Development of digital twin interface for Industry 4.0 production line

Yuriy Skorenkyy*,† Viktor Voroshchuk†, Tetiana Vitenko† and Oleksandr Kramar†

Ternopil Ivan Puluj National Technical University, 56 Ruska St, Ternopil, UA46001, Ukraine

Abstract

Within Industry 4.0, the augmented reality (AR) interfaces may become important components of industrial digital twins (DT) enabling human operators to manage smart manufacturing processes. Different aspects of DTs' design have to be analyzed in context, including relevant data identification, taking into account AR-interface data flow. Development of augmented reality-enhanced interface for a DT in the metal processing industry is proposed which takes into account the data flows specific for IoT devices and DT architecture. An integration of essential stages of AR-enabled DT development will assure compliance with the concept of Industry 4.0 and allow new innovative solutions.

Keywords

Digital Twin, Internet of Things, Industry 4.0, Augmented Reality

1. Introduction

The advent of the Internet of Things (IoT) has paved the way for novel opportunities to enhance industrial processes through the integration and intricate management of sensor-equipped machines and actuators [1, 2]. In process operations, the Industrial Internet of Things (IIoT) empowers manufacturers to gain a comprehensive view of every stage in the manufacturing process, facilitating real-time adjustments to ensure seamless production flow and mitigate the probability of defects and failures stemming from human errors, in accordance with principles of Industry 4.0 [3, 4]. The positive implications of smart manufacturing transcend the realms of production operation, equipment, and inventory optimization. Coupled with improved flexibility of highly specialized production adapted for rapid reconfiguration, this factor offsets the substantial costs associated with creating, operating, and ensuring the security of IIoT systems [5, 6].

This paper considers a task of development of the intuitive and efficient interface for the digital twin of the Industry 4.0 compliant production line. The paper is organized as follows. In Section 2, literature review is presented to substantiate the research topic. In Section 3

CITI'2024: 2nd International Workshop on Computer Information Technologies in Industry 4.0, June 12–14, 2024, Ternopil, Ukraine

* Corresponding author.

† These authors contributed equally.

skorenkyy@tntu.edu.ua (Yu. Skorenkyy); voroschuk_v@tntu.edu.ua (V. Voroshchuk); vitenko@tntu.edu.ua (T. Vitenko); kramar_o@tntu.edu.ua (O. Kramar)

0000-0002-4809-9025 (Yu. Skorenkyy); 0000-0002-8943-1493 (V. Voroshchuk); 0000-0003-4084-0322 (T. Vitenko); 0000-0003-0805-3732 (O. Kramar)

the methodology of study is described. In Section 4 the results of our study and the interface development are presented. Section 5 is devoted to conclusions.

2. Related Works

Digital twins (DTs), widely used in Industry 4.0 to model and control production processes [7-10], are virtual replicas of physical objects or systems that can be created and manipulated using augmented reality (AR) and virtual reality (VR) technologies [11-15]. These technologies facilitate the creation of realistic 3D models that can interact with the real world and offer a myriad of functionalities [12, 16].

DTs have emerged as a distinctive hallmark of smart manufacturing [10, 17-21], offering multiple benefits. In the industrial domain, DTs can be harnessed to simulate, control, and optimize production processes, enable predictive maintenance of equipment [10, 22-24], and foster collaboration among workers [25].

The efficacy of augmented reality (AR) assistance frameworks in manufacturing workflows is contingent upon the underlying software and hardware capabilities, as well as the system's design attributes that facilitate the seamless integration of human operator performance across relevant use cases (e.g., assembly/disassembly, maintenance/inspection) [26-28]. Immersive visualization layered upon physical environments using AR enables industrial personnel to assimilate and manipulate digital interactivity with enhanced perceptibility and workflow integration [29]. Associated improvements in specialized employee training and developmental modes also arise [30, 31], facilitated by tailored simulations of manufacturing operations, including emergency contingencies – executed safely in virtual factory environments [16, 32]. Through such immersive learning functionality, the AR-based platforms significantly augment contextual employee environmental awareness and competencies. Consequently, quantitatively fewer deviations can be projected, stemming from superior comprehension of workplace dynamics [33].

AR integration within production environments can enhance real-time recognition of hazardous situations for industrial personnel, enabling expeditious assessment of probable risk exposure from discrete processes. Prior investigations [34-36] delineate the capacity for AR to mitigate error-induced harm on the production floor through sequential occupational safety, equipment operation, and maintenance instruction mapped to precise spatial worksite coordinates. Additionally, the AR-enabled warning systems demonstrate applicability within construction verticals [37] for advance notification of violations of safety protocols before accidents occur. Workers will be able to determine risks with improved precision in comparison to conventional techniques, subsequently adjusting behaviors to amplify on-site protections [38].

However, there are challenges that need to be addressed to fully realize the potential of AR application in production processes. One of the primary challenges is the presence of spatial inaccuracies in the binding to markers recognized by computer vision [39]. AR systems may experience technical glitches, such as network issues, and sometimes have difficulties in interpreting complex scenarios, which may lead to incorrect information being provided to staff. Consequently, there is a risk of emergencies if employees rely solely on AR systems. Therefore, it is crucial not only to improve the tools themselves to support AR but also to carry out a continuous process of staff training, for whom these tools are merely one of many tools in the production environment [40]. Another issue with production-type AR systems is their potential to distract attention and partially block the field of vision, which can potentially lead to a violation of the safety of production processes. The solution to such challenges lies in further optimization of the user interface, active utilization of sound prompts, and the use of tools that will evaluate the priority of information delivery and ensure the balancing of the AR layer's saturation, enabling employees to remain focused on their primary tasks.

The adoption of extended reality (XR) technologies in manufacturing offers numerous potential benefits and additional opportunities for producers and consumers [41] as a tool for simulations, computer-aided design of systems and components, professional training, and equipment maintenance. Machine learning algorithms can play a pivotal role [42] in resolving common challenges of marker-based AR by visual recognition of dynamically changing patterns. This will lead to a new quality of AR interfaces and create more realistic experiences with novel applications. However, this is contingent upon considerable improvement of user interfaces, as AR interface efficiency depends on the recognition of certain images and sounds, which can be easily compromised in production environments.

3. Proposed methodology

The effective integration of AR technology into smart manufacturing environments necessitates a meticulous design of the software platform architecture, with particular emphasis on the velocity and variety of data to be harvested and processed, as well as the resource constraints of the IIoT components embedded within the production equipment. Furthermore, the architectural considerations must account for the need to seamlessly integrate high-resource and high-load AR interface devices, while simultaneously addressing the potential cybersecurity risks arising from the processing of sensitive information within such a diverse and interconnected system. The synergistic convergence of AR technology and smart manufacturing practices demands a holistic approach that harmonizes the data processing capabilities, resource optimization, and security measures, thereby enabling the realization of an efficient industrial ecosystem.

Metrological assessments should be conducted at various stages of the production process to ensure adherence to quality standards and technological specifications. The initial phase (00) involves shape and size verification of the workpieces through optical inspection utilizing camera systems and laser measurement sensor upon completion of metal processing operations. Subsequently, in the internal production silo (phase 01), the quantity and assortment of the workpieces are accounted for based on their weight and geometrical parameters. Welding procedures performed by a Kuka robotic system (phase 03) necessitate the examination of weld seams through multispectral imaging and conductivity analyses. After the corrective press operation (phase 04), the workpieces are evaluated against a predefined template or through laser measurement sensor data. Upon completion of the painting process (phase 06) the quality assessment is done with use of an ultrasound meter, the finished products undergo visual inspection via camera imaging, and ready parts are laser marked (phase 07). Measurements and metrological assessment are to be performed after procedures 00, 03, 04, 06, however internal (phases 02, 08) and external logistics (phases 09, 10) may require additional measurements as well.

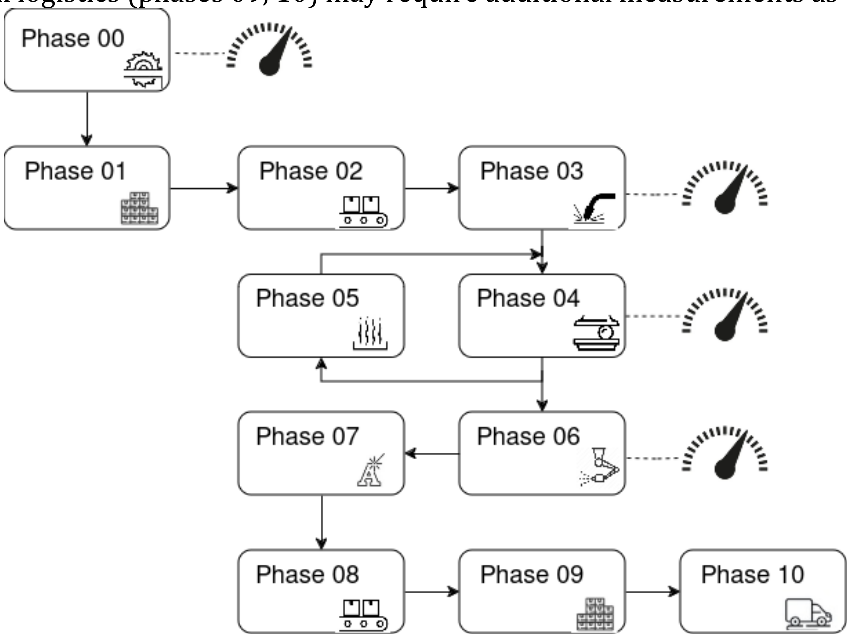

Figure 1: Process diagram for the modeled production line.

Compliance of the entire complex of measured characteristics with the technological production map is a prerequisite for achieving high product quality. In instances where a processed component deviates from the product specification, it is redirected to a heating stage (phase 05), after which the correction procedure (phase 04) is repeated iteratively until conformance is attained. Furthermore, the incorporation of laser-imprinted QR codes onto the products facilitates compliance with the European Digital Product Passport initiative, enabling access to product-related data essential for ensuring sustainability and circularity throughout the product lifecycle.

The diagram depicted in Figure 2 illustrates data processing in the digital twin (DT) for a metal parts manufacturer. It comprises several blocks that group uniform processes or data processing hubs, with the aim of avoiding data processing centralization, restricting information propagation within and outside the DT, and ultimately enabling fast distributed decision-making and implementation of augmented reality (AR) tools for smart manufacturing. From the manufacturer's perspective, the most fundamental block is the digitized industrial platform. While the existing infrastructure simplifies further development, it also introduces complexities due to the necessity of ensuring system consistency, especially when legacy equipment interacts with novel components. In such scenarios, the presence of an architectural diagram becomes a critical requirement to promptly identify bottlenecks and resolve issues.

The enterprise requirement for the DT was to enable on-site personnel training and enhance simulation capabilities through a personal AR assistant, justifying connection to a well-structured, expandable knowledge base, which may be an external component to the business entity but must be a part of the DT. To leverage the capabilities of AR-enabled human-machine interfaces optimally, a separate infrastructure and resources must be allocated for AR development. This block will be most effective if deployed on a cloud environment that can guarantee high computing power for processing AR images, coupled with elastic and cost-effective storage. While there is a debate regarding whether storing data in the cloud may compromise sensitive information and comply with national legislation, it should be emphasized that a hybrid data infrastructure can be designed (and subsequently improved) to mitigate such risks. Finally, for implementing the AR interface on the factory floor, a set of physical devices must be in place.

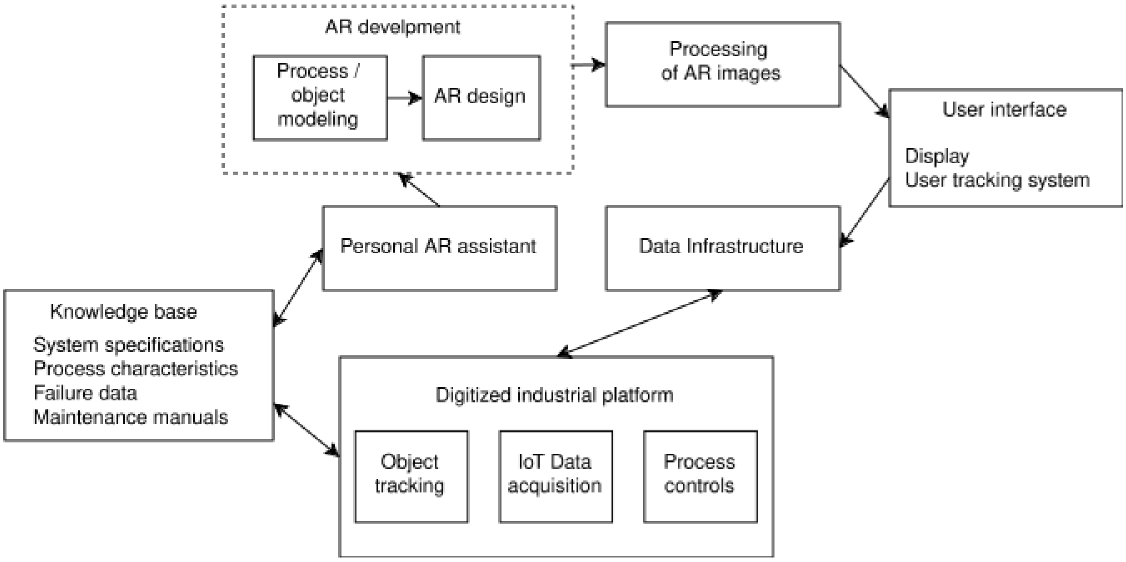

Figure 2: Processing of data in AR-enabled industrial digital twin.

With the architecture designed, the actual selection of edge electronic devices and software development necessitate the specification of a model for the product manufacturing cycle, which will serve as a tool for process optimization and a data flow model for cybersecurity purposes. From an operator's perspective, the modules of the digitized industrial platform and the simulation and training modules will be indistinguishable, provided that the training scenarios are highly realistic and encompass all possible operations, malfunctions, and that the AR processing device possesses sufficient computing power. This condition can be easily fulfilled by modern-day smartphones and tablet devices.

In contrast to a conventional web-oriented digital twin, our workflow assigns equal value to physical and virtual assets, rendering them interchangeable for simulation purposes. This approach may offer enhanced flexibility and faster informed decision-making cycles. The AR layer will essentially enhance on-site information comprehension by incorporating scene capture and visual recognition. There exists an opportunity to avoid critical failures through an AI-assisted digital twin, whose improvement will be a natural extension of the present work. The reprocessing of AR layers is prompted by state changes, reflecting both the evolution of parameters and the outcomes of optimization. In this manner, the industrial digital twin empowers human operators to make well-informed real-time decisions.

4. Results

The present research is grounded in a holistic view of the industrial DT for Industry 4.0, encompassing models for manufacturing facility equipment, manufacturing processes, the product and its characteristics, interfaces for harvesting data and providing support for decision-making, quality assurance, and equipment maintenance [43-47]. The showcased metal processing enterprise, with its peculiar features and commonalities, allows for the design of a secure-by-design architecture if the data, energy, and material flows are considered on equal footing in the DT model [48].

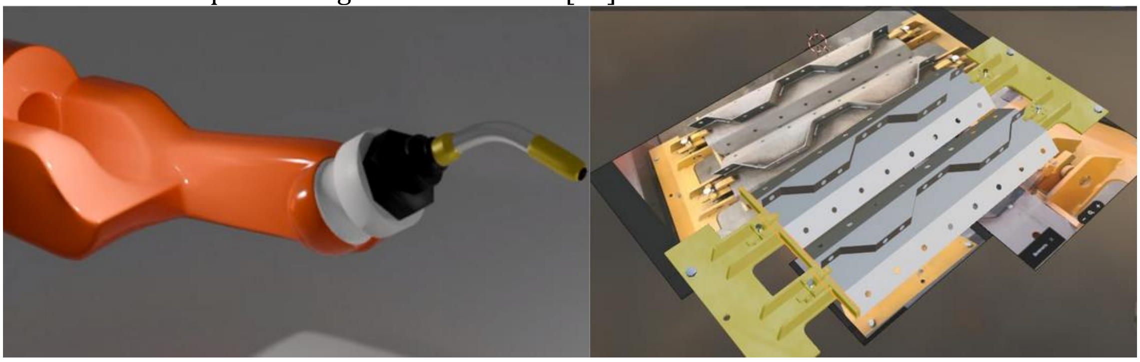

Figure 3: Virtual models of the robotic welding apparatus (left) and the support structure (right).

The proposed development workflow, as illustrated by Figures 3-4, enables intuitive, efficient and safe AR-enabled monitoring of the metal processing, allowing to represent all relevant data from industrial IoT sensors, as well as real-time data processed by DT, to optimize manufacturing processes and avoid hazards and malfunctions [4, 18, 49, 50]. The enterprise personnel will be supplied with accurate and relevant data for decision-making and predictive maintenance [22, 23]. This will allow management and personnel to focus on choosing and implementing innovative solutions for greater customer satisfaction and improved production efficiency.

Figure 4: Window of the mobile application with the superimposed AR objects, messages and alerts.

It is known that when developing an effective interface for a digital twin of a production line compatible with Industry 4.0 to ensure natural and precise movements, imitating the functions of human hands, artificial neural networks are used in feedback loops to improve the coordination of movements, accuracy and speed of production processes [51].

The article [52] presents the results of a qualitative study of a neural network, including discrete and distributed time delays. A method for calculating the exponential decay rate for a neural network model based on differential equations with a discrete delay was developed and applied [53], [54].

When developing an effective interface for a digital twin of a production line compatible with Industry 4.0, the direction of using sensors [55], [56], in particular for monitoring the coordination of movements, accuracy and speed of production processes, is promising. An important characteristic [57] of different types of biosensors is stability [58], [59]. Scientific studies [60], [61] provide examples of modeling sensor responses. Numerical modeling in cyberphysical biosensor systems [62], [63] is important at the stage of their design.

5. Conclusions

Digital Twins with augmented reality interfaces can serve as a powerful tool for realizing human creativity in smart manufacturing, ensuring numerous advantages such as higher product quality, better energy efficiency, and more efficient predictive maintenance [10, 16]. As an information technology, the implementation of AR interfaces holds great potential for industrial DTs. AR can provide more realistic visualizations of relevant data, enabling informed decision-making by human operators and facilitating communication in spatially distributed teams [64]. Consequently, digital twins for smart manufacturing, developed in accordance with the Industry 4.0 model, will be greatly enhanced by incorporating AR interfaces for human-machine interaction. The central challenge faced in DT development is the adequate implementation of connectivity between the physical facility and the DTs [4, 65].

For a characteristic example of a metal processing line with a high level of digitization, industrial data-based modeling allows for the design of an appropriate DT architecture. The paper emphasizes the importance and practical viability of the following workflow for DT design for Industry 4.0: industry-specific data analysis, manufacturing process modeling, human-machine interface design prior to the actual development and deployment of the DT. While each of these steps individually depends on the peculiarities of the manufacturing process, the industrial data platform design, specifications of embedded sensors and actuators, the general approach is quite universal, and none of the stages can be skipped.

Acknowledgements
This work was partially supported by the European Institute of Technology through the project “Smart Manufacturing Innovation, Learning-labs, and Entrepreneurship” (HEI grant agreement No 10044).

References

[1] H. Lasi, P. Fettke, H.G. Kemper, Th. Feld, M. Hoffmann. Industry 4.0. Business & Information Systems Engineering, 6 (2014) 239-242. doi:10.1007/s12599-014-0334-4.

[2] Yang Lu. Industry 4.0: A Survey on Technologies, Applications and Open Research Issues. Journal of Industrial Information Integration, 6 (2017) 1-10. doi:10.1016/j.jii.2017.04.005.

[3] H. Boyes, B. Hallaq, J. Cunningham, T. Watson. The industrial internet of things (IIoT): An analysis framework. Computers in Industry, 101 (2018) 1-12. doi:10.1016/j.compind.2018.04.015.

[4] P. Zheng, H. Wang, Z. Sang, R.Z. Zhong, Y. Liu, C. Liu, Kh. Mubarok, S. Yu, X. Xu. Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. Frontiers of Mechanical Engineering, 13 (2018) 137-150. doi:10.1007/s11465-018-0499-5.

[5] J. Wan, S. Tang, Zh. Shu, D. Li, S. Wang, M. Imran, A. Vasilakos. Software-Defined Industrial Internet of Things in the Context of Industry 4.0. IEEE Sensors Journal. 16(20) (2016) 7373-7380. doi:10.1109/JSEN.2016.2565621.

[6] J. Tupa, J. Šimota, F. Steiner. Aspects of risk management implementation for industry 4.0. Procedia Manufacturing, 11 (2017) 1223-1230. doi:10.1016/j.promfg.2017.07.248.

[7] W. Kritzinger, M.Karner, G. Traar, J. Henjes. Digital Twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine, 51(11) (2018) 1016-1022. doi:10.1016/j.ifacol.2018.08.474.

[8] F. Tao, H. Zhang, A. Liu, A. Nee. Digital twin in industry: State-of-the-art. IEEE Transactions on Industrial Informatics, 15(4) (2019) 2405-2415. doi:10.1109/TII.2018.2873186.

[9] Y. Lu, C. Liu, I. Kevin, K. Wang, H. Huang, X. Xu. Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics and Computer-Integrated Manufacturing, 61 (2020) 101837. doi:10.1016/j.rcim.2019.101837.

[10] D. Mazurkiewicz, Smart maintenance with time series modelling and digital twin, Wydawnictwo Politechniki Lubelskiej, Lublin, 2021.

[11] R. Azuma, M. Billinghurst, G. Klinker. Special Section on Mobile Augmented Reality. Computers & Graphics 35(4) (2011) vii–viii.

[12] J. Egger, T. Masood. Augmented reality in support of intelligent manufacturing – a systematic literature review. Computers & Industrial Engineering 140 2019 106195. doi:10.1016/j.cie.2019.106195.

[13] C. Qiu, S. Zhou, Z. Liu, Q. Gao, J. Tan. Digital assembly technology based on augmented reality and digital twins: a review. Virtual Reality & Intelligent Hardware 1(6) (2019) 597–610. doi:10.1016/j.vrih.2019.10.002.

[14] Y. Skorenkyy, R. Zolotyy, S. Fedak, O. Kramar, R. Kozak. Digital Twin Implementation in Transition of Smart Manufacturing to Industry 5.0 Practices. CEUR Workshop Proceedings 3468 (2023) 12–23.

[15] S. Fedak, Y. Skorenkyy, M. Dautaj, R. Zolotyy, O. Kramar. Digital Twins for Optimisation of Industry 5.0 Smart Manufacturing Facilities. CEUR Workshop Proceedings 3628 (2023) 344–349.
[16] A. Nee, S. K. Ong, G. Chryssolouris, D. Mourtzis. Augmented reality applications in design and manufacturing. CIRP Annals - Manufacturing Technology 61 (2012) 657–679. doi:10.1016/j.cirp.2012.05.010.
[17] Q. Qi, F. Tao. Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. IEEE Access 6 (2018) 3585-3593. doi:10.1109/ACCESS.2018.2793265.
[18] F. Tao, Q. Qi, A. Liu, A. Kusiak. Data-driven smart manufacturing. Journal of Manufacturing Systems 48 (2018) 157-169. doi:10.1016/j.jmsy.2018.01.006.
[19] M. Singh, E. Fuenmayor, E. P. Hinchy, Y. Qiao, N. Murray, D. Devine. Digital Twin: origin to future. Appl. Syst. Innov. 4 (2021) 36. doi:10.3390/asi4020036.
[20] A. Rasheed, O. San, T. Kvamsdal. Digital Twin: values, challenges and enablers from a modeling perspective. IEEE Access. 8 (2020) 21980. doi: 10.1109/ACCESS.2020.2970143.
[21] D.M. Botín-Sanabria, A.-S. Mihaita, R.E. Peimbert-DefGarcía, M.A. Ramírez-Moreno, R.A. Ramírez-Mendoza, J.d.J. Lozoya-Santos. Digital Twin technology challenges and applications: a comprehensive review. Remote Sens. 22 (2022) 1335, doi:10.3390/rs14061335.
[22] D. Mazurkiewicz, Yi Ren, Cheng Qian. Novel Approach to Prognostics and Health Management to Combine Reliability and Process Optimisation. Springer Series in Reliability Engineering, in: Yu Liu & Dong Wang & Jinhua Mi & He Li (ed.), Advances in Reliability and Maintainability Methods and Engineering Applications, Springer (2023) 559-580.
[23] J. Lee, H.-A. Kao, S. Yang. Service innovation and smart analytics for industry 4.0 and big data environment. Procedia CIRP 16 (2014) 3-8. doi:10.1016/j.procir.2014.02.001.
[24] L. Sun, H. Qin, K. Przystupa, M. Majka, O. Kochan. Individualized Short-Term Electric Load Forecasting Using Data-Driven Meta-Heuristic Method Based on LSTM Network. Sensors 22 (2022) 7900, doi:10.3390/s22207900.
[25] A. Rasheed, O. San, T. Kvamsdal. Digital Twin: values, challenges and enablers from a modeling perspective. IEEE Access 8 (2020) 21980, doi: 10.1109/ACCESS.2020.2970143.
[26] J. Zhu, S. K. Ong, A. Nee. A context-aware augmented reality system to assist the maintenance operators. International Journal on Interactive Design and Manufacturing (IJIDeM) 8 (2014) 293-304. doi:10.1007/s12008-013-0199-7.
[27] G. Dini, M. Dalle Mura. Application of augmented reality techniques in through-life engineering services. Procedia CIRP 38 (2015) 14-23. doi:10.1016/j.procir.2015.07.044.
[28] R. Palmarini, J.A. Erkoyuncu, R. Roy, H. Torabmostaedi. A systematic review of augmented reality applications in maintenance. Robotics and Computer-Integrated Manufacturing 49 (2018) 215-228. doi:10.1016/j.rcim.2017.06.002.

[29] M. Fiorentino, A.E. Uva, M. Gattullo, S. Debernadis, G. Monno. Augmented reality on large screen for interactive maintenance instructions. Computers in Industry 65 (2014) 270-278. doi:10.1016/j.compind.2013.11.004.
[30] O. Kramar, Y. Drohobytskiy, Y. Skorenkyy, O. Rokitskyi, N. Kunanets, V. Pasichnyk, O. Matsiuk. Augmented Reality-assisted Cyber-Physical Systems of Smart University Campus, 2020 IEEE 15th International Conference on Computer Sciences and Information Technologies (CSIT) 2 (2020) 309-313.
[31] N. Zagorodna, Y. Skorenkyy, N. Kunanets, I. Baran, M. Stadnyk. Augmented Reality Enhanced Learning Tools Development for Cybersecurity Major. CEUR Workshop Proceedings 3309 (2022) 25–32.
[32] B. Schwald, B. Laval, T. Sa, R. Guynemer. An Augmented Reality System for Training and Assistance to Maintenance in the Industrial Context. Journal of WSCG 11 (2003).
[33] T. Ho, J. Albajez, J. Santolaria, J. Yagüe-Fabra. Study of Augmented Reality Based Manufacturing for Further Integration of Quality Control 4.0: A Systematic Literature Review. Applied Sciences 12 (2022) 1961; doi:10.3390/app12041961.
[34] T. Pettersen, J. Pretlove, Ch. Skourup, T. Engedal, T. Lokstad. Augmented reality for programming industrial robots. Proceedings - 2nd IEEE and ACM International Symposium on Mixed and Augmented Reality, ISMAR 2003 (2003) 319-320. doi:10.1109/ISMAR.2003.1240739.
[35] D. Tatić, B. Tešić. The application of augmented reality technologies for the improvement of occupational safety in an industrial environment. Computers in Industry 85 (2017) 1,doi:10.1016/j.compind.2016.11.004.
[36] D. Tatić. An augmented reality system for improving health and safety in the electro-energetics industry. Facta Univ.-Ser. Electron. Energetics 31 (2018) 585.
[37] S. Wu, L. Hou, G. Zhang, H. Chen. Real-time mixed reality-based visual warning for construction workforce safety. Automation in Construction 139 (2022) 104252. doi:10.1016/j.autcon.2022.104252.
[38] A. Chen, M. Golparvar-Fard, B. Kleiner. Design and Development of SAVES: A Construction Safety Training Augmented Virtuality Environment for Hazard Recognition and Severity Identification. Computing in Civil Engineering - Proceedings of the 2013 ASCE International Workshop on Computing in Civil Engineering (2013) 841-848. doi:10.1061/9780784413029.105.
[39] A. Maffei, M. Dalle Mura, F.M. Monetti, E. Boffa. Dynamic mixed reality assembly guidance using optical recognition methods. Appl. Sci. 13 (2023) 1760, doi:10.3390/app13031760.
[40] J.E. Naranjo, D.G. Sanchez, A. Robalino-Lopez, P. Robalino-Lopez, A. Alarcon-Ortiz, M.V. Garcia. A scoping review on virtual reality-based industrial training. Applied Sciences 10 (2020) 8224. doi:10.3390/app10228224.
[41] E. Spadoni, M. Bordegoni, M. Carulli, F. Ferrise. Extended reality in industry: past, present and future perspectives. Proceedings of the Design Society 3 (2023) 1845, doi:10.1017/pds.2023.185.
[42] A. Malta, T. Farinha, M. Mendes. Augmented Reality in maintenance - history and perspectives. J. Imaging 9 (2023) 142, doi:10.3390/jimaging9070142.

[43] K. Antosz, D. Mazurkiewicz, E. Kozłowski, J. Sep, T. Żabiński. Machining Process Time Series Data Analysis with a Decision Support Tool. Lecture Notes in Mechanical Engineering (2022) 14 - 27. 10.1007/978-3-030-79165-0_2.
[44] Y. Lu. Industry 4.0: A survey on technologies, applications and open research issues. Journal of Industrial Information Integration 6 (2017) 1-10. doi:10.1016/j.jii.2017.04.005.
[45] K. Antosz, J. Machado, D. Mazurkiewicz, D. Antonelli, F. Soares. Systems Engineering: Availability and Reliability. Appl. Sci. 12 (2022) 2504. https://doi.org/10.3390/app12052504.
[46] H. Lypak, A. Rzheuskyi, N. Kunanets, V. Pasichnyk. Formation of a Consolidated Information Resource by Means of Cloud Technologies. 2018 International Scientific-Practical Conference on Problems of Infocommunications Science and Technology (2018) 157-160. doi: 10.1109/INFOCOMMST.2018.8632106.
[47] S. Yevseiev, V. Ponomarenko, O. Laptiev, O. Milov, O. Korol, S. Milevskyi, S. Pohasii, A. Tkachov, O. Shmatko, Y. Melenti, O. Sievierinov, S. Ostapov, A. Gavrilova, O. Tsyhanenko, S. Herasimov, E. Nyemkova, B. Tomashevsky, I. Hrod, I. Opirskyy, V. Zvieriev, O. Prokopenko, V. Savchenko, O. Barabash, V. Sobchuk, G. Shuklin, V. Khvostenko, O. Tymochko, M. Pavlenko, A. Trystan, S. Florov. (2021). Synergy of building cybersecurity systems: Monograph. Kharkiv: PC TECHNOLOGY CENTER, 188. doi:10.15587/978-617-7319-31-2
[48] M. Schluse, J. Rossmann. From simulation to experimentable digital twins: Simulation-based development and operation of complex technical systems. 2016 IEEE International Symposium on Systems Engineering (ISSE), Edinburgh, UK (2016) 1-6, doi: 10.1109/SysEng.2016.7753162.
[49] C. Favi, M. Marconi, M. Mandolini, M. Germani. Sustainable life cycle and energy management of discrete manufacturing plants in the industry 4.0 framework. Applied Energy 312 (2022) 118671, doi:10.1016/j.apenergy.2022.118671.
[50] L. Bartolucci, S. Cordiner, V. Mulone, M. Santarelli, P. Lombardi, B. Arendarski. Towards net zero energy factory: a multi-objective approach to optimally size and operate industrial flexibility solutions. International Journal of Electrical Power and Energy Systems 137 (2022) 107796. doi:10.1016/j.ijepes.2021.107796.
[51] F. Tahir, M. Arshad, M. Saeed, A., U. Ali. Integrated process for simulation of gasification and chemical looping hydrogen production using Artificial Neural Network and machine learning validation. In Energy Conversion and Management. 2023. Vol. 296, p. 117702. https://doi.org/10.1016/j.enconman.2023.117702.
[52] V. Martsenyuk, I. Andrushchak, A. Sverstiuk, A. Klos-Witkowska. On investigation of stability and bifurcation of neural network with discrete and distributed delays.) Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). 2018. Vol. 11127. LNCS, pp. 300 – 313. DOI: 10.1007/978-3-319-99954-8_26.
[53] V. Martsenyuk, A. Sverstiuk. An exponential evaluation for recurrent neural network with discrete delays. System Research and Information Technologies, 2019. Vol. 2. pp. 83 – 93. DOI: 10.20535/SRIT.2308-8893.2019.2.07

[54] O. Nakonechnyi, V. Martsenyuk, A. Sverstiuk. On Application of Kertesz Method for Exponential Estimation of Neural Network Model with Discrete Delays. Mechanisms and Machine Science. 2020. Vol. 70. pp. 165 – 176.
[55] V. Martsenyuk, A. Klos-Witkowska, S. Dzyadevych, A. Sverstiuk. Nonlinear Analytics for Electrochemical Biosensor Design Using Enzyme Aggregates and Delayed Mass Action. Sensors 2022, 22(3), 980; https://doi.org/10.3390/s22030980.
[56] O. Saiapina, K. Berketa, A. Sverstiuk, L. Fayura, A. Sibirny, S. Dzyadevych, O. Soldatkin. Adaptation of Conductometric Monoenzyme Biosensor for Rapid Quantitative Analysis of L-arginine in Dietary Supplements. In Sensors. 2024. Vol. 24, Issue 14, p. 4672. https://doi.org/10.3390/s24144672.
[57] V. Martsenyuk, O. Soldatkin, A. Klos-Witkowska, A. Sverstiuk, K. Berketa. Operational stability study of lactate biosensors: modeling, parameter identification, and stability analysis. In Frontiers in Bioengineering and Biotechnology. 2024. Vol. 12. Frontiers Media SA. https://doi.org/10.3389/fbioe.2024.1385459.
[58] A. Sverstiuk. Research of global attractability of solutions and stability of the immunosensor model using difference equations on the hexagonal lattice. Innovative Biosystems and Bioengineering. 2019. Vol. 3 (1), pp. 17 – 26. DOI: 10.20535/ibb.2019.3.1.157644.
[59] V. Martsenyuk, A. Sverstiuk, I. Andrushchak. Approach to the study of global asymptotic stability of lattice differential equations with delay for modeling of immunosensors. Journal of Automation and Information Sciences. 2019. Vol. 51 (2), pp. 58 – 71. DOI: 10.1615/jautomatinfscien.v51.i2.70.
[60] A. Nakonechnyi, V. Martsenyuk, A. Sverstiuk, V. Arkhypova, S. Dzyadevych. Investigation of the mathematical model of the biosensor for the measurement of α-chaconine based on the impulsive differential system CEUR Workshop Proceedings. 2020. Vol. 2762, pp. 209 – 217.
[61] V. Martsenyuk, O. Bahrii-Zaiats, A. Sverstiuk, S. Dzyadevych, B. Shelestovskyi. Mathematical and Computer Simulation of the Response of a Potentiometric Biosensor for the Determination of α-chaconine. CEUR Workshop Proceedings. 2023. Vol. 3468, pp. 1 – 11.
[62] V. Martsenyuk, A. Sverstiuk, A. Klos-Witkowska, K. Nataliia, O. Bagriy-Zayats, I. Zubenko. Numerical analysis of results simulation of cyber-physical biosensor systems. CEUR Workshop Proceedings. 2019. Vol. 2516, pp. 149 – 164.
[63] V. Martsenyuk, A. Sverstiuk, O. Bahrii-Zaiats, A. Kłos-Witkowska. Qualitative and Quantitative Comparative Analysis of Results of Numerical Simulation of Cyber-Physical Biosensor Systems. CEUR Workshop Proceedings. 2022. Vol. 3309, pp. 134 – 149.
[64] D. Mourtzis, J. Angelopoulos, N. Panopoulos. Operator 5.0: a survey on enabling technologies and a framework for digital manufacturing based on extended reality. Journal of Machine Engineering 22 (2022) 43. doi:10.36897/jme/147160.
[65] Y. Yin, P. Zheng, C. Li, L. Wang. A state-of-the-art survey on Augmented Reality-assisted Digital Twin for futuristic human-centric industry transformation. Robotics and Computer-Integrated Manufacturing 81 (2023) 102515. doi:10.1016/j.rcim.2022.102515.