think, IoT, devices. The general approach is also considered for „traditional" industries which come to be I4.0 and as a suitable element for virtual training and decision-making system for industrial e non -industrial customers in a vision of future application in a Virtual reality, VR, environment. In particular, this research defines a formula - CMon - representative of the digitalization of any system and the realization of an API, DTNet, able to create in real- time a Digital Twin, DT, of a single object from a video, realized through any device, using Deep Learning Techniques and then integrate it in a VR environment for a more accurate predictive analysis.

Keywords: Digital Twin, I4.0, Artificial Intelligence.

1 Introduction

The I4.0 [1] [2] panorama introduces new development and service concepts in the name of a digital transformation fostering the disruption side of the smart technologies.

This disruption is evident not only at the technological level, but, according to [3] it represents a potential way to decrease the production costs by 10-30%, logistic costs by 10-30% and quality management costs by 10-20%. There are also a number of other advantages and reasons for the adoption of this concept including, just to mention a few, a shorter time-to-market for the new products, improved customer responsiveness [4] and also optimization of environmental-friendly best practices.

Including a technological mix of robotics, sensors, connection and IoT integration, I4.0 represents a new revolution with respect to the way of traditional manufacturing products and traditional work organization, which does not exclusively imply a new process but also allows transformation of traditional industry into a smart industry in a sustainable way, following a and non-linear development as in the recent past.

The improvement provided by digitalization, in particular referring to the Smart Factory, proposing three levels [5]: smart production, smart services and smart energy. But,

considering a wide application panorama, the digitalization thanks to the interconnection with machine learning technique, in particular deep learning, offers the possibility for advanced forecast and consequently prevention and optimization of the potential solution and best management also in other sectors, as mentioned before, like environment and health.
These innovative renewing processes and systems also bring new managed communication and service rules, firstly for workers/managers with adequate skills. In this process towards the smart factory, cloud computing, which arises from the combination of information technologies that have developed in recent decades, plays a fundamental role, covering the application of an end-to-end solution using information and communication technologies that are embedded in a cloud.
On the one hand, cloud computing can be considered mainly as a cost reduction technology, and also as a choice for quick solutions to respond to specific operational problems in the context of a global business strategy based on agility and reactivity [6].
The true value of cloud computing is how it can be used to support a global strategy designed to create business agility [7].
Companies that create a business strategy based on agility put reactivity before efficiency. This strategy emphasizes the ability to make both continuous incremental changes to products and adjustments to operating procedures so that the company can respond to the development of new economic conditions. This is where Human-Machine collaboration enters. Daughter of that digital transformation that is progressively changing habits and customs, triggering a cultural revolution on a global scale, Industry 4.0 in recent years has also become a new dimension of communication and business.
In the landscape of smart devices, another important trend for the future is the augmented humanity surrounding the AR, Augmented Reality.
In general, AR / VR devices, which initially attracted mainly private consumers, begin to enter companies to manage internal processes and customer-oriented services [8], generating much of the business market value, in the next years.
The Augmented Operator paradigm is related to the worker's technological support that is required in the manufacturing environment, which represents a challenge since the operators will face a large variety of new tasks. Industry 4.0 introduces new types of interactions between operator and machines, as well as the coexistence between human and robots/cobots, which will completely change the current industrial workforce in order to answer the changing requirements and the increasing production variability [9].
In light of the impact of these disruptive technologies, this article presents a new holistic formulation for the I4.0, considering the key elements for the digitalization of any system, for example for „traditional" industries which come to be smart, and a concept base of a new API system in the field of Digital Twin - DTNet - for industrial integrated smart solutions in a VR environment.

1.1 Components of Smart Factory: CPS and Digital twins

The modern meaning of "Digital Twin" refers to the "Conceptual Ideal for PLM" presentation by Dr. M. Grieves published in 2002 at the University of Michigan. This term, however, originally dates back to the 1960s and was used by NASA in reference to the creation of a "terrestrial" duplicate of the systems within the spacecraft. Later it was also used as a basis for the development of computer simulations.

The two macro-elements to be connected are virtual space and real (or physical) space. This connection takes place through a “mirroring” or “twinning” process which follows the product throughout its life cycle.

In essence, it is a question of collecting all the data, information and processes of a physical element, such as a product and dividing it into a virtual version. This allows the possibility to examine and study it in all its parts and also opens up multiple possibilities for simulations and predictive analyses. The current technological evolution has been characterized in recent years by an extension from the physical world (world of atoms) to the virtual world (world of bits), thanks to the creation of static mathematical models (2D and 3D CAD drawings), models of manufacturing processes (CAM) and dynamic simulation of the behaviour of objects, machinery, plants and processes (CAE).

The I4.0 paradigm introduced the concept of integration between physical objects and their mathematical models by means of cyber-physical systems (CPS - Cyber-Physical System): computer systems capable of interacting continuously with the physical systems with which they are associated. A CPS is composed of a physical asset with computational, communication and control capabilities, which can be an object, a system or an industrial process (physical twin), to which a digital twin is associated with which it interacts. in a mono-directional way (the digital twin acquires the data produced by the physical twin, which are then analyzed and used off-line) or in a bi-directional way (the digital twin can intervene with alarms or directly on the behaviour of the physical twin if it detects abnormal or in any case optimizable behaviour).

The future will allow the development of real “digital twins”, or digital representations that reflect objects, processes or systems of real-life; these can also be linked together, to create twins of larger systems, such as a power plant or a city, and in perspective, even an individual.

Digital twins allow both to monitor the activity of a plant or process and to predict its behaviour in advance. Digital twins can be created with various levels of complexity, up to a complete virtual simulation of a system, product or physical process that combines technical and managerial information on the components and processes that make up an asset, the technical characteristics of all the components, the documentation connected to the component (certifications, operating manuals, technical documents, drawings, etc.), the links between the elements of the asset and the document management systems, such as PDM (Product Data Management) and PLM (Product Lifecycle Management), production control systems such as MES (Manufacturing Execution System) or DCS (Distributed Control System), up to ERP (Enterprise Resource Planning) management systems, to integrate them in real-time with process data. The most advanced systems are based on neuronal networks and artificial intelligence algorithms that identify abnormal behaviours by comparing data from sensors with predictive models and make use of human-machine interfaces (HMI - Human Machine Interface) based on virtual reality environments and augmented reality to communicate with users immediately and immersively.

The CPS is a mechanism controlled or monitored by computerized algorithms, closely integrated with the internet and its users [10-11]. Cyber-physical Systems (CPS) are simply physical objects with embedded software and computing power. In Industry 4.0, more manufactured products will be smart products. Based on connectivity and computing power, the main idea behind smart products is that they will incorporate self-management capabilities [12-13]. In cyber-physical systems, the software and physical components are closely connected, each operating in different spatial and temporal scales, exhibiting multiple and distinct behavioural modes, and interacting with each other in a myriad of ways that change according to the context in real-time [12].
Through the CPS, it's possible to collect the data used in the data-mining through analytical tool working with Algorithms and relevant Model Accuracy [9-13].
The devices, equipped with intelligent sensors, allow the combination of different data into flows of useful information, as well as to monitor and optimize resources from any point in real-time, integrating control and information systems. A cyber-physical system, therefore, has computational, processing, communication and control (cyber) capabilities; integrates hardware and software objects with its own "intelligence" (smart); it consists of automated and intelligent technologies that operate autonomously and in contact with the surrounding environment (Internet of Things) which process an enormous flow of information transforming it into predictive corporate know-how (Big Data) [15-17].

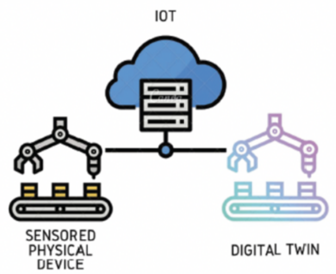

Fig. 1. Digital Twin [34].

1.2 Usefulness of the Digital Twin

The usefulness of the digital twin is transversal to all manufacturing industries operating in the most diverse industrial sectors, for example, to get to intelligent buildings controlled by BIM (Building Information System) systems and Smart Cities. The sectors particularly affected by the implementation of a digital twin are design, sustainable production, quality control, performance optimization, maintenance and in general after-sales services. The main goal of a digital twin is to respond immediately to external changes to [13]:

- anticipate and prevent problems;

- resolve problems promptly, making all the necessary changes in the virtual world to ensure that the physical asset works exactly as expected;
- save time and money in the simulation, test and analysis phases and speed up time to marketing;
- improve the performance of the physical twin. The ability to monitor products during their operation allows you to check their functionality and how they are used, and allows you to continue testing in real-life situations to refine the product and update the software embedded in the product in real-time;
- the digital model can also be used to make durability tests, accelerating the scrolling of the time in order to evaluate several years of operation in a few hours. If a problem arises, time can be 'slowed down' to allow the designer to observe what happens in critical moments;
- the presence of digital twins also potentially opens up a space for third parties, such as insurance companies, SMEs and start-ups, who can develop services based on the information produced by digital twins and create an interconnected ecosystem over time.

The manufacturers of vehicles, ships and planes build digital models on which they carry out all the tests and simulations necessary to arrive at a satisfactory project (digital prototyping). When the digital model is ready, the bits are converted into atoms with various types of machines (such as 3D printers) and the prototype is obtained. This process can involve the whole logistic chain. For example, aircraft manufacturers such as Boeing send suppliers the digital specifications of the parts with which their component will interface, and these, in turn, must provide the customer with a digital representation of the component that they will have to make. The manufacturer integrates all components digitally, performs tests and simulations and, after verifying the correct functioning of the models, activates its own production and that of suppliers. With virtual commissioning, you can evaluate the behaviour of the automation of a system even before having the product assembled, verifying its goodness and consistency in advance. GE applies a dense network of sensors to its turbines (used both in wind systems and within jet engines) that communicate with the virtual Digital Twin in almost real-time. From the moment of sale, the real turbine informs its virtual copy of the current use and this allows not only to record data continuously but also to detect faults, discrepancies, forecasts of decay and resolution of problems already in the testing phase. General Electric has for some years extended the use of the digital models of its turbines (both those used in wind systems and those operating in turbo-jets) to their maintenance and control. The turbine is sold associated with its digital twin: a specific digital model of that turbine. The physical turbine contains various sensors that send all the operating data to the virtual turbine, such as rotation speed, instantaneous power, temperatures, pressures, vibrations, etc. These data allow the digital twin to simulate the operating situation and to detect any operating differences between the virtual model and the physical turbine, which trigger control mechanisms to identify and solve the problem.
Every Tesla car has a digital twin on board. Tesla receives information from hundreds of thousands of cars every day (over 2 million km per day, adding up the contributions

of all cars). This huge amount of data allows you to check and solve the presence of design-dependent problems [17].

In the two examples shown, we focused on the application of the Digital Twin concept in IoT, but the applications to predictive analyses and tests that are put in place before the release of the product / service still remain to be evaluated. All those phases of conception and creation of virtual models that provide data and information that condition the subsequent decisional and project phases are relevant, especially considering the needs of a sustainable and eco-friendly production [18].

The benefits of adopting Digital Twins are innumerable and typically change according to the need and use of the company. For some companies they are linked to data collections of products already in use, for others they allow to test new designs, for still others they constitute the virtual phases of real processes.

CPS are entering mainstream use, represent a primary tool for organizations implementing IoT projects and are becoming an integral part of digital strategies. The main players in the digital twin market are large industrial groups such as General Electric, IBM, Robert Bosch, Siemens and software houses such as ANSYS, Dassault Systèmes, Microsoft, Oracle, PTC and SAP, as well as dozens of smaller companies and start-ups.

Today a fundamental requirement to create a DT is to have high-quality CAD data of all geometric objects in all phases of the planning process. Fast production scans and subsequent object recognition and identification of CAD models from a reference are required library and transfer of geometry and other object data (e.g., machine types) such as modular objects directly from the library significantly reduce scan times

The definition of suitable interfaces allows the transfer of information in a simulation program they can be production systems and a digital twin of precision manufacturing generated - almost without manual intervention in a cloud environment. [12] [14].

The general procedure for the automatic preparation of a Digital Twin as a solution involves scanning, modelling and simulation modelling. Modelling must be strongly supported by object recognition to save time which would be spent in the manual remastering phase. The object parameter (e.g., machine characteristics) are stored in the CAD library and/or in an external dataset.

Scalability is an important requirement for this approach because theoretically each of the infinite objects constructed must be recognized. Expert knowledge of construction the environment must be acquired through modules or interviews with experts and also included in the simulation process. At this time, real-time processing and recognition is a desirable option, but not a mandatory one. *For older objects that don't have 3D documentation, an alternative approach must be developed to derive a feature-based model with the recognition of singular characteristics. This is one of the challenges on this research.*

1.3 IoT

The communication path represented by the IoT and Industrial Internet of Think, IIot, which represents the interconnection of physical devices, vehicles, buildings integrated with electronics, software, sensors, actuators and network connectivity allows them to

collect and exchange data. The IoT allows these objects to be detected and / or controlled remotely through the existing communications infrastructure. The utilization of these smart objects is allowing a real revolution within companies that are now always connected and leverage data to optimize their production processes [17] [19].
An Industrial Internet of Things, IIoT, object is actually a newly developed IoT device designed exclusively for its application within the fourth industrial revolution. The purpose of IIoT objects is to optimize production processes through the connection between the machines, to create useful data for an analysis center, to have a preventive check on the health of the machines in use and to control the times of industrial production [20].
A company that invests in new technologies can use both, IoT and IIoT. But the two technologies are not synonymous. The IIoT is an evolution of the IoT that allows an intelligent device to have multiple connections simultaneously and to work with a greater amount of data [21] [22].
It thus happens to direct the production towards one or another model based on the availability and the current cost of the raw materials or to make changes or customizations during the work by accepting customer inputs.
The direction is agile manufacturing: a lean supply chain and a production cycle tailored to the market as better as possible: Adidas, Toyota and many other companies in various sectors have already done. Research in academia and industry shows that retailers can achieve up to a 15% –20% increase in return on investment by introducing smart technologies [23].
In particular, as presented before, these elements closely interconnected with each other, IoT (Internet of Things) technologies and Big Data, Devices, Cloud computing, are crucial within the Smart Factory only supported by human-machine collaboration [24].

2 Research Challenge

The principle behind the integrations between digital twins is the practical application of their real twins. In operation, each component interacts with others and this entails additional aggregate data. The Digital Twins of each of these components if linked to the others and placed in simulation, can provide much more precise data on wear, failures and any other problems, using cloud-connected sensors integrated into the machines to upload operational data in real-time, producing updated virtual simulations of real machines. Producers can then use margin analysis to analyze and evaluate the performance of their products in the field. The main goal is to have a digital context running for every real-world resource in the field, with virtual replication ready to update its status thanks to data reception and analysis. *But the main challenge is the realization of a DT when the technical engineering properties are unknown and it is necessary to define all aspects to implement a smart system.*
The aim of this research is to define a "formula" for the digitalization of any system

(industrial and non-industrial) - called CMon - and the parameters for an API - "DTNet", allowing the possibility to realize in real-time a Digital twin for all type of machine and a suitable definition of the proposed Digital Twin model in Virtual reality environment. The ultimate goal is also to study the potential benefits of applying knowledge management powered by adequate techniques of Artificial Intelligence proposing the new approach to Smart Factory in the context of I4.0 in a sustainable way.
The Internet of Things, as mentioned, is the key to implementing this technology. The growing convenience of sensors, the widespread use of Wi-Fi and the ability to transmit data from the cloud combine to make the application of digital modeling accessible on a large scale for a wide range of solutions and a wide audience of companies.
The formula considers the life cycle of a digital twin composed of three macro-phases, each of which is divided into further steps, each important for the purpose of a particular function (parrot) as defined in [25].

1. See

It is the phase in which a digital twin continuously updates itself to reflect the precise conditions of the environment; to do this, if necessary, it is also able to communicate with other products in the process line. In this phase we identify:

- the creation step, in which the sensors collect the data that are created in the process; these data, as already said, can be environmental or concern the production process;
- the data communication sub-phase, in which the various sensors send everything they have just detected to the data collection server.

2. Think

For the area in which it is purely used, and therefore that of IIoT, it is the most important phase because it is the one where, through machine-learning and advanced learning techniques, all possible problems are calculated that could occur in the future.
At the end of this phase, the results are shown in the real world and solutions are proposed which can be manual or automatic. In the next point, the difference between these two types of solutions will be explained. In this phase we identify:

- the aggregation sub-phase, where first and elementary processing is performed on what has been received, after which it is stored in a repository or database. The data processing phase can be done before transmitting them, or in the cloud, once they have been received in the control panel;
- the analysis sub-phase, in which the data are analysed and then displayed;
- the forecasting sub-phase, in which we try to understand the data received by searching to draw conclusions in the long run.

3. Do

It is the final phase, the one with which you interact with the production process. If the manual solution was chosen then the system says what needs to be done to make improvements after which the engineers, based on the data received and the system structure, study the proposed situation and find ways to apply it; if instead the automatic

solution has been chosen then the task of applying the improvements will be fulfilled directly by the digital twin, through the actuators present in the system.
It is important to note that the transition from digital to real-world occurs only through raw data or through forecasts.
In light of the previous considerations, the building blocks of the key elements of the digitalization of any system, representing the fundamental elements of the proposed formula CMon, are identified in the workflow of Figure 2. This workflow presents the fundamentals steps of the realization of a smart system starting from the realization of a DT for an existing element of an industrial plan or an existing single industrial element especially when it's not possible to acquire the technical design project features.
In particular, it's important to highlight that the widespread use of Wi-Fi and the ability to transmit data from the cloud combine to make the application of digital modelling accessible on a large scale for a wide range of solutions and devices, included mobile-phone, it is one of key elements of the design of a DT in real-time.
The workflow has three main part.
The first phase is the "Implementation" of a digital system through:

1. Realization of a Digital Twin through the proposed API, DTNet;
2. Installation of a series of sensors, distributed along the whole chain that processes the signals and allows the digital twin to capture operational and environmental data, and actuators that instead operate directly on the production process itself in order to optimize it;

The second phase considers:

3. Data collection which is part of the digital world and are nothing more than aggregations of more information received by sensors from the physical world thanks to IoT;

The third phase are the:

4. Analytical techniques that are used to analyze data and, through simulations and daily routine visualizations, produce forecasts aimed at improving the system itself;

This research defines a formula - CMon - representative of the digitalization of any system considering the fundamentals elements mentioned in the proposed Workflow.

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2.1 Workflow of DTNet

API

The digital representation of an object through numerical modelling and simulation techniques is certainly not a new concept: in the past decades more or less sophisticated

IT tools have been developed that allow assisting designers and builders in the phases ranging from conception to production or assembly.
In the proposed model, the innovation is the realization of a DT from a video in real-time using Deep Learning techniques.
In Figure 2 the DTNet workflow is presented.
In general, the available tools normally operate in a context of pure simulation (i.e., without any interaction with the physicality of the systems they represent), and also for this reason they are gradually less effective as the complexity of the modelled system increases. Numerical models also have limits in situations in which it is intended to observe (simulating) behaviours that are articulated over a wide time span, in which complex phenomena that can have an important impact on performance, such as wear of mechanical parts, intervene - in the real world or tools. The quality of the simulation of complex phenomena can be significantly improved if, for the realization of a DT, we use, as proposed for DTNet, CCNs, to realize a model from real-world and combining, through embedded sensors, the data from measurements made in the physical world. In Figure 3 we can see, for example, how a ConvNet is able to identify and recognize a computer by object detection with a high rate of accuracy from a video [26]. Now it is time to give a more accurate definition of DTNet, stating that it is the model of an object to which data exchange features are added with its correspondence in the physical world and which follows its evolution over time keeping the virtual representation updated.
Starting from this relatively generic definition, it is possible to identify some essential requirements for the physical objects of which you want to create a digital twin, as well as some functionalities necessary for the information system in charge of managing their virtual representations. It is important to note that, although the context referred to below is that of manufacturing (the one in which the concept of digital twin originated), the considerations made can be applied to any digitization process [26-29].
In particular, referring to the first point, the digital representation of an object through numerical modelling and simulation techniques is certainly not a new concept: in the past decades more or less sophisticated IT tools have been developed that allow assisting designers and builders in the phases ranging from conception to production or assembly.
The innovation of this research is also the realization of an API, DTNet, able to create in real-time a DT of a single object or an element of an existing plant from a video, realized through any device, using Deep Learning Techniques and then integrate it in VR environment for a more accurate predictive analysis.

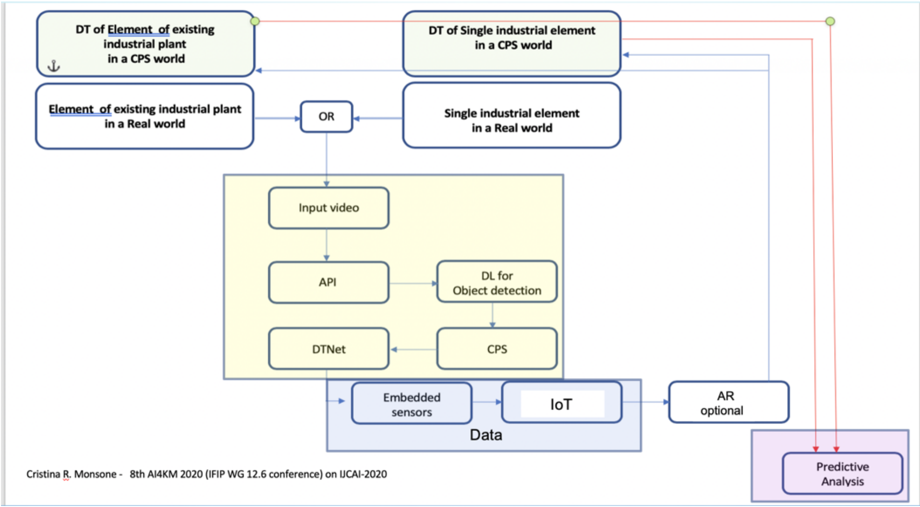

Fig. 2. Workflow of DTNet

However, the quality of the simulation of complex phenomena can be significantly improved if for the realization of a DT, we use, as proposed for DTNet, CCNs, to realize a model from real-world and combining, through embedded sensors, the data from measurements made in the physical world [27].

Fig. 3. Deep Learning for DTNet: example of object detection in real-time using a mobile phone

Data

The other main component of the digitalization puzzle is the communication between the physical object and its digital twin, which must take place in the most effective way and in line with the requirements: the communication architecture in terms of protocols must therefore be precisely defined network and HW, Hardware, and SW, Software, interfaces. The latest generation machines have HW and SW components that allow

communication with the outside world, while the older generation ones - still widely used in production plants - are not equipped in this sense.
The management of a large amount of information is a "conditio sine qua non" to optimize the production dynamics of smart factories and to ensure the passage of companies to Industry 4.0. in light of self-awareness and self-maintenance machines for industrial big data environment [28]. However, most of the time, the datasets are either too generic or too specific so you often have to create a dataset for your needs, as it will be demonstrated in the following sections [29-30].
In light of this and thanks to the use of new technologies, data acquisition is possible not only via the internet (site, social media) but also via wireless networks, mobile devices, heat detectors and NFC in real-time [31-33]. In fact, the IoT devices play a crucial role. The sensors allow the measurement of selected physical quantities to be sent periodically to the digital twin, and actuators that enable the digital twin to be able to send data that can be translated into actions in the physical world [2].
The adaptation to the typical canons of Industry 4.0 can also be obtained for this equipment by adding sensors and processing modules (embedded systems) capable of detecting and transmitting the quantities of interest (a technique called refitting, which must be implemented without interfering with the control electronics possibly already present).
It must have as a fundamental component a database designed to manage very heterogeneous information, which can range from the master data of the machinery (static information, unchanging over time such as date of purchase, cost, manufacturer, model etc), to the history of maintenance operations (variability relatively slow), up to the data collected in near-real-time by the on-board sensors, flows much more significant than the previous ones which generate a much greater volume of data. The structure responsible for data management is joined by one or more SW modules that make up the intelligence of the digital twin. These can include simulation tools (of the machine) and sophisticated algorithms which, being able to act on information measured in the physical world in addition to the estimated one, are able to provide extremely accurate results and information.

Prediction and optimization

The last part of the Workflow proposed is the predictive analysis phase.
Within this phase, the data collected is mainly used for two very distinct reasons:

- for current investigations, to know when a certain anomaly occurs and how to remedy it;
- for future investigations: in this case, the data are not used for a purpose that is poured into the product immediately but are used to try to anticipate what may happen in the future; anticipating malfunctions, improving over time certain features that the product offers are an example of what could concern these analyzes.

3 Proposed approach – A holistic view of Smart Factory

3.1 New approach to Smart Factory in the context of I4.0: CMon formula to implement digitalization in any system

This paper wants to define a formula – CMon (Figure 3) - in a holistic way to identify the basic parameters for the digitalization of the industrial sector, reflecting its main characteristics:

$$H + 3D + 2C + IoT \rightleftarrows I4.0$$

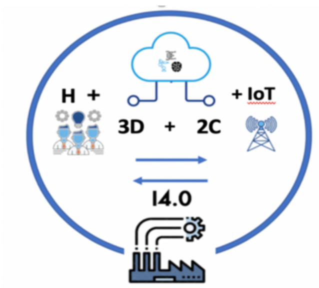

Fig. 4. CMon-formula for I40

Where:

- **H** : Human capacity/skills-Human-machine interaction
- **3D** : The 3 key-elements: data, deep learning, devices
- **2C** : Cloud computing and Communication
- **IoT**: Internet of Things

The elements of the proposed formula are here presented in light of their main characteristics and represent the key elements to be a smart industry in light of the requirements of I4.0, following the building blocks of the workflow presented in the previous paragraph. The results are focused, in this paper, on the relationship between 3D and IoT. In particular, how built in a real-time and easy way a DT complying the needs of the digitalization of traditional industries.
Further details, including the technological and architectural choices for the information system and the methods of communication, can only be defined and tailored by analyzing the specific case of interest, through the proposed API “DTNet®”

3.2 The definiton of the research parameters for DTNet

Design phase

As presented, in the previous section, the research is focused on how to realize a tool to design a DT through Deep Learning. Here are considered the main design parameters of the proposed DGNet model.
The concept of a new product is created according to needs dictated by users and particularities of the current fashion. Even characteristics of old products affect the development of the new.
The proposed API, DTNet, is the model of an object to which data exchange features are added with its correspondence in the physical world and which follows its evolution over time keeping the virtual representation updated.
Starting from this relatively generic definition, it is possible to identify some essential requirements for the physical objects of which you want to create a digital twin, as well as some functionalities necessary for the information system in charge of managing their virtual representations. It is important to note that, although the context referred to below is that of manufacturing (the one in which the concept of digital twin originated), the considerations made can be applied to any digitization process.
As presented, in the previous section, the research is focused on how to realize a tool to design a DT through Deep Learning [33-39].
Here are considered the main design parameters of the proposed DTNet model.
The concept of a new product is created according to needs dictated by users and particularities of the current fashion. Even characteristics of traditional products affect the development of the new.
As a concept, that is, an initial development phase, it represents an initial project of how the product will be created without taking into account its software or hardware characteristics. More than anything else, we will take into account the functionalities and how the assigned tasks will have to be carried out: at each creative cycle a design will be proposed and it will be necessary to verify whether the functionality and the foreseen tasks respect in an adequate and advantageous way the user needs.
It is therefore useful to be in possession of a virtual element that acts as a support for these continuous iterations, relating if necessary, with the previous versions of the concept itself. It will therefore be necessary, as the product concept develops, that the digital twin grows hand in hand.
Another very important element that affects the design phase is the opportunity for communication of the digital twin with other digital twins in order to obtain from them information concerning them. Thanks to this particularity, it is thus possible to obtain further information concerning, for example, products already on the market in order to foresee and correct problems connected to them in advance.
However, creating a digital representation of a tool assembly for simulation purposes is far from simple.
Traditionally, to obtain the most accurate representation of a tool assembly in a CAM system, the operator must first search for the necessary information in the various sup-

plier catalogues, then download the 3D model files and assemble them in a CAD program. This is today the only way to obtain a tool assembly in the CAM system, including all technical parameters.
It's possible to distinguish the:

- Digital Twin Prototype (DTP), which describes the prototype physical artifact and contains the information sets necessary to describe and produce a physical version that duplicates or twins the virtual version;
- Digital Twin Instance (DTI), which describes a specific physical product corresponding to which a single Digital Twin remains connected for the entire life of the product itself.

According to a Gartner study, in 2018 48% of the companies interested in the IoT are planning the use of Digital Twin, which would allow testing the solutions before they are applied and would agree in economic terms: it would save about 50% of the time and production would increase by 20%, demonstrating potential growth in short term and long term [40-44].
The model of this research, instead, consider the realization of a DT in real-time and without downloading a 3D model. The model is based on Deep Learning applied to video recognition and on the Human-Machine collaboration in a Virtual Reality environment, in particular through CCNs (Convolutional Neural networks) [33].

4 Conclusion and Future work

Up to now, the operating and design phases, for example the industrial level, have always been conceived as two totally unrelated phases that did not need to communicate with each other. Thanks to the digital twins, it is possible to combine these phases and keep an eye – before, during and after the engineering phase – on potential weaker parts/process more carefully in order to understand where and how the problem could actually occur through the elaboration of the data collected in real-time using artificial intelligence techniques [40]. This represents a benefit for the future of the product itself and it can bring benefits to new possible products that will be created instead of recognizing the problem only once the complete product is on the market.
Up to now, moreover, the operating and design phases have always been conceived as two totally unrelated phases that did not need to communicate with each other: the data collected during this phase as well as having a benefit for the future of the product itself can bring benefits to new possible products that will be created.
During the engineering phase, parts could be identified that in the future could easily create problems to the product structure and decide to want to find a solution to this problem only once the complete product is on the market. Thanks to digital twins, it is possible to keep an eye on these weaker parts more carefully in order to understand where and how the problem could actually occur also taking into account the needs of a more sustainable and eco-friendly industrial production [45].
At the same time this large amount of data, related to the simulation models always built in the engineering phase, improves all those services that could be requested by

the user, such as maintenance; in this way, intervention times and times to find the cause and solution to the problem decrease drastically, bringing benefits to the company both for evident savings in maintenance costs and for customer satisfaction.
In this research, in particular, as reported in the proposed workflow (Figure 2), it is the combination in real-time through smart technologies of the aforementioned phases the basic parameter for the digitalization of a system, specified in the proposed formula CMon. In the proposed "smartification" the key element is the realization of a Digital Twin. In fact, the core and next step of the research will be the API realization – DTNet- for the design of a Digital Twin of any system from any device in real-time through deep learning techniques - without downloading 3D model - and potential integration in the VR environment.

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