Industry 4.0, Cyber-Physical Systems and Smart Cyber-Physical Systems

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Modern society is experiencing a significant transformation. Thanks to the digitization of society and manufacturing, mainly because of a combination of technologies, such as the Internet of Things, cloud computing, machine learning, smart cyber-physical systems, etc., which are making the smart factory and Industry 4.0 a reality. Most of the intelligence of smart cyber-physical systems is implemented in software.

Industry 4.0 | artificial neural networks | multilayer perceptron | smart cyber-physical systems

1. Industry 4.0 (I4.0)

At present, modern society is experiencing a significant transformation concerning the production of products thanks to the digitization of society and manufacturing [1]. This transition is being called Industry 4.0 (I4.0), which is integrated by new, modern, smart, and disruptive technologies. It refers to the intelligent networking of machines and processes with the help of new information and communication technologies (NTICs) such as the Internet of Things (IoT), cloud computing (CC), fog computing (FC), Artificial Intelligence (AI), among others [2][3][4][5], that have increased the speed and breadth of knowledge within the modern economy and society of knowledge.

From the first industrial revolution, distinguished by mechanization through water and steam power [6], to the mass production and assembly lines using electricity in the second [7], I4.0 adopted computers and automation, which began in the third industrial revolution [8], and enhanced it with smart and autonomous systems, which work in IoT environments, fed by digital data analyzed by machine learning (ML) technology [9].

When computers were introduced in the third industrial revolution, it was disruptive compared to the technology used during the second one [10]. Thanks to the addition of this entirely new technology, at present, computers are connected, communicate with one another, and are capable of making decisions without human involvement because of the NTICs of I4.0 [11][12][13], where cyber-physical systems (CPS), IoT, AI, and ML stand out.

A combination of CPS, IoT, the Internet of Systems (IoS), and ML are making I4.0 possible and the smart factory a reality. With the support of smart machines that access more data to get smarter themselves, the actual factories will be less wasteful and more efficient and productive [14]. Indeed, the true power of I4.0 is provided by the digital connection between network CPS and one another to create and share information.

2. Cyber-Physical Systems

CPS are systems that integrate constituents from the cyber and physical domains [15][16] for monitoring and controlling the physical processes through a network of actuators and sensors and could be implemented on many scales between the nano-world and large-scale systems [17]. A CP system is a computer system controlled and/or monitored by computer-based algorithms, which integrates networking, computation, and physical processes where embedded networks and computers control and monitor the physical processes, with feedback loops where physical processes affect computations reciprocally [18]. CPS form the basis of smart machines of I4.0 mainly because they use modern control systems and have and dispose of an internet address to connect and be addressed via IoT environments [19].

As previously mentioned, there is great potential for CPS in modern society. Economy and major research and investments are being made worldwide to develop this technology [20] based on older technologies, such as embedded systems, computers, networks, and embedded software.

CPS hold the potential to reshape our world with more precise, responsive, efficient, and reliable systems, enabling a revolution of smart devices and systems ranging from smart cars, medical and household appliances, etc., and passing to smart grids towards smart cities [21].

3. Smart Cyber-Physical Systems

In computing applications, smart cyber-physical systems (SCPS) are the next generation, in which communication, computation, process control, and AI technologies are integrated in a transparent and novel way, developing intelligent autonomous systems [22][23]. The term smart indicates highly cooperative behavior, self-awareness, self-adaptation, and self-optimization [24].

In this sense, the SCPS are complex due to the combination and composition of the components and physical elements that integrate them, and where the main drawback for becoming smart is the enabling of different AI techniques and technologies under a variety of IoT constraints [25]. Nowadays, new developments are allowing the emergence of new SCPS where the continuously generated data is utilized to build AI models used to perform specialized tasks within the systems, such as image, character, voice recognition, and more applications [26][27]. Therefore, SCPS must be studied as a whole, which sets this emerging discipline apart from the older technologies on which it is based.

SCPS have evolved beyond what was identified by the traditional definitions of CPS. The SCPS describes the upcoming generation of CPS, equipped with some level of computational intelligence that makes them capable of building awareness, reasoning concerning states of operations and objectives, and adapting to their environment and work conditions [28].

SCPS implement a higher level of integration of hardware, software, AI, and cyberware technologies than any other system before [29][30]. Under an I4.0 scenario, traditional CPS need to deal with the dynamicity of the environment effectively, be scalable and tolerant to threats, and control their emergent behavior; hence, CPS have to be smart. In this sense, SCPS are complex engineered systems empowered by cyber-physical computing, such as CC and FC. They tend to be smart due to AI technology, which gives them the capability of reasoning, learning, adapting, and evolving [31].

AI can provide cognition to SCPS, an essential ability to smart devices, which allows the modeling, representation, and learning of complex interactions and behaviors between the system components and the system data. Through supervised or unsupervised training, cognition can be achieved using AI models, which are designed to perform these specific tasks [32]. Moreover, AI models can continuously learn from the system, conferring an adaptive ability to the SCPS.

Within the issue of image recognition, networks have been widely used since they have demonstrated their high effectiveness in recognizing objects, detecting anomalies, and tracking objects in real-time [33]; however, there are still significant challenges in its implementation in equipment, with few hardware resources in processing and RAM primarily.

Currently, most of the intelligence of SCPS is implemented in software. For this reason, the focus was on the design of the AI software, which is one of the most complex and critical components of SCPS.

From this arises the purpose for implementing artificial neural networks in SCPS in order to integrate the learning and adaptability capabilities of neural networks that enable intelligent and autonomous decision-making.

Multilayer perceptron artificial neural network (MLPANN) was selected because of its simple and easy-to-implement architecture in comparison with other more complex neural networks [34], in addition to considering the advantages it provides in the case of application to SCPS, such as the capacity to handle large data sets, capacity to learn in a non-linear way, efficient data processing and fast training time, which makes it a viable option for real-time applications [35].

References

1. Jiang, J.-R. An improved cyber-physical systems architecture for Industry 4.0 smart factories. Adv. Mech. Eng. 2018, 10, 1687814018784192.
2. Duo, W.; Zhou, M.; Abusorrah, A. A Survey of Cyber Attacks on Cyber Physical Systems: Recent Advances and Challenges. IEEE/CAA J. Autom. Sin. 2022, 9, 784–800.
3. ERDİL, A. Industry 4.0 Perception regarding to New Developments and New Trends of Industries. Eur. J. Sci. Technol. 2021.

4. Shrivastava, A.; Krishna, K.M.; Rinawa, M.L.; Soni, M.; Ramkumar, G.; Jaiswal, S. Inclusion of IoT, ML, and Blockchain Technologies in Next Generation Industry 4.0 Environment. Mater. Today Proc. 2021, 80, 3471–3475.
5. RZhong, Y.; Xu, X.; Klotz, E.; Newman, S.T. Intelligent Manufacturing in the Context of Industry 4.0: A Review. Engineering 2017, 3, 616–630.
6. Pivoto, D.G.S.; de Almeida, L.F.F.; Da Rosa Righi, R.; Rodrigues, J.J.P.C.; Lugli, A.B.; Alberti, A.M. Cyber-physical systems architectures for industrial internet of things applications in Industry 4.0: A literature review. J. Manuf. Syst. 2021, 58, 176–192.
7. Dalenogare, L.S.; Benitez, G.B.; Ayala, N.F.; Frank, A.G. The expected contribution of Industry 4.0 technologies for industrial performance. Int. J. Prod. Econ. 2018, 204, 383–394.
8. Klingenberg, C.O.; Borges, M.A.V.; Antunes, J.A.D.V. Industry 4.0: What makes it a revolution? A historical framework to understand the phenomenon. Technol. Soc. 2022, 70, 102009.
9. Lee, J.; Davari, H.; Singh, J.; Pandhare, V. Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. Manuf. Lett. 2018, 18, 20–23.
10. Shah, K.; Patel, N.; Thakkar, J.; Patel, C. Exploring applications of blockchain technology for Industry 4.0. Mater. Today Proc. 2022, 62, 7238–7242.
11. Kotsiopoulos, T.; Sarigiannidis, P.; Ioannidis, D.; Tzovaras, D. Machine Learning and Deep Learning in smart manufacturing: The Smart Grid paradigm. Comput. Sci. Rev. 2021, 40, 100341.
12. Raval, M.B.; Joshi, H. Categorical framework for implementation of industry 4.0 techniques in medium-scale bearing manufacturing industries. Mater. Today Proc. 2022, 65, 3531–3537.
13. Pereira, A.C.; Romero, F. A review of the meanings and the implications of the Industry 4.0 concept. Procedia Manuf. 2017, 13, 1206–1214.
14. Navickas, V.; Kuznetsova, S.; Gruzauskas, V. Cyber–Physical Systems Expression in Industry 4.0 Context. Financ. Credit. Act. Probl. Theory Pract. 2017, 2, 188–197.
15. Tepjit, S.; Horvath, I.; Rus, Z. The state of framework development for implementing reasoning mechanisms in smart cyber-physical systems: A literature review. J. Comput. Des. Eng. 2019, 6, 527–541.
16. Yaacoub, J.-P.A.; Salman, O.; Noura, H.N.; Kaaniche, N.; Chehab, A.; Malli, M. Cyber-physical systems security: Limitations, issues and future trends. Microprocess. Microsyst. 2020, 77, 103201.
17. Villalba-Díez, J.; Molina, M.; Ordieres-Mer, J.; Sun, S.; Schmidt, D.; Wellbrock, W. Geometric Deep Lean Learning: Deep Learning in Industry 4.0 Cyber–Physical Complex Networks. Sensors 2020, 20, 763.

18. Persson, M.; Håkansson, A. A Communication Protocol for Different Communication Technologies in Cyber-Physical Systems. Procedia Comput. Sci. 2015, 60, 1697–1706.
19. Xu, H.; Yu, W.; Griffith, D.; Golmie, N. A Survey on Industrial Internet of Things: A Cyber-Physical Systems Perspective. IEEE Access 2018, 6, 78238–78259.
20. Tyagi, A.K.; Sreenath, N. Cyber Physical Systems: Analyses, challenges and possible solutions. Internet Things Cyber-Phys. Syst. 2021, 1, 22–33.
21. Delicato, F.C.; Al-Anbuky, A.; Wang, K.I.-K. Editorial: Smart Cyber–Physical Systems: Toward Pervasive Intelligence Systems. Future Gener. Comput. Syst. 2020, 107, 1134–1139.
22. Skowronski, R. The open blockchain-aided multi-agent symbiotic cyberphysical systems. Future Gener. Comput. Syst. 2018, 94, 430–443.
23. Bures, T.; Weyns, D.; Schmer, B.; Tovar, E.; Boden, E.; Gabor, T.; Gupta, P.; Kang, E.; Knauss, A.; Patel, P.; et al. Software Engineering for Smart Cyber-Physical Systems: Challenges and Promising Solutions. ACM SIGSOFT Softw. Eng. Notes 2017, 42, 19–24.
24. Radanliev, P.; De Roure, D.; Van Kleek, M.; Santos, O.; Ani, U. Artificial intelligence in cyber physical systems. AI SOCIETY 2021, 36, 783–796.
25. Nacchia, M.; Fruggiero, F.; Lambiase, A.; Bruton, K. A Systematic Mapping of the Advancing Use of Machine Learning Techniques for Predictive Maintenance in the Manufacturing Sector. Appl. Sci. 2021, 11, 2546.
26. Fei, X.; Shah, N.; Verba, N.; Chao, K.-M.; Sanchez-Anguix, V.; Lewandowski, J.; James, A.; Usman, Z. CPS data streams analytics based on machine learning for Cloud and Fog Computing: A survey. Future Gener. Comput. Syst. 2019, 90, 435–450.
27. Tav, J.; Horvath, I. A Review of the Principles of Designing Smart Cyber-Physical Systems for Run-Time Adaptation: Learned Lessons and Open Issues. IEEE Trans. Syst. Man Cybern. Syst. 2019, 49, 145–158.
28. Kalluri, B.; Chronopoulos, C.; Kozine, I. The concept of smartness in cyber–physical systems and connection to urban environment. Annu. Rev. Control. 2021, 51, 1–22.
29. Tavcar, J.; Duhovnik, J.; Horvath, I. From Validation of Medical Devices towards Validation of Adaptive Cyber-Physical Systems. J. Integr. Des. Process Sci. 2019, 23, 37–59.
30. Varadarajan, V.; Kommers, P.; Piuri, V. Preface of Special Issue on Advanced techniques and emerging trends in Smart Cyber–Physical Systems. Future Gener. Comput. Syst. 2022, 135, 299–302.
31. Al-Jaroodi, J.; Mohamed, N. PsCPS: A Distributed Platform for Cloud and Fog Integrated Smart Cyber-Physical Systems. IEEE Access 2018, 6, 41432–41449.

32. Bousdekis, A.; Apostolou, D.; Mentzas, G. A human cyber physical system framework for operator 4.0–artificial intelligence symbiosis. Manuf. Lett. 2020, 25, 10–15.
33. Bi, T.; Liu, Q.; Ozcelebi, T.; Jarnikov, D.; Sekulovski, D. PCANN: Distributed ANN Architecture for Image Recognition in Resource-Constrained IoT Devices. In Proceedings of the 2019 15th International Conference on Intelligent Environments (IE), Rabat, Morocco, 24–27 June 2019; pp. 1–8.
34. Del Campo, F.A.; Neri, M.C.; Villegas, O.O.; Sánchez, V.G.; Domínguez, H.D.; Jiménez, V.G. Auto-adaptive multilayer perceptron for univariate time series classification. Expert Syst. Appl. 2021, 181, 115147.
35. Hoffmann, L.F.S.; Bizarria, F.C.P.; Bizarria, J.W.P. Detection of liner surface defects in solid rocket motors using multilayer perceptron neural networks. Polym. Test. 2020, 88, 106559.