Man is not a machine – anthropocentric human-machine symbiosis for ultra-flexible smart manufacturing

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Abstract

Smart manufacturing is characterized by self-organizing manufacturing systems and processes that can respond to dynamic changes. We envision the rapid advancement of smart machines with empathy skills will enable anthropocentric human-machine teams that can maximize human flexibility and wellness at work while maintaining the required manufacturing productivity and stability. In this paper, we present a future-proofing human-machine symbiosis framework that features human centrality, social wellness, and adaptability. The essential technical challenges and methods are discussed in detail.

Keywords: Human-machine collaboration; Anthropocentric production; Smart manufacturing; Empathy; Collaborative intelligence.

1. Introduction

“The real question is not whether machines think but whether men do” – Burrhus Frederic Skinner

Dedicated manufacturing systems are fading out as future manufacturing (i.e., Industry 4.0 [1]) demands ultra-flexible smart manufacturing systems that can self-adapt to production process changes resulting from varied batch sizes of personalized products [2–4]. The manufacturing shop-floor can become an unstructured environment where manufacturing systems and processes change their configurations dynamically via adaptive near real-time decision-making. One emerging trend to make manufacturing flexible and reconfigurable is to introduce collaborative machines working alongside humans with high productivity [5–7]. While these atoms, powered by artificial intelligence [7], are radically changing how work gets done and who does it in what way, we believe the more substantial impact will be in augmenting human capabilities and enhancing human wellbeing. Future societies will see a harmonious ecosystem that humans and machines team up to meld the human cognitive strengths with the unique capabilities of smart machines to create intelligent teams adaptive to rapidly changing circumstances [8,9].

In our view, we are at the point in time where Rosenbrock’s predicament that “humans should never be subservient to machines and automation, but machines and automation should be subservient to humans” has become a foreseeable possibility [10]. Future smart machines can establish trustworthy relationships with humans via proactive communication, empathic understanding, and need-driven collaborations, which, as a result, can lead to high-performance human beings and productive yet flexible manufacturing processes. However, little work has been reported on developing a human-centric manufacturing system that places human benefits at the center of the system optimization goal. Research on human-machine collaboration in the manufacturing domain has been only focusing on human-machine interfaces [11] and human factors in manufacturing systems, e.g., ergonomics and mental workload, to improve the overall system performance [12]. To bridge this gap, we, in this paper, present an anthropocentric human-machine symbiosis framework that augments

human capabilities and wellbeing in an industrial working environment. The essential elements of this framework and the enabling technologies are discussed.

2. Human-machine symbiosis framework

In the next sections, we describe a general human-machine symbiosis framework for the future of collaborative manufacturing. Of particular interests are the following features attributed to human-machine symbiosis: (a) *human-centrality* – as the ability to focus on human desire and judgment, (b) *social wellness* – as the ability to detect and respond to human physical and mental performance to maximize human wellness, and (c) *adaptability* – as the ability to learn from the environment and change behavior based on that learning.

Figure 1: Anthropocentric human-machine symbiosis framework

Figure 1 presents a human-machine symbiosis framework in which humans and machines form intelligent teams to collectively sense, reason, and act to respond to incoming manufacturing tasks and contingencies. The main communication channels between humans and machines are discussed in section 2.1. Human-machine understandings are addressed in Section 2.2. Section 2.3 presents our perspective on human-machine collaborative intelligence. Section 2.4 discusses human-centered collaboration mechanisms, which is a crucial feature of future human-machine teams.

2.1 Human-machine communication

Human-machine communications can be established via a variety of communication channels, such as voice commands [13,14], gestures [13,15–17], body pose [15,18], brainwave [19,20] and Augmented Reality/Virtual Reality [21–23], in addition to traditional humdrum human-machine interfaces. These new communication channels enabled by AI technologies, such as image processing and speech recognition, have made human-machine communications much closer to natural human interactions. Table 1 lists typical human-machine communication channels by application scenario and usability. Voice commands, physical interactions, text, image, video, AR and VR can be used for bidirectional communications between humans and machines. They are in general easy to use if developed properly. Gesture, body pose and brainwave recognition, though look promising, are more suitable for human-to-machine communication and can be cumbersome to implement in a factory environment.

Table 1: Human-machine communication channels

Method	Human-to-machine	Machine-to-human	Usability*
Voice commands	✓	✓	High
Physical inputs/outputs	✓	✓	High
Text	✓	✓	High
Image	✓	✓	Medium
Video	✓	✓	Medium
AR/VR	✓	✓	Medium
Gesture	✓	-	Medium
Body pose	✓	-	Medium
Brainwave	✓	-	Low

*: The usability evaluation of these technologies is the authors' qualitative assessment on their effectiveness, efficiency, and satisfaction. No solid quantitative comparison between these technologies in the context of human-machine communication is available yet.

Apart from exchanging information between humans and machines, communication also needs to adapt to content, context, and identity. Human-machine communication is dynamic, contingent upon the messages being exchanged at a specific moment within a particular context. Effective machine-to-human communications tailor the communication style based on (1) the nature of the content, e.g., whether the content is a suggestion, warning or instruction; (2) the context, e.g., whether a machine is taking the assistive role or not and the situation is time-critical or not; (3) the culture, education background, and communication style of the human partner, e.g., whether the human partner is from a high context or a low context culture [24].

2.2 Human-machine understanding: Empathy skills

Physical and mental state can have a significant influence on personal work performance [25,26]. Physical responses, such as muscle fatigue build-up [12] and bad posture [27], can lead to increased difficulty performing manufacturing tasks [28,29]. Mental responses, such as a high cognitive workload, can result in higher stress levels and lower satisfaction, ultimately reducing productivity [12,30]. Therefore, accurate assessment of human physical workload, cognitive workload, and the psychological reactions (e.g., emotions) in human-machine collaborations is essential for improving human performance. In a human-machine collaboration context, dynamic human physical, cognitive and psychological states can be detected via indirect inference from signals, such as emotional prosody [31,32], facial expressions [33–35], body poses [36,37], electromyography (EMG) [38], eye gaze and pupil dilation [38,39]. In the future, machines would have to possess the skills to observe a human counterpart's physical and mental state, establish a human-centric world model and generate empathic behaviors that would be perceived as compassionate interactions in human environments. The ultimate goal of developing empathy skills in smart machines is to establish trust and respect between humans and machines, which were found to be fundamental to many social interactions [40], including collaborations, to boost human-machine team performance and satisfaction.

It is also vital for humans to understand and care about the health of the smart machines, through which healthier human-machine relationships can be developed in return. Machine

health can include quantitative measures associated with workload, task fluctuation levels, etc. Dynamic task allocation and adjustment based on human and machine health state can help maximize human-machine teaming performance.

2.3 Human-machine collaborative intelligence

Human-machine symbiosis also requires rethinking of how control algorithms are developed in intelligent systems. A survey of 1,500 companies in 12 industries found that companies achieve the most significant performance improvements when humans and systems join forces to form collaborative intelligence, rather than dominating by AI algorithms [41]. In an intelligent human-machine collaboration setting, human agents and machine agents form a partnership aiming for optimizing team benefits and maximizing their own long-term returns, via interactions with the environment and other agents. A smart machine can generate adaptive execution strategies to tailor to the dynamic working environment and state of its human partners. In a high-performing team, smart machine agents and human agents will establish a fully cooperative planning and control relationship via leveraging each other's complementary strengths. In this regard, learning-based algorithms, such as Multi-Agent Reinforcement Learning, could be a promising option to achieve adaptive collaborative decision-making in a human-machine team.

2.4 Human-centered collaboration mechanisms

Based on natural human-machine communications, empathic understandings, we believe anthropocentric production [42] will become possible. Future human-machine teams will need to place human needs and wellbeing at the center of manufacturing planning and control, instead of continuing the current practices of system-oriented optimization in manufacturing control. The transition from dedicated manufacturing systems to flexible unstructured human-machine collaboration creates huge challenges and opportunities in ensuring manufacturing productivity and human worker wellness [43,44]. Highly adaptive and reconfigurable systems with real-time data processing capabilities are required to address the ergonomics issues while ensuring productivity in human-machine collaboration. For example, the physiological or psychological state of a human worker can be considered in human-in-the-loop manufacturing control, resulting in adaptive labor demands planning without affecting the overall production efficiency [45]. More importantly, humans will need to be given maximum working freedom, supported by empathic machines that can adaptively assist human workers in completing manufacturing tasks. Real-time planning and re-planning algorithms are required to handle human behavior contingencies and refine plans based on real-time observation of task progress and human wellness.

3. Discussions

Human-machine symbiosis can create significant changes to future production systems and human workers. We believe anthropocentric human-machine symbiosis can enable the following long-term benefits:

Human wellbeing: Human-machine symbiosis can significantly improve human wellness and satisfaction at work due to the change from a subservient role to a dominant role in manufacturing. The physical and emotional state of a human worker will be constantly tracked and optimized in human-machine collaborations.

Manufacturing flexibility: Human-machine symbiosis can increase the flexibility of manufacturing systems and processes. Manufacturing systems and processes can be

reconfigured on the fly to respond to the dynamics of products, human behavior, and production systems. The shift from rigid manufacturing setups to flexible systems will enable on-demand manufacturing strategies for producing individualized products with dynamic batch sizes.

Human and machine capacity development: With intelligent algorithms backbone by AI, humans and machines can learn and develop their capacities from co-working experiences. Humans can gain new knowledge and skills by osmosis via trustworthy and intimate interactions with intelligent machines that can assist and guide human workers in a socially appropriate way. On the other side, machines can also improve their technical and interpersonal skills based on interactions with different people.

4. Conclusions

The authors believe the advancement of AI technologies will make anthropocentric production possible. Humans will be liberated from repetitive, fixed tasks that were designed to maximize manufacturing system performance; instead, humans can work in a dominant role with on-demand assistance from smart machines. Empathic machines and high-performance human coworkers in dynamic co-existence settings will make manufacturing more resilient, flexible, and sustainable. We encourage more research into redefining human roles in the future of manufacturing.

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Compliance with ethics guidelines

The authors declare that they have no conflict of interest or financial conflicts to disclose.

References

- [1] Kagermann H, Helbig J, Hellinger A, Wahlster W. Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0: Securing the Future of German Manufacturing Industry; Final Report of the Industrie 4.0 Working Group. Forschungsunion; 2013.
- [2] Lu Y, Xu X, Wang L. Smart manufacturing process and system automation – A critical review of the standards and envisioned scenarios. *Journal of Manufacturing Systems* 2020;56:312–25. doi:10.1016/j.jmsy.2020.06.010.
- [3] Mittal S, Khan MA, Romero D, Wuest T. Smart manufacturing: Characteristics, technologies and enabling factors. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 2017;095440541773654. doi:10.1177/0954405417736547.
- [4] Zhong RY, Xu X, Klotz E, Newman ST. Intelligent Manufacturing in the Context of Industry 4.0: A Review. *Engineering* 2017;3:616–30. doi:10.1016/J.ENG.2017.05.015.
- [5] Bauer A, Wollherr D, Buss M. Human–robot collaboration: a survey. *International Journal of Humanoid Robotics* 2008;5:47–66. doi:10.1142/S0219843608001303.
- [6] Wang L, Gao R, Váncza J, Krüger J, Wang X V., Makris S, et al. Symbiotic human-robot collaborative assembly. *CIRP Annals* 2019;68:701–26. doi:10.1016/j.cirp.2019.05.002.

- [7] Wang L. From Intelligence Science to Intelligent Manufacturing. *Engineering* 2019;5:615–8. doi:10.1016/j.eng.2019.04.011.
- [8] Zhou J, Li P, Zhou Y, Wang B, Zang J, Meng L. Toward New-Generation Intelligent Manufacturing. *Engineering* 2018;4:11–20. doi:10.1016/j.eng.2018.01.002.
- [9] Gao L, Shen W, Li X. New Trends in Intelligent Manufacturing. *Engineering* 2019;5:619–20. doi:10.1016/j.eng.2019.07.001.
- [10] Rosenbrock HH. *Machines with a purpose* 1990.
- [11] Gorecky D, Schmitt M, Loskyll M, Zühlke D. Human-machine-interaction in the industry 4.0 era. *Proceedings - 2014 12th IEEE International Conference on Industrial Informatics, INDIN 2014, Institute of Electrical and Electronics Engineers Inc.*; 2014, p. 289–94. doi:10.1109/INDIN.2014.6945523.
- [12] Peruzzini M, Grandi F, Pellicciari M. Exploring the potential of Operator 4.0 interface and monitoring. *Computers and Industrial Engineering* 2020;139:105600. doi:10.1016/j.cie.2018.12.047.
- [13] Rogalla O, Ehrenmann M, Zollner R, Becher R, Dillmann R. Using gesture and speech control for commanding a robot assistant. *Proceedings. 11th IEEE International Workshop on Robot and Human Interactive Communication, IEEE*; 2002, p. 454–9.
- [14] Cohen PR, Oviatt SL. The role of voice input for human-machine communication. *Proceedings of the National Academy of Sciences* 1995;92:9921–7.
- [15] Neto P, Norberto Pires J, Paulo Moreira A. High-level programming and control for industrial robotics: using a hand-held accelerometer-based input device for gesture and posture recognition. *Industrial Robot: An International Journal* 2010;37:137–47.
- [16] Tellaeche A, Kildal J, Maurtua I. A flexible system for gesture based human-robot interaction. *Procedia CIRP* 2018;72:57–62.
- [17] Pavlovic VI, Sharma R, Huang TS. Visual interpretation of hand gestures for human-computer interaction: A review. *IEEE Transactions on Pattern Analysis & Machine Intelligence* 1997:677–95.
- [18] Liu H, Wang L. Human motion prediction for human-robot collaboration. *Journal of Manufacturing Systems* 2017;44:287–94.
- [19] Mohammed A, Wang L. Brainwaves driven human-robot collaborative assembly. *CIRP Annals* 2018;67:13–6.
- [20] Stephygraph LR, Arunkumar N. Brain-actuated wireless mobile robot control through an adaptive human-machine interface. *Proceedings of the International Conference on Soft Computing Systems, Springer*; 2016, p. 537–49.
- [21] Majewski M, Kacalak W. Human-machine speech-based interfaces with augmented reality and interactive systems for controlling mobile cranes. *International Conference on Interactive Collaborative Robotics, Springer*; 2016, p. 89–98.
- [22] Lee T, Hollerer T. Handy AR: Markerless inspection of augmented reality objects using fingertip tracking. *2007 11th IEEE International Symposium on Wearable Computers, IEEE*; 2007, p. 83–90.

- [23] Grajewski D, Górski F, Zawadzki P, Hamrol A. Application of virtual reality techniques in design of ergonomic manufacturing workplaces. *Procedia Computer Science* 2013;25:289–301.
- [24] Hall ET, Hall MR. Understanding cultural differences. Intercultural press; 1989.
- [25] Marcora SM, Staiano W, Manning V. Mental fatigue impairs physical performance in humans. *Journal of Applied Physiology* 2009;106:857–64.
- [26] Yung M, Kolus A, Wells R, Neumann WP. Examining the fatigue-quality relationship in manufacturing. *Applied Ergonomics* 2020;82:102919.
- [27] Busch B, Maeda G, Mollard Y, Demangeat M, Lopes M. Postural optimization for an ergonomic human-robot interaction. 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE; 2017, p. 2778–85. doi:10.1109/IROS.2017.8206107.
- [28] Kim W, Lorenzini M, Balatti P, Wu Y, Ajoudani A. Towards Ergonomic Control of Collaborative Effort in Multi-human Mobile-robot Teams. *IEEE International Conference on Intelligent Robots and Systems, Institute of Electrical and Electronics Engineers Inc.*; 2019, p. 3005–11. doi:10.1109/IROS40897.2019.8967628.
- [29] Marin AG, Shourijeh MS, Galibarov PE, Damsgaard M, Fritzsche L, Stulp F. Optimizing Contextual Ergonomics Models in Human-Robot Interaction. *IEEE International Conference on Intelligent Robots and Systems, Institute of Electrical and Electronics Engineers Inc.*; 2018, p. 8603–8. doi:10.1109/IROS.2018.8594132.
- [30] Ding Y, Cao Y, Duffy VG, Wang Y, Zhang X. Measurement and identification of mental workload during simulated computer tasks with multimodal methods and machine learning. *Ergonomics* 2020. doi:10.1080/00140139.2020.1759699.
- [31] Schuller B, Rigoll G, Lang M. Hidden Markov model-based speech emotion recognition. 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2003. *Proceedings.(ICASSP'03).*, vol. 2, IEEE; 2003, p. II–1.
- [32] El Ayadi M, Kamel MS, Karray F. Survey on speech emotion recognition: Features, classification schemes, and databases. *Pattern Recognition* 2011;44:572–87.
- [33] Busso C, Deng Z, Yildirim S, Bulut M, Lee CM, Kazemzadeh A, et al. Analysis of emotion recognition using facial expressions, speech and multimodal information. *Proceedings of the 6th international conference on Multimodal interfaces, ACM*; 2004, p. 205–11.
- [34] Ioannou S V, Raouzaoui AT, Tzouvaras VA, Mailis TP, Karpouzis KC, Kollias SD. Emotion recognition through facial expression analysis based on a neurofuzzy network. *Neural Networks* 2005;18:423–35.
- [35] Cohen I, Garg A, Huang TS. Emotion recognition from facial expressions using multilevel HMM. *Neural information processing systems*, vol. 2, Citeseer; 2000.
- [36] Schindler K, Van Gool L, de Gelder B. Recognizing emotions expressed by body pose: A biologically inspired neural model. *Neural Networks* 2008;21:1238–46.
- [37] McColl D, Zhang Z, Nejat G. Human body pose interpretation and classification for social human-robot interaction. *International Journal of Social Robotics* 2011;3:313.

- [38] Sadrfaridpour B, Saeidi H, Burke J, Madathil K, Wang Y. Modeling and control of trust in human-robot collaborative manufacturing. *Robust Intelligence and Trust in Autonomous Systems*, Springer US; 2016, p. 115–42. doi:10.1007/978-1-4899-7668-0_7.
- [39] Hogervorst MA, Brouwer AM, van Erp JBF. Combining and comparing EEG, peripheral physiology and eye-related measures for the assessment of mental workload. *Frontiers in Neuroscience* 2014;8. doi:10.3389/fnins.2014.00322.
- [40] Lee J, Moray N. Trust, control strategies and allocation of function in human-machine systems. *Ergonomics* 1992;35:1243–70.
- [41] Wilson HJ, Daugherty PR. Collaborative intelligence: humans and AI are joining forces. vol. 96. 2018.
- [42] Rauch E, Linder C, Dallasega P. Anthropocentric perspective of production before and within Industry 4.0. *Computers and Industrial Engineering* 2019. doi:10.1016/j.cie.2019.01.018.
- [43] Hägele M, Schaaf W, Helms E. Robot assistants at manual workplaces: Effective co-operation and safety aspects. *Proceedings of the 33rd ISR (International Symposium on Robotics)*, vol. 7, 2002.
- [44] Ferraguti F, Villa R, Landi CT, Zanchettin AM, Rocco P, Secchi C. A Unified Architecture for Physical and Ergonomic Human–Robot Collaboration. *Robotica* 2019;1–15. doi:10.1017/S026357471900095X.
- [45] Stankovic JA. Research Directions for the Internet of Things. *IEEE Internet of Things Journal* 2014;1:3–9. doi:10.1109/JIOT.2014.2312291.