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Review article

A comprehensive study on current and future trends towards the characteristics and enablers of industry 4.0

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ABSTRACT

Since the first Industrial Revolution the trends in manufacturing have evolved a lot, from mechanical production to the era of smart manufacturing via technologies like Cyber Physical Systems, Internet of Things, Big Data, Cyber Security, Cloud Computing, Additive Manufacturing, Advanced robots, Modelling and Simulation and Augmented Virtual Reality. These technologies are enabling Interoperability and integration of various processes and departments in an organization because of the attribute of real-time inter-connectivity. Due to high inter-connectivity advantages like shorter development time, mass customization and modularity, configurability can be brought into existence. This will not only change the dynamics of the production lines but also add to the profit ratio of an organization by controlling over inventory via virtualization and predictive manufacturing. Due to such attributes of the Industry 4.0 paradigm, understanding them in depth is necessary. Hence, this paper aims to review many such characteristics, enablers, and main drivers of the Industry 4.0 paradigm and ultimately provides insight on the future scopes of each of the main pillars of Industry 4.0.

1. Evolution of industry 4.0

Industrial Revolution (IR) began in the late 18th century, which changed the world's perspective about manufacturing and production. With the First IR, which brought Walter's steam engine to light, the focus of production shifted from manual craftsmanship to mechanical production [1]. The first IR gave importance to charismatic leadership. The decision-making power of an organization completely relied on the leader and his personal characteristics. The manufacturing practice emphasized more on high-speed mass production due to the introduction of electrical power and transfer line by Henry Ford, with the Second IR. The management of an organization in the Second IR was influenced by scientific and hierarchal assessment with directive leadership [2]. The Third IR introduced the combination of information technology and automation via Programmable Logic Controller (PLC) to increase the efficiency of manufacturing and to increase productivity [3]. The Third IR focused on relational leadership and gave scope to newer ideas for innovation and collaboration. With the help of Information Communication Technology (ICT), applications like computer numerical control (CNC) and industrial robots, technologies for computer-aided design (CAD), computer-aided manufacturing (CAM) and computer-aided were developed in the third IR [4]. The Fourth IR gave limelight to an existing era of Cyber Physical Systems (CPS), Internet of Things (IoT) which enable integration of physical and digital domain in real time [5]. Industry 4.0 paradigm has shifted focus to transformational and swarm leaderships, where organizational elements are highly capable of taking decisions on their own [2]. This decision making process is accelerated via real time data acquisition through sensors, actuators and inter-connectivity of the physical and digital realm. The evolution of Industry 1.0 to Industry 4.0 as shown in Fig. 1, has indeed changed the outlook of manufacturing processes and organizations towards a more flexible, smart, predictive, and controlled environment. Thus, this paper sheds light on the technological advancement in the Industry sector while concentrating on novel approaches employed by each enabler of Industry 4.0.

2. Architecture of industry 4.0

The application push for Industry 4.0 is due to ever increasing demands and mass customization requirements of customers. These are related to increased mechanization and automation, increased digitalization and increased miniaturization of devices [6]. In the initial IR's

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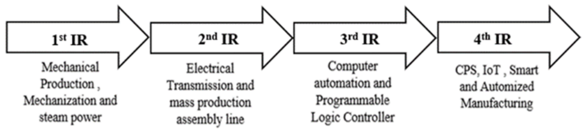

Fig. 1. Evolution of Industry 1 to 4 from Mechanical to Smart Manufacturing [5].

hierarchical and heterarchical architectures were prominent but these have failed to show satisfactory performance in today's dynamic environment [7]. Hybrid architectures with decentralized control are in major focus in the Fourth IR. Industry 4.0 helps in integrating physical objects, operators, production lines, machines, and customers to generate a one of its kind value chain and architecture as shown in Fig 2. [8].

This is enabled via CPS, IoT, big data, simulation and modelling, integrated value chains, augmented reality, robotics and additive manufacturing [9]. Networked and interconnected manufacturing helps in increasing interaction within the organization, productivity, flexibility, efficiency and assists in inventory control. Using these technologies applications like smart factory and manufacturing, smart product and Business model can be achieved [10,11]. In Smart Factory and Manufacturing with the help of sensors, actuators and automation systems factories can be made highly flexible, intelligent, and dynamic. High-level of optimization and automation can be expected from using the enabling technologies of Industry 4.0. Due to increased exposure of industries to information, various integration methods and techniques have been introduced to the Industry 4.0 architecture like Business Process Management (BPM), Workflow Management (WM), Enterprise Resource Planning (ERP), Service Orientated Architecture (SOA), Supply Chain Management (SCM), Enterprise Application Integration (EAI), Operational Execution, Control Level and Field Level [4,12]. Reference Architecture Model Industry 4.0 and Industrial Internet Reference Architecture, which are standardized have been used effectively in some industries [13].

3. Characteristics of industry 4.0

The characteristics of Industry 4.0 leads to a significant change in productivity, quality, lead time, time and cost to market, employment, and economic growth. The Industry 4.0 era focuses more on real-time analysis and dynamic control so that the data collection throughout the whole process, feedback and monitoring can be acquired in real-time [14]. Interoperability is an important characteristic which leads to process integration via software and real-time systems by unifying product and process data beyond organizational boundaries [15,16]. Another characteristic is flexibility, that is the factory's capability to adapt to changing situations and demands. This should be acquired in such a way that there is minimum or no disturbance to other production processes [14]. In a centralized approach decisions are taken by a central control unit. This requires a more responsive approach which is delayed due to long duration of feedback loops making decisions. Therefore, decentralization is a characteristic which allows each element of the process to make decisions and makes the system fit for dynamic environment. Organizational hierarchies are reduced to cope up with faster decision making [17] and hence making each and every element of the system autonomous and independent. Predictive manufacturing is another characteristics which helps in monitoring the performance of machines and connected products [15]. Configurability of the system refers to the capacity to reuse and replace hardware and software for integration and extension [18]. Controllers are reconfigurable and help in generating various ranges of products in the same line as emphasis is on minimization of reconstruction complexity and maximization of recyclability [19]. Hence all above characteristics have increased competitiveness through smart equipment, use of IT, resource efficiency, energy conservation and urban production [20].

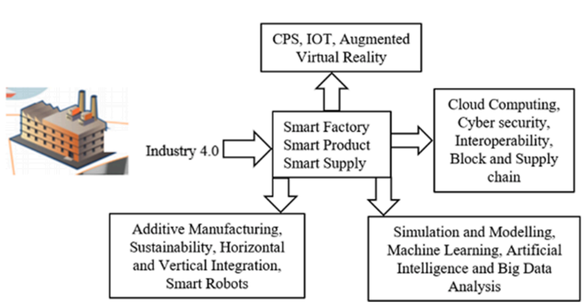

Fig. 2. Architecture with Organizational and Technological Enablers of Industry 4.0 [7].

4. Enablers of industry 4.0

The enablers of Industry 4.0 have been divided into two types Organizational and Technological enablers [21–23]. Organizational Enablers consist of organization design for inter and intra operability and organizational linkages. Even organizational structures are used for decision making and business models for data driven services and new forms of production. The present study focuses on technological enablers which are divided in four types as shown in Table 1.

4.1. Additive manufacturing

The fervent need of bulk fabrication of tailored products in Industry 4.0 can only be met by development or replacement of non-conventional manufacturing processes [24]. The capability to create refined entities with enhanced features makes additive manufacturing fit for fabricating customized products [25]. In the industrial sector, the fourth revolution will drive changes in the sourcing of raw materials, delivery of finished goods and assembly processes making them more efficient, flexible, and inter-connected. Moreover, it can be programmed to produce less waste and maintain sustainability during the processes, with its ability to produce products at the point of application [26]. For a drop on demand customised production system, it can play a crucial part in overcoming the design boundaries, thus making industry economically competitive [27]. Most of the AM technologies comprise of features like recycling of material that helps to meet the sustainability standards which can be represented as an shift of industrial paradigm [28]. This section reviews the advancements in materials, processes and capabilities of AM technologies along with the constraints.

4.1.1. Advanced materials used in AM technologies

With the rapid shift in manufacturing process requirements, research in material science has increased steeply with the ease of designing flexible complex composites using AM technologies. In additive manufacturing of metals advanced materials like titanium alloys have been utilised extensively in industries like aerospace, defence and marine industry to manufacture parts with notable differences in terms of

Table 1
Technological enablers of industry 4.0.

Categories of Technologies	Enablers
Digital/Physical Process Technologies	Additive Manufacturing, Sustainability, Horizontal and Vertical Integration, Smart Robots.
Data Processing Technologies	Simulation and Modelling, Machine Learning, Artificial Intelligence and Big Data Analysis
Network Technologies	Cloud Computing, Cyber security, Interoperability, Block and Supply chain,
Physical / digital Interface Technologies	CPS, IOT, Augmented Virtual Reality

processing parameters [29–31]. Investigation has been done by the fabrication of products made of α- β alloys of Ti-6Al-4 V for commercial purpose by additive manufacturing methods [32,33]. Other derived alloys that are of significant interest include Ti-6.5Al-3.5Mo-1.5Zr-0.3Si (aerospace applications) and Ti-24Nb-4Zr-8Sn and Ti-6Al-7Nb (biomedical applications) [34].

Shape Memory alloys and polymers (SMAs and SMPs) are currently being utilised as 4D printing material to produce functional parts of folding structures and soft robotic components such as micro-electronic devices and biomedical structures [35]. Also due to the sensitivity of SMPs to external stimulus (temperature gradient, humidity and light) digital light processing techniques are employed in the area of clothing and jewellery to produce customised products [36]. A study presented the idea of utilising hydrophilic polymer in combination with water, to generate 3D shapes based on design inputs which concludes the favourable evidence of designing self-assembled structures [37].

Most of the biodegradable polymer based resins which have been suggested for usage in Stereo lithography have largely been based on polypropylene fumarate, Poly- lactic Acid (PLA) and Poly(caprolactone) [38,39]. For instance, PLA copolymers have been utilised for modifying tissues based on products developed using Vat-Polymerization process [31,38]. Printed active composite (PAC) structures demonstrate equivalent functionality characteristics when processed via material jetting process [40]. In the clothing and jewellery industry, increased usage of AM has been witnessed with added advantages of quick design process and decreased costs allocated to transportation and packaging [41,42] . Food industry has also made giant leaps by introduction of AM in production of customised packaged goods based on desired surface texture using the deposition based technique [43].

4.1.2. AM processes and technologies

Most of the prevalent AM processes are distinguished on the basis of type of setup they require and the stock material form. Powder based techniques like Selective Laser Sintering (SLS), Selective Laser Melting (SLM) and Electron Beam Melting (EBM) [44], whereas in Direct Energy Deposition (DED), techniques like laser engineering net shape (LENS) are prevalent [33]. In Laser Metal Deposition, usually argon or helium lasers are used, where a coaxial nozzle is used to feed the metal powder [45]. Similar to Binder Jetting, Nanoparticle Jetting is used to form very thin layers of the manufactured part by the means of heated metal nanoparticles inside a liquid medium that are jetted using fine nozzles [46]. Another novel process referred to as Atomic diffusion additive manufacturing (ADAM) was developed where layer by layer fabrication of metal can be done [47]. In unconventional layer-wise VP processes, computed axial lithography (CAL) has appeared recently, where a light energy is incident on to a rotating vat containing the photosensitive resin [48]. Apart from general material extrusion techniques, direct ink writing (DIW, 3D dispensing, 3D extrusion, 3D plotting) is a process which prints by solidification through a defined process of drying, cooling and chemical reactions using viscous inks [49–51]. Based on DIW, a multi-nozzle 3D printing system was recently developed, which can be revolutionary for multimaterial printing industry [52].

4.2. Horizontal and vertical integration

Synchronization within the industry provides an edge within the manufacturing system and supply chain. Implementation of agile operational processes and efficient flow of information needs to be ensured along with technological advancements in the production system [53]. This makes integration of systems a crucial aspect in the Industry 4.0 vision to achieve desirable goals [54]. Hence, conceptual model of integration needs to be developed that can describe the layout of vivid activities in the manufacturing, operations and management [55]. Vital processes like 3C mechanisms (Coordination, Collaboration, Cooperation) can help in tackling issues of interoperability between various links in an Industry 4.0 based value chain [56].

Horizontal integration involves the binding of industry and customer in an intertwined network of information, management systems and products. Through the integration of the Network IT technologies and manufacturing systems an exchange of data and information can be established between the firms and the geographically remote sites [57]. Transformation in terms of digital architecture will make supply chains smarter, more transparent and more efficient at every stage, from customer needs to delivery. On the other hand, vertical integration involves the combination of basic elements such as the, employees, departments, organizational structure and technology in the development and execution of company activities [58]. It inculcates intelligent working with its products and production processes simultaneously managing the levels of inventory and maintaining the failures of machinery, to support the cyber-physical production systems [59]. It helps in identification of criteria to measure different segments in the industry on the ground of various parameters. This helps in recognition of asset entities in the firm, thus boosting socio-economic behaviours [60].

4.3. Augmented reality

Augmented Reality (AR) can be characterized as a facet that enriches the real world with virtual objects generated on a computer which look as if they exist in a similar location to the real world. A few instances of AR applications consist of tele robotics, medical domain, repair and maintenance, entertainment, military training and manufacturing [61,62]. Presently, AR content creation may require redesign of infrastructure such as camera and fiducial marker placement. It may also need unique knowledge of domains such as interface design, modelling in 3D, spatial tracking and programming [63]. This enabler of Industry 4.0 ensures higher levels of awareness on the shop-floor and speedy information distribution due to enhanced technologies for communication like the 5 G network with high speed data transfer [64]. Symmetrical communication amongst parties with the correct information in the correct place is one of the major advantages of Augmented Reality [65].

4.3.1. AR in design and development of products

AR is significantly used in the product design and development domain as it prevents errors in design in early development stages, moderates the number of prototypes (physical) and saves the enterprise's time and money [66]. Decision-making actions during the product design process play a key role for the realization of the final product. AR in Industry 4.0 requires a high level of interconnectivity and thus Machine learning acts as base for providing it with the tools required for implementation [67]. A certain study proposed an application that uses Augmented Reality (AR) to obtain feedback with the help of the internet from a target user. This is used to explore the aesthetical appeal of discrete products in the conceptual stage itself [68]. Another research focused on a real case study in the oil and gas department where improvements and modifications in the design of pipes need to be made on site. An augmented view of the final product is provided by the AR tool developed in this case-study by carrying out a precise superimposition of the 3D models that the technical officer designs which is beneficial for the on-site engineers during the design process [69]. In the automotive sector, AR is used for the assessment of interior design in the early stages of development which is done by superimposing various car interiors [70].

4.3.2. AR applications in assembly

Augmented reality technology brings about a unique approach towards assembly guidance in the conventional manufacturing sector. AR supports the assembly tasks by providing the necessary instructions in the field of view of the operator which helps in saving time for retrieving and sending vital information [71]. Determining 'when, what and where' to display this information (virtual) in the augmented reality world is one of the major AR assembly constraints. A certain research paper proposed the use of an AR based smart glass that would run a self-developed software for instructing new workers about the assembly process of printed circuit boards (PCB) [72]. In another article a worker orientated system that consisted of a multi-modal AR system integrated with deep learning for tool detection during the assembly process was developed to reduce time and error [73]. The experimentation of this system was carried out on the mechanical assembly of a CNC machine for carving. The conclusion of the experiment showed that this AR system reduced the time by 33.1% and the error by 32.5%.

4.3.3. AR-based maintenance and repair

Industry 4.0 has built an ecosystem wherein there is a substantial increase in the digitisation of the manufacturing environment. This type of digitisation has mainly taken place for maintenance and repair manuals which were all printed by hand before [74,75]. There are mainly two types of AR systems used for supporting maintenance tasks: mobile collaborative (MCAR) and online mode systems [65]. All the important information should be uploaded and converted into virtual models beforehand in the online mode systems. The MCAR system, however, permits quite a few people to use their mobiles devices to share an AR experience. A novel approach for remote maintenance using AR programs develops an application which connects an unskilled operator who is located where the maintenance task is performed with a skilled operator in a control room [76]. Aeronautics is a challenging and intricate field from a maintenance point of view as the aviation industry needs to provide spare parts in a short time to remote places. In this industry problematic maintenance tasks are many a times needed from unskilled local operators. AR can be used to define 'Augmented Maintenance Manuals' and 'Illustrated Parts Catalogues' where the position of the part that needs to undergo maintenance is shown by an intuitive way to the operator on the real aircraft [77].

4.3.4. Robotics and augmented reality

For increasing the production output and efficiency of processes, industries who have implemented Industry 4.0 for automation tasks have often used robotic manipulators [78]. Industrial robot programming is done using a teach pendant or offline programming. Both these methods have their own disadvantages as offline programming using software requires CAD models and teach pendant method requires shutting down of the entire production line. A research using marker based and marker-less AR technologies was carried out to develop a user-friendly and extremely intuitive method for robotic manipulator teaching [79]. In the AR environment, the virtual robot model and the actual object co-exist. Hence, the workers can ensure that there is no robot singularities or collision by jogging the virtual robot to reach target points on the actual workpiece [80]. Human-robot collaboration is another sector which has developed greatly due to the adoption of Industry 4.0. In a study, researchers introduced AR for human-robot collaborative manufacturing that consisted of four sub-systems as shown in Fig. 3. This research made a worker-support system that was made of an AR-centred instruction system, planning and re-planning of the task sequence, monitoring of workers, and industrial robot control [81].

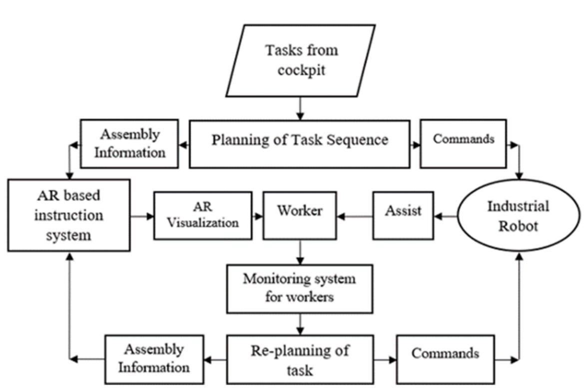

Fig. 3. Flowchart of the Worker support system (AR-based) [81].

4.4. Advanced robots

To meet the requirements of intelligent and collaborative manufacturing, robotic technology plays an important role in contributing towards the boom in Industrial Internet of Things and Industry 4.0 [82]. The significant increase in the need of automation has been met by fully automated workstations which use high-performance Industrial robots [83]. To ensure operator safety, high rates of production and limited workspaces, pick and place machines with Anthropomorphic manipulators have been implemented. Various enabling technologies such as deep learning [84], adoption of Raspberry Pi as an embedded computer board, Natural Language Processing (NLP) [85], cognitive robots that are human-friendly [86] and physical industrial systems that are collaborative [87–89] have resulted in a 'Big Bang' in the industrial robotics field. Industrial Internet of Things [90,91], Cloud based systems [92] and secure and faster connectivity were integrated into robotic systems to ensure better functioning. Robotics 4.0 (beyond 2020) [93] systems are generally cloud based, allow natural interactions, and have a hybrid intelligence level when it comes to cognition, motion, perception and computing.

4.4.1. Collaborative robots (cobots)

Research based on integrating operators problem solving skills and flexibility with a robots durability has led to great interest in cobots or collaborative robots [94]. On the shop floor Human-robot collaboration (HRC) can range from robots and humans working together on a shared object to both these entities coexisting in a shared workspace. A study describes a collaborative robot system (dual-arm) that allows flexibility in manufacturing and is generally used to disassemble mock up mobile phones [87]. The robot is fit at the rear of an Industry 4.0, line of production which consists of FESTO Cyber-Physical (CP) modules. Major drawback of these cobots lies in their ability to work with humans and guarantee their safety. To overcome these limitations, a novel workstation is proposed in a study, called "Meta-Collaborative workstations" (MCWs). In these either a virtual or physical safety cage is present behind which the robot operates and the operator interacts with either the Industrial or Collaborative robot naturally and intuitively [83]. A novel software tool based on 'Maximum entropy inverse optimal control' was developed for shared collaboration workspaces for humans and robots [88]. The theme of humans focusing on tasks requiring creativity while the other work is done by robots is an emerging characteristic of Industry 4.0 [89].

4.4.2. Robot programming

The two founding pillars of Industry 4.0 are agility and flexibility in production. However, robot programming is generally a time consuming, detailed task that requires highly skilled personnel [95,96]. A company may own robots of various companies like ABB, Fanuc or Kuka which further complicates this process. To uncomplicate this process a paper suggested a robot program builder software called MEGURU (meta-collaborative gesture-based robot program builder) that uses R-FCN Object Detector's to recognize gestures (commands) and the software is ROS (Robot Operating System) based [83]. For medium scale industries, the software used for teaching robots needs to be simple and non-time consuming as they do not have the resources to hire specialised personnel. To ease this programming of Industrial robots a research was carried out to develop a task-orientated control system that is cloud based with perception of the environment and has plausibility check functions [97]. A framework for programming that uses paradigms like (LBD) Learning By Demonstration, (LBI) Learning By Interaction and (LBP) Learning by programming to overcome the challenges faced while programming collaborative robots [98]. Many of these new ways of programming robots requires physical interaction with the robot. Hence the need for developing and integrating artificial skins, robust methods of teaching and control schemes are essential for developing faster programming techniques and safer ecosystems for Industry 4.0 [99].

4.5. Simulation

Simulation has been used to assess the behavioural performance of different processes over time. Initially Simulation was just limited to specific applications. With development of technologies and advancements due to the fourth IR multi-level simulation with development of a concept called Digital twin has been possible [100]. Simulation is an important technology for development and creation of models for purpose of optimizing decision making. It helps in assessing risks, inventory, barriers for implementation and effect on performance of different processes in an organization. The key components of the simulation process are Modelling, System and processes and Simulation Analysis [101]. Many modelling techniques like the 3D modelling via CAD/M, AutomationML, Business process modelling, Entity Relation models, Simulink, FlexSim, SysML, UML, XML, Metamodelling have been used to model real-time products, processes, businesses for simulation purpose [102,103].

4.5.1. Simulation techniques used in the industry 4.0 paradigm

Due to requirement of mass customization and direct exposure of the organization to customer needs planning, organizing, and dynamic scheduling of the shop floor is significant [104]. Simulation has enabled predictive and cost-effective manufacturing via technologies like digital twin and simulation-optimization methods which are discussed further. The various simulation techniques that have been used are discussed in Table 2.

4.5.2. Digital twin (DT)

Simulation depends on the mathematical or logistic models, whereas the DT depends on actual data from physical parts of the process. A DT is the replica of a physical element or process interconnected via dual mapping in the physical and digital realm. The architecture of the DT consists of 3 main layers [105], as shown in Fig. 4.

The DT has two parts a digital master and a digital link. The digital master is the universal model of an asset or a machine which is connected to the real world via an intelligent digital link through algorithms

Table 2
Simulation techniques used in industry 4.0 [101].

Sr No.	Simulation Technique	Description
1.	Agent- Based Modelling and Simulation (ABMS)	Simulation of complex models compromising of interactive autonomous agents.
2.	Discrete Event Simulation (DES)	With help of Process Flow-charts changing variables at certain discrete points in an event are simulated.
3.	System Dynamics (SD)	Analysis of dynamic systems using stock, flows and feedback loop diagrams
4.	Augmented Virtual Reality (VR)	Experimental simulation in the virtual world via ICT Technologies to increase user's perception, via various activities.
5.	Petri Nets Simulation (PN)	To model more flexible production units graphs of discrete events are obtained via analytical tools.
6.	Hybrid Simulation (HS)	Hybrid Simulation means combining two or more types of simulation like the Simulation Optimization method, DES-ABMS, SD-ABMS etc.
7.	Digital Twin	Built in different levels the digital twin mirrors the real world in the virtual world and helps in analysing various situations for better decision making.

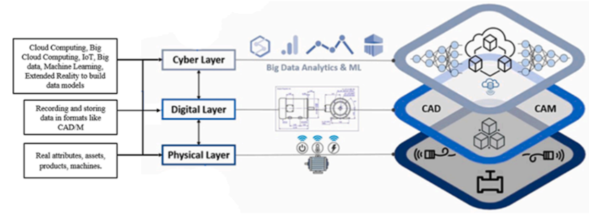

Fig. 4. Three layers of DT [105].

and correlations of the two components. The DT allows the operator to train on virtual machines until the required skills and confidence is acquired by the operator. This accelerates the learning process without any damage to the actual machine [100]. With the help of DT verifying product functions, behaviour, structures and manufacturability, Product life cycle, finding defects in a design in the virtual world, improving the design is possible. DT reduces the product development cycle, increases efficiency of production, ensures stability, accuracy and quality [106]. This involvement and continuous interaction of the manufacturing facilities and line with the simulation models may change dynamics of the production process [107]. Simulation optimization works as the smart brain to improve efficiency of manufacturing systems [108]. Depending on the type of problem to be analysed there are different optimization techniques in combination with simulations that can be exercised in the industry 4.0 paradigm [109,110].

4.6. Industrial Internet of Things (IIoT)

IIoT deals with interconnected sensor-cloud systems which sense, analyse, store, and solve real time data. It utilizes IoT frameworks which are specifically generated for the application it is utilized in. The word 'Industrial' in IIoT portrays the utilization of IoT only for specific industrial application ranging from optimization of production lines to monitoring in-process environment and real-time data analysis [111]. IIoT also provides surveillance, health and hazard monitoring as well as smart grid applications which are important for preventive measures and safety [112]. These applications are important for ensuring smooth running of industries through remotely operated machines and systems. The architecture of IIoT is an important aspect as it deals with the implementation aspect for specified industrial applications. The architecture is generally a three-tier system which is designed based on services and requirement [113]. The three tiers are enterprise tier (application layer), platform tier (management/access layer) and edge tier (data collection layer) as shown in Fig. 5. These architectures are utilized for several applications from healthcare to military industries [114–116]. Presently, it is the era of 5G- based technology, blockchain

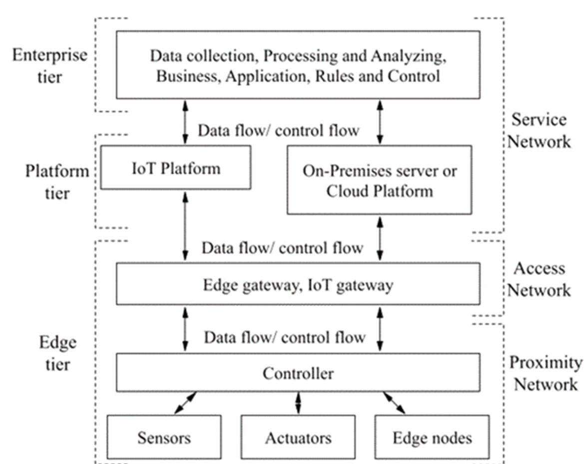

Fig. 5. A 3-tier Architecture of IIoT [113].

and edge computing, which have aided the growth and implementation of IIoT based systems. These emerging technologies are discussed in further sections.

4.6.1. 5 G technology for IIoT

Currently, 5 G is still a developing technology in many geographical areas. Even then, its utilization for IIoT has already begun in several applications. 5 G communication technology is integral for industrial implementation as it brings added advantages such as low latency, improved communication across different modes such as M2M (Machine-to-Machine/Man), D2D (Device-to-Device) and high reliability [117]. In turn, it will also aid in the large-scale interconnection of several machines at reduced number of network levels. Presently, some major applications of 5 G that are shaping the smart factories are related to smart manufacturing [118–120], positioning of industrial robots [121] and secure network for autonomous electric vehicles [122]. These applications are yet to be implemented at a large scale as there are many factors to be considered in terms of safety, network availability and also availability of skilled technicians to work with advanced technologies.

4.6.2 Blockchain for IIoT

Blockchain is an emerging technology used to record data in a digital form using cryptographic methods to make them less susceptible to hacks, leaks or precarious access [123,124]. As IIoT is a data driven technology, it needs secure and trusted modes of handling and recording data. Blockchain provides a safer system which can utilize the data only for improving the application and not for any threatful actions. Blockchain applications in IIoT range from medical record analysis and storage systems, Electric Vehicle Cloud and Edge (EVCE) [125] and e-commerce for industries (cryptocurrency) [146]. It is also utilized for general applications like smart homes, smart cities and smart factory [126]. Recently, Blockchain Technology (BCT) has been used for enhancing Business Project Management (BPM) framework. The aim of the framework is to enhance the trustworthiness of a business and hence ensure quality service selection and composition [127]. The potential of blockchain in IIoT is quite promising but also faces several technological, security and privacy-based challenges which will improve over time [128].

4.6.3 Edge-computing in IIoT

Edge computing is a technology succeeding cloud computing. It brings the computation and data storage capabilities closer to the client location where it is utilized which improves response time and bandwidth. Edge computing improves the networking capabilities and also the efficiency of IIoT based systems. Current applications are related to Mobile edge computing (MEC) based Machine Learning task distribution for IIoT [129], BlockEdge [130] and edge security [131]. Currently Fog computing [132] is one of the successors for edge computing but it is still under intensive research.

4.7. Cyber physical systems (CPS)

Cyber Physical Systems or CPS are an integration of calculation and physical process, consisting of an embedded computer and networks that monitor and control the physical processes [133,134]. As an enabler, the emergence of CPS is assisted by several developments in IIoT. Advancements in networking systems enabled CPS's to be utilized for user-specific applications like cyber-physical production systems (CPPS) [135], cyber physical agricultural system (CPAS) [136], and also in conjunction to various IIoT based systems. The development in IIoT has improved the integration of sensor-cloud system with intelligent communication methods of the current IIoT architecture. This development forms the backbone of a stable and secure CPS [137]. Fig. 6 shows a general service-orientated architecture of a CPS with the internet forming a backbone for handling and integrating different sub-systems. Systems like control systems, equipment, sensor-actuator systems and the desired/target environment utilise this architecture where the CPS is to be employed [138,139]. Currently, there are many modern day developments in CPS as discussed in the further sections.

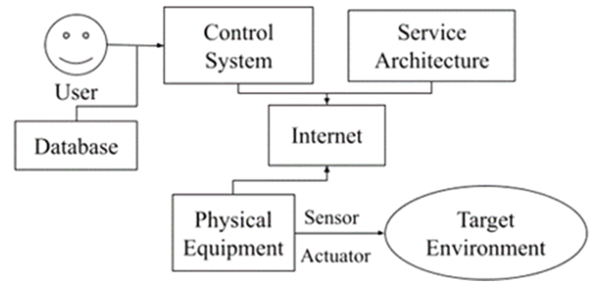

Fig. 6. General service-orientated architecture of a CPS [137].

4.7.1. Socio-cyber physical work systems

As CPS are an integration of physical component and cyber component, industries have begun working on creating socio-cyber physical work systems [140] which aims to improve the security, industrial output and also improve collaboration of workers with the systems [141]. Furthermore, developments in socio-cyber networks and utilization of big data are the forefronts of socio-cyber physical systems. The primary focus of such technologies is to improve the human-response and behaviour simulation which would aid in improving the collaborative nature of the system [142]. Currently, even though these are limited to manufacturing work systems, these systems are the future of collaborative workspaces for all industries.

4.7.2. Fog-computing industrial CPS

As an emerging trend, fog computing industrial CPS is under intensive research. The ultimate aim is to reduce latency between the industrial network and components involved [132] and also efficient task scheduling [143]. Furthermore, fog-enabled network architecture and services can meritoriously leverage the locally available resources in order to assist delay-sensitive IoT-applications in specific regions [144]. Integration of such technologies and physical systems has been at the core of several industries and the use of digital twins for CPS has been the latest work. It finds applications in smart factories [145] and as monitoring systems in manufacturing and process industries [146].

4.8. Big data analytics (BDA)

The amount of data in the world approximately doubles every two years, which results in huge amounts of data called as Big Data [147, 148]. Figuratively, the big data constantly changed in volume from Terabytes in 2005 and Petabytes in 2010 to Exabyte (Zettabye) in 2017. This seriously affects the computing and analytics required to manage such huge sizes of data [149]. Furthermore, with industry 4.0, the transition to integrated or cyber physical systems has led to an increase in the amount of data generated and hence has led to many analytical systems to be made to store, filter and analyse the data generated [150, 151]. As data continuously changes, the analytics or understanding of data has also evolved alongside it [152]. Currently, Big data forms a backbone for business intelligence as the data analysis and processing methods make the data more useable for specific applications [153, 154].

4.8.1. Big data for CPS

Big data has a huge potential to aid in reducing the breakdown rates and improve product quality and production rate for a better supply chain [155]. Fig. 7 shows a breakdown of the elements of big data important for CPS under the industry 4.0 framework. The system infrastructure deals with gathering, storing and computing of data from the CPS IT devices. On the other hand, data analytics is used to analyse

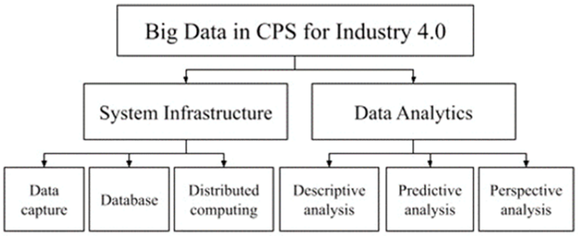

Fig. 7. Big data elements in CPS for Industry 4.0 [157].

the data and utilise it as per the required application. The two main components of CPS IT devices (cyber system) and physical devices collaborate together and communicate with other IT devices through big data techniques in conjunction to IoT. Data processing plays a major role as the communication across different devices needs to be efficient and seamless [156]. The aim of big data for CPS is to make this systems even more adaptive, intelligent and reliable [157].

4.8.2. Smart manufacturing using big data

Manufacturing has taken the shape of being "smart" which means being heavily deployed with sensors, RFID based devices and many more interconnected devices [106]. As more and more things and devices are interconnected to the Internet, a vast size of data is generated from the devices. This led BDA to become an essential tool for an efficient establishment of smart manufacturing technologies [118]. The key utilization of BDA for smart manufacturing in comparison to the conventional manufacturing is based on the adaptative learnings from previous information. BDA as a tool enables us to accelerate and optimize the product design faster than the conventional methods. Smart production planning is one of the most essential steps in manufacturing [158]. During the process, real-time data enables process monitoring, which makes use of wireless sensor networks (WSNs) [159]. The associated fast processing methods could help reduce plant shutdowns due to single process failures with early warning detection due to real-time monitoring. The virtue of predictability of BDA changes the traditional MRO (maintenance, repair and operation) methods as this predictability may be used for product life monitoring and fault diagnosis which would in-turn reduce or nullify the need of constant MRO.

4.9. Cybersecurity

In the present era as more and more physical devices are interconnected, the concerns of cybersecurity become more prominent [160]. A study proposed a cybersecurity mindset to move from "Human-as-problem" to "Human-as-solution" [161]. Cybersecurity is highly dependent on ethical practices followed by individuals and companies. Another study proposes 6 strategic principles of cybersecurity, namely, Confidentiality, Integrity, Availability, Authenticity, Nonrepudiation and Privacy [162]. These are principles to keep in mind while setting up any chain of interconnected devices and are a part of ethical practices to ensure security and privacy of users. The major effects of weak cybersecurity are related to IIoT [163] and CPS. Fig. 8 depicts the elements of Cybersecurity in the professional environment.

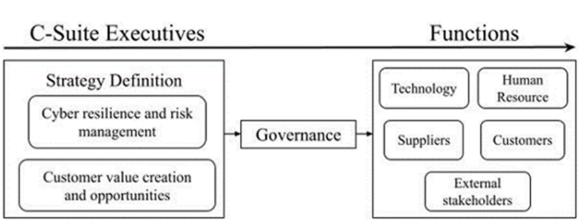

Fig. 8. Elements of Cybersecurity [164].

4.9.1. Layers of cybersecurity

A research proposed 6 layers of cybersecurity for ensuring safety of the technologies and data. These are the barriers through which hackers may gain access to an Industrial Control System (ICS) or any other CPS [165]. The foremost layer is Network Firewall which is the first line of defence against hackers, viruses, and malware. It is analogous to walls around a facility. The second layer is Physical security which involves use of surveillance systems to monitor the various locations such as main room, entry/exit points to enhance visible security. The third layer is eliminating loopholes by taking aid of experts to scan the systems for vulnerabilities which ensures that the software, antivirus and firewalls are updated with latest industrial standards. The fourth layer is Data encryption which basically means using passwords or digital locks to secure the systems and data. Longer and complex passwords ensure stronger encryption and lesser chance of hackers breaking into the systems. The fifth layer is deployment of trained personnel during the normal shift. The organizations needs to ensure certain individuals have the basic expertise to counter any successful data thefts and take necessary actions. The outermost layer is Business Continuity and Disaster Recovery (BCDR) which necessitates spotting potential threats (such as cyberattacks, natural disasters, IT system failures and fires) and preparing a continuity and recovery plan [166]. For this, backups are an integral part of BCDR as it stores all the crucial data, encrypted documents and sensitive information of the organizations [167,168].

5. Future scope

Industry 4.0 has revolutionized the way goods are manufactured on the production line and distributed across the globe. With continuous advancement in technology, various new developments will take place in the enablers and drivers of Industry 4.0. 4D and 5D printing has been an area of thriving research for exploiting the additive manufacturing techniques [169,170]. The recent advances in multi-material printing with material jetting has boosted developments in the area of biomimetic composite structures, microfluidic devices and sensors [171]. Even though most of the applications of AR at this point in time are experimental, it shows great potential due to its application in the manual assembly process and for visual tracking [172,173]. The major aspects of Augmented Reality that will be developed in the future are the Hardware devices needed for AR, Tracking or Recognition Algorithms and the Interaction that takes place between the User and AR [174]. Bionics and synthetic biology integrated with robots is another sector that might emerge as a unique part of Industry 5.0 [175]. The use of soft robotic grippers that work on either pneumatic actuator or shape memory alloys may play a significant role in the next Industrial revolution due to their ability to grip objects without causing any deformation [176]. Use of experimental digital twins for the development of future systems along with a development of a common database library for simulation algorithms will be required in the future [177] . The future scope of IIoT is prevalently based on technologies such as enhanced millimetre wave networks/5 G mobile communication, software-based interfacing solutions, edge and fog computing and blockchain based cryptographic applications [178]. The next step for CPS mainly involves large-scale interconnected devices (millions of devices), which will in-turn improve monitoring activities, remote control of factories and strong collaborative work environments across several industries [179]. Better acquisition techniques, improved data processing methods and integration with cloud and drastic improvement in security and privacy are future scopes of BDA [180–182]. The potential of BDA is quite detrimental as data will only increase in volume and the need to store, analyse, and draw conclusions from such enormous data set will become the future of data analytics. The future of cybersecurity is defined by a better model to define and understand it, more industry level standards for level of technologies, political laws to assist hacked facilities or companies and lastly proper training for incoming professionals to a basic counteractions guide against cyberattacks to prevent long term cybersecurity breaches.

6. Conclusion

Implementation of Industry 4.0 proves highly beneficial due to its ability to provide interoperability, flexibility, real-time processing, autonomy, predictability, and configurability to improve the functioning of traditional industries. This paper aimed at providing a brief overview on the characteristics and enablers of Industry 4.0 while also shedding light on the future scope for development. The novelty of the present study is the overview of modern-day applications which provide an interconnection across the various enablers. Additive manufacturing overcomes various challenges faced by traditional manufacturing processes; however, dimensional tolerances and reproducibility of products needs to be improved further. Well implemented horizontal and vertical integration in the industry provides good logistic and activity control throughout the supply chain which in the end leads to customer satisfaction. Augmented Reality offers fast distribution of information that enhances the manual assembly process while providing interactive guidelines to operators. Advanced Robots provide a unique solution to manufacturing problems in industries by improving the efficiency, productivity and reducing the cycle time for the various task. Further research on reducing downtime for robot programming and collaborative robots will prove essential in the upcoming Industry 5.0 revolution. Simulation techniques like the digital twin will prove helpful in predicting the behavioural performance of industrial processes.

Industrial IoT has always been one of the most important pillars of Industry 4.0 which has further progressed due to 5 G technology, Blockchain and Edge-computing. Security and privacy issues, lack of skilled labour, standardization and interoperability are the major challenges faced by IIoT. Cyber Physical Systems provide integration of systems and improves service; however, it faces challenges like scale, efficiency, pattern abstraction and robustness of systems when used in an industrial environment. Big Data Analytics provides smart manufacturing solution to industries and provide Business Intelligence to improve the business model. Cybersecurity is crucial when it comes to Industries and thus Industry 4.0 systems must be free of surface attacks, all loopholes must be eliminated, and all data must be encrypted. These enablers of Industry 4.0 provide a comprehensive solution towards increasing profit ratios, better supply chain management and faster manufacturing. Further development of these enablers will lead to enhancement of industrial systems for the next industry 5.0 revolution.

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The authors have no conflicts of interest to declare that are relevant to the content of this article.

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