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SPECIAL SECTION
Machine modelling and simulations

Modern methods in the field of machine modelling and simulation as a research and practical issue related to Industry 4.0

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Abstract. Artificial intelligence (AI) is changing many areas of technology in the public and private spheres, including the economy. This report reviews issues related to machine modelling and simulations concerning further development of mechanical devices and their control systems as part of novel projects under the Industry 4.0 paradigm. The challenges faced by the industry have generated novel technologies used in the construction of dynamic, intelligent, flexible and open applications, capable of working in real time environments. Thus, in an Industry 4.0 environment, the data generated by sensor networks requires AI/CI to apply close-to-real-time data analysis techniques. In this way industry can face both fresh opportunities and challenges, including predictive analysis using computer tools capable of detecting patterns in the data based on the same rules that can be used to formulate the prediction.

Key words: Industry 4.0; Internet of Things; Artificial intelligence; models; simulation.

1. Genesis

Today the economy is undergoing continuous change due to the development of artificial intelligence (AI) [1]. Since the twenties of the 20th century, we have witnessed ingenuity in the creation of many new branches of industry and the jobs assigned to them, but few of them related to traditional production or distribution. Since 1910 the number of people employed in industry, agriculture, etc. decreased rapidly. At the same time, the number of employees in specialist, managerial, office, sales and service positions increased threefold, the share changing from a quarter to three-quarters of total employment. Moreover, traditional production jobs have been largely replaced by machine work. The quick development of automation, robotics, mechatronics, AI and computational intelligence (CI) has created entirely new occupations. Working time may be shortened and even release the dormant potential of people, enabling them to implement their own projects, ideas and visions. Current development of the economy depends on innovation and the ability to implement new solutions, but we should be aware that emerging barriers and/or lack of effective support may significantly limit dynamic development [2].

Industry, in general, is one of the most technologically advanced areas of human endeavour in the world, with at least 60 years of increasing use of automation and robotisation. However, it is now much less susceptible to innovation than, for example, the IT industry, where the world's giants of innovative products operate. This leads to difficulties in implementing novel solutions – especially when the new methods or devices relate to safety issues in production facilities or allowing external access to production data (e.g., the creation of industrial teleinformation networks for Internet of things – IoT needs) [2].

Novel points may be linked in the production chain by using 3D scanning and printing technologies. Thus, there is need for a fresh approach to how we design and expand factories. Instead of the traditional architectural approach, it will become vital to take into account other, additional aspects in the organisation of the processes and product flows (e.g., in production buildings and elsewhere), internal logistics, the application of modern production technologies, support for efficiency and personalisation, automation of production and transport, robotisation, digitisation and additive manufacturing [3, 4].

The term "Industry 4.0" (the fourth industrial revolution) has been used for almost 10 years. This refers to the almost exponential growth in the industrial use of automation and data exchange in manufacturing technologies, including autonomous robots, smart sensors, the internet of things, big data and artificial intelligence, augmented reality and virtual reality (VR), 3D scanning and 3D printing, horizontal and vertical systems integration, and cloud computing and simulation in the form of virtual twins. This enables strong support for integrating and connecting physical objects, production lines and processes at all stages of the product and service lifecycle. The overall goal is to build highly agile value chains based on continuous, systematic, faithful processing of novel technical parameters that can be extracted through i.a., deep learning [5–7].

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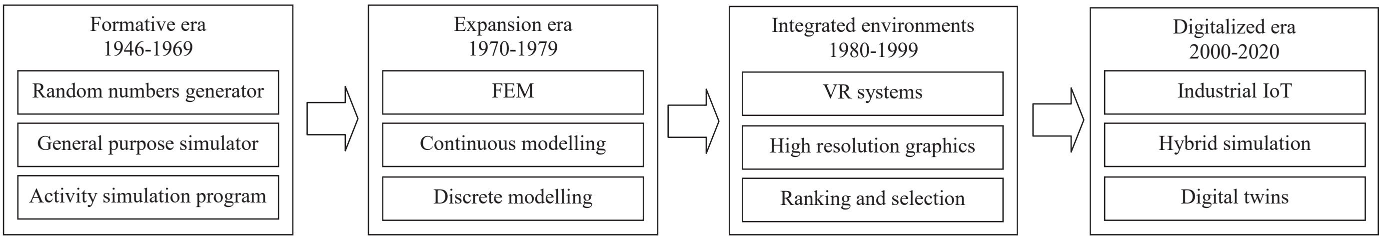

Fig. 1. Genesis of simulation (FEM – Finite Elements Method) [10]

Conceptually, the genesis of Industry 4.0 stems from Industry 1.0, which began in the 18th century with the introduction of water and steam to industry, which revolutionised mechanical production and agriculture. Then, in the 19th century, came Industry 2.0 characterised by the transition to the use of electricity, production lines and, consequently, mass production (both of materials such as steel and finished products) and the massification of transport and logistics in the broad sense. In the 20th century, with the advent of the digital revolution, Industry 3.0 developed – it was the result of the development of computers and information and communication technologies in industrial applications [8–9]. Industry 4.0 will develop the aforementioned concepts not only towards greater autonomy of production processes and their better optimisation and environmental friendliness, but also towards better use of information.

Machine modelling and simulation emerged from the construction of electrical computers in 1940s, when computational tools for creating models for system simulation became available (Fig. 1). Such models constitute a simplified view of system functioning for selected aspects of its operation, similar to the actual modelled phenomenon/object – assuming sufficient accuracy from the application. The behaviour of an object or the course of a process may be predicted through a series of calculations. Thus, a computer model is essentially programming which aims to describe the relationship between at least two quantities or a numerical representation of some features.

In this way the quantitative and qualitative description of a modelled process/phenomenon/object, assuming an adequate level of accuracy (e.g., using simplifying assumptions, etc.), allows the creation and testing of a structure (e.g., mathematical) that reflects this description. The speed and accuracy of the simulation may be enhanced using computational methods. We build simulation tools that allowed research into system behaviour taking into consideration various factors and levels of system complexity (Fig. 2). Usually computational models complement experimental studies, and since they lack complete understanding of the mechanisms of action, they may not take into account all the variables/parameters. Often a computational model is the only way to prove the appropriateness of a description or predict the behaviour of an object/process – due to time and/or space limitation, costs, legal restrictions, etc.

2. Current background

Research by Murtzis showed that simulation in the design and operation of manufacturing systems includes the following areas:

- Intertwined lifecycles of product and production.
- Product and production lifecycle simulation tools: CAD, CAM, CAPP, digital mock-up, material flow simulation, process simulation, layout planning simulation, ergonomic simulation, manufacturing execution systems, supervisory control and data acquisition, supply chain simulation, and the design and planning of the manufacturing network.

The volume of research has increased significantly since 1981 (1600% between 1981 and 2020). The most popular types constitute (related to the whole number of research):

- Simulation in manufacturing systems: 59.80%.
- Simulation in the design of manufacturing systems: 25.44%.
- Simulation in the operation of manufacturing systems: 10.28%.
- Simulation in the design and operation of the manufacturing systems: 4.48% (Fig. 3) [10].

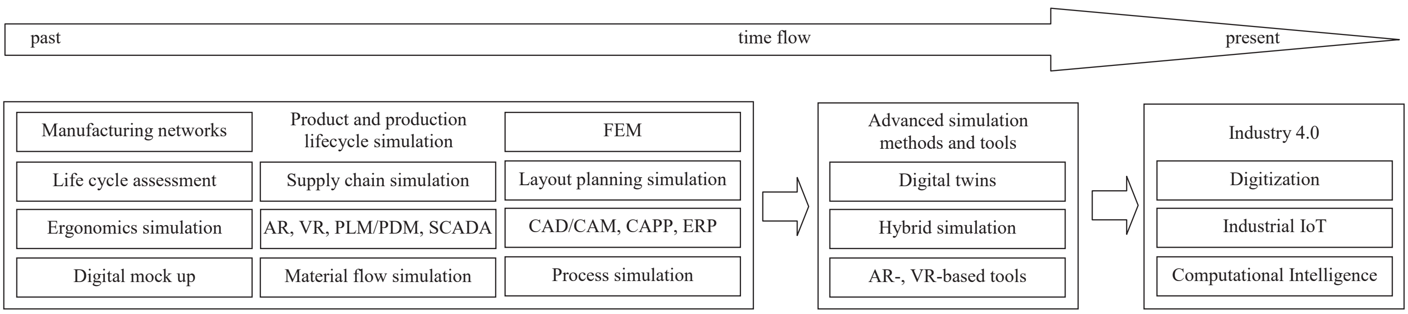

Fig. 2. Historical view of technological development (AR – augmented reality, PLM – product lifecycle management, PDM – product data management, SCADA – Supervisory Control And Data Acquisition, CAPP – computer aided process planning, ERP – Enterprise Resource Planning) [10]

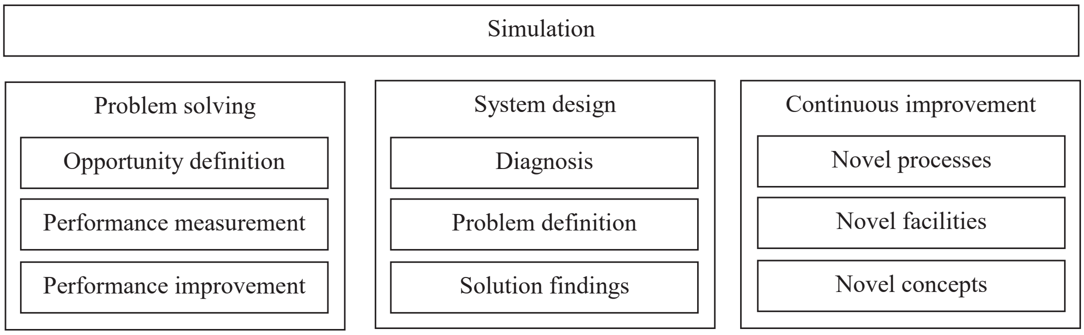

Fig. 3. The three pillars of simulation [10]

The most popular domains of research were computer assisted exercises (CAx), manufacturing systems, network planning and control, virtual factories, as far as material and information flow [10]. These relatively novel domains of study have developed dynamically recently in machine modelling and simulation history (some in the past few years). Such a situation emphasises the significance of the computational tool in our work.

At the end of the 1990s, special attention was being paid to the advantages of implementing such CAx tools as: creation of barrier-free production, minimisation of the expenses incurred during the technological phase of production preparation, reduction of production costs and product prices, while maintaining high quality. This was complemented by other achievements in the area of IT, thanks to which computer networks were able to control the state of the production process, auxiliary processes and financing, as these activities require efficient data exchange between different information systems, known as information islands [11].

At that stage additional advantages were discussed, such as doubling production, reducing unit costs by 15–25%, launching a new product 6 months before the competition, and increasing profitability by 25–30%. The implementation of CAx technology made it possible to include systems that play an essential role in data processing in many areas of the company. The main functions are planning, preparation and control of production processes, material supply, workstation and socket loads and the active control of work in progress. The percentage relations between these areas are shown in Fig. 4 [11].

Concepts that incorporate intelligent facilities or cyber-physical systems have already proved to have great potential, especially in the area of decentralised production planning and control. In this context, decentralised communication, new sensor technologies and the increased use of simulation and monitoring systems lead to a huge increase in production data [12].

In addition, a new approach is proposed for production quality assessment based on process signals from machine tools, to provide up-to-date information on tool condition and surface roughness for each production process [13]. These concepts have already proven their significant potential, especially in terms of decentralised production planning and control. The first concepts were evaluated based on test cases and led to individualised product-based production [14, 15].

In this context, decentralised communication, new sensor technologies and the increased use of simulation and monitoring systems can lead to a huge increase in available production data, such as machine data, product quality data or information on faults and disturbances. In recent decades, topics such as object technology, expert systems and data format standardisation (e.g., STEP-NC) have been studied as the basis for knowledge-based computer decision support systems [16]. Fayyad et al. proposed a procedure model that includes five stages of data processing: selection, pre-processing, transformation, exploration and interpretation of data [17]. Various algorithms are used, some of which have already proved their usefulness in the analysis of production data [18]. At this stage, we are dealing with huge amounts of very detailed information, and to this end it is necessary to follow the established structures of information systems in production, which leads to database inconsistencies [19].

The ability to produce trends in future production using the cloud should be of great assistance in this area, and provide

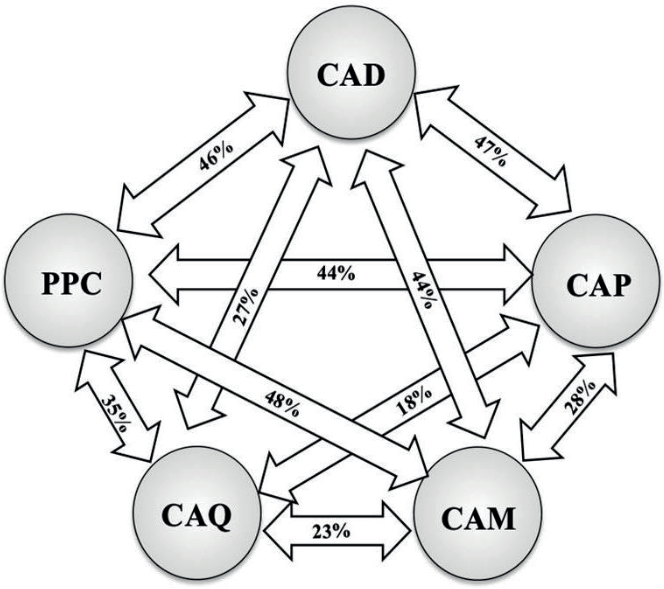

Fig. 4. CAx technologies – data exchange (CAQ – computer aided quality, CAM – computer aided manufacturing, PPC – production planning and control, CAP – computer aided planning) [11]

companies with cost-effective, flexible and scalable solutions by sharing such production resources as services, with consequent lower support and maintenance costs [20].

The use of innovative and systematic approaches to production process planning and schedule optimisation is well known. This approach consists of a process and system stage, complemented by intelligent mechanisms to increase adaptability and the response to the dynamics of machining facilities. During the process stage, the key operational parameters for milling parts are optimised adaptively to meet many targets/restrictions, i.e., energy efficiency of the milling process and productivity with targets and surface quality as limitations [21].

The key areas are, from basic and theoretical to the most advanced and practical:

- Theoretical and applied mathematics in engineering.
- Physical and chemical properties of materials.
- Methods and systems in machine design.
- Machine dynamics and multibody systems simulations.
- Modelling and simulation, structural optimisation.
- Experimental mechanics, identification and validation.
- Advanced industrial, automotive and green energy applications.
- Applications of artificial intelligence and computational intelligence in mechanical engineering.

Digital representations of processes and objects (digital twins) allow the quicker generation of more precise insights into the complex processes, associated with the deep analyses of associated parameters and factors influencing their values and the dynamics of their change.

2.1. Industrial applications of IT. Modern industry constitutes a driving force in the development of local and global economies. The lack of such expansion may doom countries to market marginalisation. Industry has used information technology for many years, mainly to optimise the manufacturing and logistics processes. The operational specificity of industrial processes includes large volumes, high costs of downtime and breakdowns, high costs and long depreciation periods of the manufacturing facility, the need to shorten product life cycles, the need for more flexible cycles in manufacturing and the logistics processes, and the increasing trend in transforming the resulting products into intelligent services. This makes industry a sector strongly oriented toward the issues of optimising performance and reducing operational risk. Simultaneously this sector faces many new challenges every day [2, 22].

The current solutions allow users to do a better job, bringing benefits to both the company and its customers while also creating added value for the national economy. Development of this technology, and technological development in general, is not an end in itself. We should take into consideration what applications of AI/CI technology can serve responsible development and implementation of the UN Sustainable Development Goals (SDGs). Another question concerns which threats to sustainable development may be caused by the development of AI technology and what would be an appropriate response to these challenges [1].

We transform our manufacturing processes away from industrial applications of CAPP, CAM, CAD towards digitalisation for simulation by integrating applications of AR, VR, hybrid simulation and digital twins [10, 23].

By the end of 2020, the global Artificial Intelligence market is expected to grow by 154%, year-on-year, reaching a market value of $22.6 billion. CAD, machine vision, mobile cars, media communication, hospital and manufacturing equipment each have a certain level of AI and machine learning in their software. There is a dominant percentage of AI in terms of automation and control systems (Fig. 5) [24].

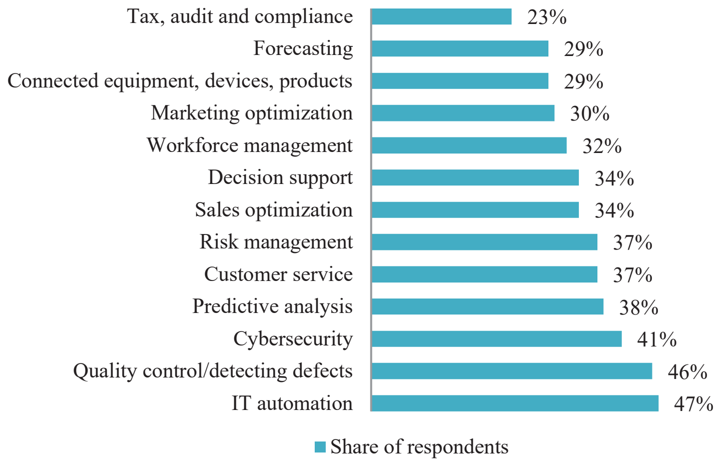

Fig. 5. Percentage share of AI in various branches and production processes [24]

Progress can be seen also at the organisational and economic levels, e.g., Lean Management (LM), at the production technology level, e.g., laser technology, additive production and robotics [25], at the manufacturing technology level, e.g., material level, such as semiconductors, nanomaterials, carbon fibres, biomaterials [26] and at the information technological level, e.g., RFID, embedded systems. This can result in a significant increase in productivity, mainly through the consistent digital integration and intelligence [27] of production processes [28]. Fully integrated and networked factories, machines and products can then operate in an intelligent and partially autonomous manner [29, 30], maintaining the latest concepts such as the Internet of Things, Industrial Internet, Cloud Production [31] and Smart. These requirements are gradually being introduced by manufacturers [32]. Therefore, it should be assumed that such a far-reaching vision will lead to increased complexity in the production processes at the micro and macro levels [33]. Maturity in this area can be assessed qualitatively or quantitatively in a discrete or continuous manner [34, 35]. In the field of production, current readiness and maturity models have been proposed, such as in energy and usage management [36], in ecological design production [37] and in lean production [38]. In relation to the emergence and development of such systems in industry, new methodological tools are proposed to assess the technological and operational criteria in companies and to place them at the right level to move toward a new industrial revolution, also taking into account the vertical and horizontal systems of Industry 4.0 [39].

2.2. Industrial applications of the Internet of Things. Elements of IoT concept appear in product architecture and increasingly affect the production processes. The creation of new product categories allows the construction of a production potential that fully utilises the potential of new technologies [2, 40]. Industries with particular potential for development in Poland based on IoT include consumer market, logistics and the transport sector and general industry. However, the whole spectrum of IoT applications covers following areas: safety and certification, finance and insurance, smart cities and buildings, health, intelligent metering, industry, agriculture and the environment, telecommunications and transport [2].

Technological companies operating in the field of Industrial IoT (IIoT) and other new technologies continue to develop dynamically, and are ready to adapt, develop and implement their best products in all industries, wherever they may be expected or prove useful. It is worth mentioning the development of companies providing design and production services for dedicated electronics, or emerging companies creating intelligent systems for intra-logistics based on the self-guided vehicles they manufacture. Many research and development centres and universities are conducting research in the fields of IIoT, AI, VR, AR, machine learning, Big Data or User Experience, which can actively support the development of IoT [2].

IIoT can be divided into two types:

- Offline IoT – solutions that support the collection of a sufficiently large amount of data and allow for their subsequent processing in order to optimise processes – they do not affect the current operation of industrial plants, until the effects of the data analysis allow the introduction of changes.
- Online IoT – tools and systems that operate operationally and influence the processes in an industrial plant on an ongoing basis [2].

In many cases, the implementation of the IoT system allows tool data to be obtained both online and offline, and these functions often overlap. It should be noted, however, that offline data access may be difficult in many situations due to the risk of collecting industrial data and the need to invest in the necessary computing power and appropriate software to analyse large data sets. The primary task of IIoT systems is to optimise industrial processes – starting from work efficiency and ending with the consumption of raw materials. In effect, it all comes down to reducing risk and operating costs [2].

2.3. Transformation toward Industry 4.0. Today's production and logistics companies are transforming, heading toward utilising the framework defined within the Industry 4.0 concept (also known as Fourth Industrial Revolution). IoT creates new opportunities for industry – production processes based on IoT devices often require innovative solutions, thanks to which the experience gained can serve as examples for industrial plants operating in other sectors of the market [3, 4].

Polish medium and large companies, especially those from the energy and fuel industries, heavy industry, electrical engineering, automotive, furniture, etc. are ready to invest in new technologies, including automation and control of the production processes. The barriers to modernisation in the spirit of Industry 4.0 include lack of knowledge, lack of patterns and uncertainty as to the economics of investments related to the digital transformation of industry. However, there is growing pressure to take these actions. For example, Polish companies cooperating with global automotive ones see that they need to adapt to a new class of processes and operational requirements (response times, flexibility, quality). Companies that successfully export their products also often see a need to adapt to the realities of digital business and digital lifestyles. Local medium-sized companies are in the most difficult situation as their lack of sufficient scale means that their modernisation investments are low efficiency, which increases the uncertainty of decision making. However, they too perceive the pressure (for example, difficulty in recruiting employees) as well the opportunities (EU funding) that may lead to increasing interest in the possibilities of IoT, especially in the context of production automation and intra-logistics [2]. The attributes of Industry 4.0 are defined by: smart robots and machines, big data, new quality of connectivity, energy efficiency and decentralisation, virtual industrialisation.

Most of the technologies that play a significant role in Industry 4.0, such as those related to industrial robots, reporting and data analysis systems, media cost reporting systems or product lifecycle management systems, are already known [3, 4].

From yet another perspective, the issues of modelling and simulation are considered in the context of guaranteeing ecological and social assumptions as well as harmonious economic and technological development. For this purpose, the production companies of the future will need the ability to manage the entire value chain in an agile and sensitive manner [41]. In addition, they will need virtual and physical structures that allow close cooperation and rapid adaptation throughout the entire life cycle, from innovation to production and distribution [42]. In this respect, system integration is the first step towards Industry 4.0 [43]. These systems are analysed as a whole, taking into account the production flow. Structural changes in the organisation are proposed, as well as the management of physical objects and establishing connections with IT systems [44, 45]. Assessment tools allow the current vertical and horizontal methods of company integration to identify gaps and opportunities for development of other blocks under consideration [46, 47].

This paper [48] presents the entrepreneurs' attitude towards Industry 4.0, indicates their willingness to implement elements of the concept and identify barriers that may threaten companies in effectively achieving higher technological and organisational levels [49–53]. It was decided to analyse a number of the publications indexed in the WoS, Scopus and Google Scholar databases in 2011–2017, including the most popular synonyms. Due to the specificity of searches in the analysed databases, the search covered several different areas (Table 1).

Table 1
Scientific papers using selected terminology of Industry 4.0 in bibliometric databases during the years 2011–2017 [48]

	Web of Science Core Collection (title, topic)	**Scopus (title, abstract, keywords)**	**Google Scholar (all fields)**
Industry 4.0	1311	2022	14 700
Industry of the Future	25	52	1490
4IR = 4.0 (Fourth) Industrial Revolution	235	976	6500
Production of the Future	7	22	539
Intelligent Manufacturing	383	579	17 200

2.4. Key role of engineers. The integration of many advanced technologies: robotics, control, automation and IT technologies will require companies to constantly develop their engineers. Moreover:

- Lower Total Cost of Ownership (TCO).
- Increase of patenting innovative solutions and know-how protection.
- Open systems to begin to win.
- Increase in significance of communication protocols based on the Ethernet standard.
- Increase in importance of standard communication architectures (e.g., OPC Unified Architecture).

According to the RB Industry 4.0 Readiness Index, European countries can be divided into four groups: leaders, potential, hesitating (low readiness), and traditionalists. Poland has been classed together with Italy, Spain, Portugal, Croatia and Bulgaria in the group of hesitating countries with low readiness to implement the idea of Industry 4.0, in need of time to change their mind [3, 4]. Despite the measures taken, too few ICT specialists are educated in relation to the needs of the economy, which also applies to AI specialists, the education system does not prepare for teamwork, AI is interdisciplinary and requires knowledge from many intertwining fields, too little is taught about the consequences of technological changes. Undoubtedly, more importance should be given to continuing education and more emphasis should be placed on experimentation and innovation, product creation, ethical and social issues [1].

2.5. Role of machine modelling and simulations. Machine modelling and simulations use models (physical, mathematical, logical representations of real devices and/or processes) as a basis for simulations to develop data utilised for technical decision making across a broad range of mechanical engineering applications for scientific and industrial purposes. This technology belongs to the key tool set for engineers in all application domains and has been included in the body of knowledge of engineering management. Modelling and simulations help to reduce costs, increase the quality of products and systems, and document the lessons learned. Additionally, models may be updated and improved using the results of real experiments.

AI and CI (computational intelligence) are increasingly important in building these models. AI and CI methods deal with methods of solving problems that cannot be effectively solved in an algorithmic way. These methods play a major role in developing inference and intelligent systems. The use of modern methods (AI and CI) in the field of mechanical engineering is particularly interesting as the research and practical nature very strongly relates to Industry 4.0. These methods simulate such natural (biological) phenomena as the theory of evolution (evolutionary algorithms) as well as the behaviour of neural systems (artificial neural networks), immune systems (artificial immune systems) and that of biological individuals (swarm algorithms). In this case the intelligent design of structures is considered to be a novel form of optimal design based on CI [53]. The proposed methodology based on CI has some heuristic and learning attributes typical of natural intelligence.

We strongly believe that the role of machine modelling and simulation will increase in the next decade, going beyond the above-mentioned areas of scientific research and engineering practice.

3. Construction policies

3.1. Regulations. Regulations associated with the topic are following:

- On 10 April 2018, 25 EU countries and Norway signed a Declaration of Cooperation on AI.
- On 25 April 2018, the European Commission (EC) published a communication in which it announced the EU's strategy on AI "Artificial Intelligence for Europe".
- As part of the review of the digital single market strategy, the European Commission conducted extensive consultations, and then announced the initiative "Building a European data-driven economy".
- The Commission, as part of the next financial perspective covering the period 2021–2027, wants to launch the "Digital Europe" program.
- In June 2018, the High-Level Expert Group on Artificial Intelligence (AI HLEG) was established.
- Guidelines on AI-related ethics were developed, developed in consultation with the European Group on Ethics in Science and New Technologies (EGE) and the European Union Agency for Fundamental Rights Union Agency for Fundamental Rights (FRA).
- The host of the European AI Alliance is the European Commission.
- AI On-Demand – Platform [1].

One of the requirements underlying reliable AI is the transparency of the algorithmic processes since governments are concerned about the omnipresence of the "black box", i.e., AI devices, systems or objects, the principles of which are not understood by humans. Moreover industry, academia and civil society are concerned about impartiality in AI systems [1].

3.2. Framework for machine modelling and simulations. There is need for the coordinated, long-term promotion of interdisciplinary engineering thought in the international arena and construction of strong and widely accepted standards in the field of high technology. Moreover, there is need to teach engineers and operational workers to think in a business manner i.e., translate the projects into business indicators showing the added value for the company generated by such an initiative. Four potential archetypes for the factories of the future are:

- Smart automated and robotised factory – realising very high production volumes thanks to full automation and robotisation of processes with a low level of cost per product.
- Digital mass individualisation factory – designed for medium to high production volumes of highly customised products (such as cars, clothes, furniture, construction elements, etc.), prepared to implement very short series, with frequent changeovers and high personalisation of the product(s).
- Mobile modular plant – can be flexibly built, commissioned, packed and transferred depending on market trends, industry standards or access to raw material.
- Handmade with the digital touch – producing handmade products with the highest unit value (e.g., in the luxury product segment) [3, 4].

Key common processes:

- Operational excellence i.e., continuous improvement programs.
- Continuous education i.e., development of the competences of managers, engineers and line workers.
- Paperless factory i.e., development of digital infrastructure and digital information flow.
- Cybersecurity [3, 4].

A properly built AI system should meet all of the following requirements:

- Protect consumers.
- Provide incentives for companies to design and deliver safe technologies and products.
- Provide flexibility to enterprises in terms of innovation.
- Avoid creation of unnecessary barriers that slow development [1].

3.3. Key issues. Key issues to solve are:

- How to expand and modernise existing factories.
- How to design and build new factories.
- How to develop production processes and technologies.
- How to use digital technologies to increase mental work time at the expense of manual work.
- How to change attitudes and develop the competences of the staff at each level of responsibility.
- How to develop employees [3, 4].

There are three technological variants of work automation to choose from process robotisation, cognitive automation, social robotics [3, 4].

Such changes can be made to automation or complete redesign of business processes, creation of new products and services, analysing big data from new angle(s) [3, 4]. Factors influencing the choice of appropriate solution are usually: types of tasks, operating mode, scope of application, changing the definition of work, products, cost of implementation and maintenance, time needed for implementation, return on investment, etc. [3, 4]. Each of the aforementioned statements may be answered using appropriate supporting AI, modelling, and simulation methods, techniques and tools.

3.4. Barriers. The operational activity of enterprises is strongly dependent on the logistical possibilities – the availability of appropriate roads, railways, ports, cargo and passenger airports – this translates into the need to involve countries in the planning of the required infrastructure development. This includes industrial activities, and which often require very specific solutions (high throughput, large tonnage, etc.). Investments in infrastructure should also take into account the possibility of ensuring a stable energy supply (guarantee of the availability of appropriate connection capacity and reliability of the transmission network) and the existence of appropriate ICT (information and communication technologies) networks (high capacity and reliability of radio and cable – fibre-optic connections). Industry also faces increasing barriers from environmental regulations, which can be divided into two categories:

- Internal – related to procedures in production plants.
- External – related to the development of the IoT market [2].

The main challenge for Industry 4.0 is the integration/cooperation of incorporated technologies in a way:

- Allowing reduced time to introduce new products to the market.
- Ensuring a cost of unit production competitive in relation to the economies of BRIC countries (Brasil, Russia, India, China), for example [3, 4].

It seems companies focusing solely on manufacturing will be put under pressure to lower prices. But if they do not automate or build new added value in the short term, e.g., in the form of R&D and design processes, they may be eliminated from the supply chain. Moreover, there is a need to monitor the costs of ownership of a product and its moral "aging" process as sources of valuable knowledge concerning developing subsequent versions and new products [3, 4].

- Automation requires long-term preparation through:
- Clearly defined business purpose.
- Technical and business analysis before the investment,
- Too short time to test the position,
- Scalability of the device,
- Service for the device,
- ROI vs. risk of R&D project.

Another problem is a lack of understanding of the role of data in industry and the whole economy, limiting the preparation of opening data sets for machine reading and a lack of API interfaces for some state or industrial websites. There is need for commonly accepted principles and construction of data governance practices in Poland, especially in relation to shared data, but also incorporating the right to disconnect from the network [1].

Digital Innovation Hubs (DIHs) in Poland fulfil tasks related to the activation of pilot solutions in the aforementioned areas. Despite the quick development of the industry worldwide the most commonly identified problem is still the lack of efficient communication and collaboration among software producers (Table 2).

Table 2
Major identified problems (based on [5])

Area (in alphabetical order)	Identified problems
Augmented reality (AR)	Low tracking accuracy, end-to-end latency
Computer –aided design (CAD)	Lack of the human-computer interface, complexity of menu
Computer-aided manufacturing (CAM)	Lack of efficient data exchange, of efficient communication and of collaboration
Computer-aided processing planning (CAPP)	Lack of adaptability and of dynamic operation adjustment
Digital MockUp (DMU)	Extension needs for service functions
Discrete Event Data Processing Notation (DPMN)	Lack of collaboration, low accuracy in data exchange
Ergonomy	Complexity, lack of models of interaction and of human quality measuring techniques
Enterprise resource planning (ERP)	Lack of mobility and of communication, need for Business Intelligence
Knowledge managemet (KM)	Lack of agent learning, lack of knowledge reuse
Life Cycle Assessment (LCA)	Need for modularisation, standardisation
Lean Production System (LPS)	Need for extensibility, lack of interoperability
Manufacturing execution System (MES)	Lack of communication and of ahead planning
Product Data Management (PDM)	Low product data accessibility
Supervisory, Control and Data Acquisition (SCADA)	Loss of separation with other IT tools, security concerns
Virtual reality (VR)	Lack of collaboration, lack of communication, need for PLM integration

4. Implications for machine modelling and simulation

Processes within Industry 4.0 are optimised through the use of various parameters and performance metrics. Tools such as production flow diagram, ontology-based contextual modelling, SysML, etc. are currently used for this, but further development of this group of solutions is required. There is some limited scope for optimising existing processes and machines, but the widest possibilities are provided by setting up the process/machine in a simulated virtual environment before the physical form is implemented. These modelling and simulation processes in the form of a virtual twin or even an entire virtual factory not only reduce time, improve quality. and reduce costs. There is no doubt that computational intelligence will make more accurate predictions than before, including taking into account future modifications of production systems towards self-organisation [54,55].

The challenges in the field of industry have generated novel technologies used for the construction of dynamic, intelligent, flexible and open applications, capable of working in a real time environment. Thus, in an Industry 4.0 environment, the data generated by sensor networks require AI/CI-based close to real-time data analysis techniques. In this way industry may face both new opportunities and challenges, including predictive analysis using computer tools capable of detecting patterns in the analysed data from the same rules that can be used to formulate predictions [56]. There are many examples of the use of artificial intelligence methods at various stages of constructing or designing technological processes. AI methods are slowly becoming one of the essential methods of creating models for machine modelling. For example, machine learning methods can be used in eco-design, especially in the selection of materials [57], the design of technological processes [58], or creating smart cities [59]. Another example of modelling and simulation is shown in the article [60, 61] on the construction and control of an exoskeleton [62]. Unfortunately, the traditional overview focuses on the technologies applied at different stages of the supply chain. With a wider approach we can assess the impact of implementing the above technologies in manufacturing, rather than just transforming traditional factories into smart factories, as well as interconnecting each customer, worker, product, device/machine and process into a Cyber-Physical System (CPS) [63]. Understanding how to use engineering software is crucial to reduce errors, save time and expand design capabilities [64–66]. Nine engineering software packages that help improve design and production processes, resulting in shorter lead times, more projects in preparation, faster time-to-market, with greater end-user satisfaction and brand awareness include:

- production control,
- structural analysis,
- geotechnical analyses,
- Finite Element Analysis (FEA),
- engineering calculations,
- 3D data modelling,
- programming,
- coding.

Future applications of various CI methods and techniques could significantly increase their capabilities.

5. Perspectives and directions for further research

Despite the many contributions that have been made, the issues analysed here are still in the early stages of development. Technologies are evolving rapidly, workforce skills are aging more rapidly, and the cost of retraining employees is rising. Therefore, some organizations are reconsidering the risks associated with hiring full-time employees and instead seeking to mitigate the risks by automating work if it can provide a cost-effective solution to these problems. Choosing the right technology to automate work and improve productivity becomes an extremely important task when it comes to harmonizing the chosen technology with a comprehensive strategy for the future. Machine modelling and simulation can significantly improve these processes and even assess a company's readiness for change. All of this is needed for application in real-world scenarios, and the best paradigms depend on the harmonized co-development of many interrelated technologies, including organizational processes (Table 3). All of them are crucial and have been developing rapidly in recent times, so their ultimate shape and impact should be watched carefully. Their development in machine modelling and simulation may require the integration of specialists from different disciplines, which may be difficult, but may also bring unexpected breakthroughs.

An important area in the field of modern technology is the increasingly popular use of prototyping. Fast, production-ready prototypes are essential for efficient production and fast market introduction. Modelling/simulation scenarios at an early stage of the design process help determine the best possible design for prototyping. Virtual reality and augmented reality programs quickly become powerful visualisation and design tools, especially in medical research and development. 3D printing and other additive manufacturing technologies (AM) can prototype parts ready for production in a matter of hours, giving engineers components they can use and test, or even repeat on the same day.

Process automation and robotisation are key in the process of preparing for Industry 4.0. Only thanks to them can companies prepare for the integration of more advanced technologies (including IT) that will allow transformation of the entire value chain. Although there is much to do in this regard, we also have someone to learn from. At the same time, we cannot forget the fundamental issues: investing in Engineers 4.0, building awareness of the inevitability of the upcoming changes, as well as business justification skills for investing in robotisation and automation.

Future CPSs form the most promising technological concept, regarded as the building blocks of future smart factories [67]. CPSs constitute systems of collaborating computational entities remaining in connection with the surrounding physical world and its processes, simultaneously providing and using data-accessing and data-processing services on the Internet [68]. It may be regarded as the Ambient Intelligence (AmI) embedded systems concept applied in an Industry 4.0 environment. To fulfil their tasks CPSs are able to gather, process, and evaluate the data that describe them and their environment, as well as to connect and communicate with other systems to initiate actions [69]. CPSs are deeply connected to and control physical entities thanks to sensors, actuators, devices, machines and robots, together creating a smart community [70]. Such solutions may combine lean production and sustainable performance [71–73], allowing the achievement of such challenging tasks as management of geometrical deviations through the whole lifecycle of the product [74].

Ambiguous digitalisation increases the complexity of manufacturing systems [75, 76]. Remote and intelligent monitoring and control systems with built-in prediction will be needed [77–79]. Customised mass production and adaptive scheduling in demanding markets potentially constitute another challenge [80–82].

Table 3
Top paradigms in machine modelling and simulations (from basic to the most advanced) (own concept based on [10])

Paradigm	Short description
Assistance of experienced professionals	Solutions become more and more interactive and intuitive to use
Digital twins market development	3D printing, especially 3D metal printing and mapping
3D printing clusters/farms	Dedicated software for managing the printing process, material delivery, scheduling and managing the entire supply chain
Adoption across diverse industries	Data-driven approach to optimise supply, scheduling and the manufacturing process, reducing energy expenditure
Industry 4.0	Increased accuracy levels of the representations thereby enhancing simulation results and scheduling plans
Industrial IoT (IIoT)	Development of the simulations in complex interconnected facilities to produce accurate results or to access process
Cybersecurity challenges	Management solutions to monitor interconnected activities, digital representations of IoT devices and also to integrate the data they produce
Simulation-based scheduling	Penetration testing tools to simulate the effects of ransomware, spyware, DDoS, and business email compromise attacks to business processes, novel secure communication protocols and standards regulating data use, especially in the area of cloud-based solutions
Quantum computing	Increased accuracy of managing business process (e.g., discrete event simulation – DES) supporting real-time handling of many unforeseen events such as machine downtime and rescheduling of operations

A new generation of engineers, known as Generation 4.0 Engineers, is emerging [75], prepared for Human-Robot-Collaboration (HRC) – work with the help of collaborative lightweight robots [83, 84], in the future as robotic human companions.

Decision making systems become a necessity. Modelling and simulation will be key technologies allowing not only planning, creating exploratory models to optimise design, evaluating the risks, costs and implementation barriers, and conducting operations in relation to complex and smart production systems [85,86], including complicated and uncertain production logistics systems [87–89], and multistage processes involving additive manufacturing [90]. To sum up: further research on machine modelling and simulation can capture a comprehensive picture of the principles of the Industry 4.0 phenomenon from diverse perspectives.

6. Conclusions

A new approach to the field of machine modelling and simulation has been proposed that fills the gaps in existing simulation approaches related to the challenges required by the Industry 4.0 paradigm (digital twins, hybrid simulation, wider use of virtual reality and augmented reality). The main advantages of this approach are:

- availability of more complex models,
- more realistic visual representation,
- improved product life cycle monitoring,
- real-time data integration,
- remote product maintenance,
- improved decision-making within processes.

However, there are also drawbacks, representing both current limitations and future challenges:

- lack of unified terminology and applications,
- lack of industrial integration,
- the need to adapt current digitization practices,
- integration of new technologies, including AI/CI,
- digitization of tacit knowledge,
- need for increased implementation competence [10, 91–93].

The next steps in machine modelling and simulation will require a tremendous effort on the part of both researchers and engineers to integrate existing relevant methods, techniques, and tools to create a connection-open environment easy to apply within the IoT and Industry 4.0 paradigms. The resulting standards and recommendations will shape the future of our industries, laying the foundation for the next decades of rapid digital development.

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