

The Operator 4.0: Human Cyber-Physical Systems & Adaptive Automation Towards Human-Automation Symbiosis Work Systems

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Abstract. A vision for the Operator 4.0 is presented in this paper in the context of human cyber-physical systems and adaptive automation towards human-automation symbiosis work systems for a socially sustainable manufacturing workforce. Discussions include base concepts and enabling technologies for the development of human-automation symbiosis work systems in Industry 4.0.

Keywords: Operator 4.0 · Human cyber-physical systems · Adaptive automation · Human-automation symbiosis · Socially sustainable manufacturing

1 Introduction

Industry 4.0 enables new types of interactions between operators and machines [1], interactions that will transform the industrial workforce and will have significant implications for the nature of work, in order to accommodate the ever-increasing variability of production. An important part of this transformation is the emphasis on *human-centricity* of the Factories of the Future [2], allowing for a paradigm shift from independent automated and human activities towards a *human-automation symbiosis* (or ‘human cyber-physical systems’) characterised by the cooperation of machines with humans in work systems and designed not to replace the skills and abilities of humans, but rather to co-exist with and assist humans in being more efficient and effective [3].

In this sense, the history of the interaction of operators with various industrial and digital production technologies can be summarised as a generational evolution. Thus, *Operator 1.0* generation is defined as humans conducting ‘manual and dextrous work’ with some support from mechanical tools and manually operated machine tools. *Operator 2.0* generation represents a human entity who performs ‘assisted work’ with the support of computer tools, ranging from CAX tools to NC operating systems (e.g. CNC machine tools), as well as enterprise information systems. The *Operator 3.0* generation embodies a human entity involved in ‘cooperative work’ with robots and other machines and computer tools, also known as - human-robot collaboration. The

Operator 4.0 generation represents the ‘operator of the future’, a *smart and skilled operator* who performs ‘work aided’ by machines if and as needed. It represents a new design and engineering philosophy for adaptive production systems where the focus is on treating automation as a further enhancement of the human’s physical, sensorial and cognitive capabilities by means of *human cyber-physical system* integration (see Fig. 1).

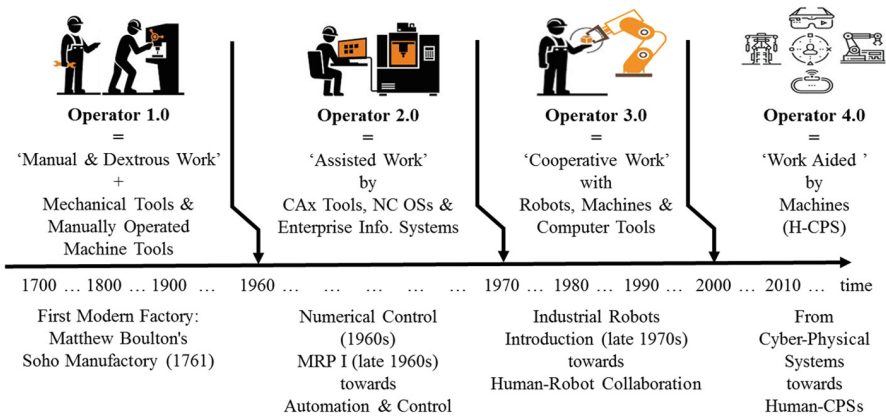


Fig. 1. Operator generations (R) evolution

This paper explores a vision for the *Operator 4.0* in the context of *human cyber-physical systems* and *adaptive automation* towards *human-automation symbiosis work systems* for a socially sustainable manufacturing workforce. The discussions within the following sections include base concepts and enabling technologies for the development of the proposed human-automation symbiosis work systems in Industry 4.0.

2 Base Concepts

The concept of *Balanced Automation Systems (BAS)* [4] was introduced in the early 90’s as an attempt to achieve the right combination of automation and manual operations (*cf.* Operator 2.0 & 3.0) in production systems, taking into account economic and socio-organisational aspects for the (re-)engineering of competitive and socially sustainable production systems. BAS implementations have mainly been based on the principles of ‘anthropocentric production systems’ [5] and the advantages offered by flexible automation as an extension of programmable automation in manufacturing systems. In [6], it has been previously defined a *Next Generation BAS* concept with the aim of stepping beyond the ‘right balance’ between automated and manual tasks in production systems, so as to the achieve ‘human-automation symbiosis’ for enhancing workforce capabilities (*cf.* Operator 4.0) and increasing manufacturing flexibility (*cf.* Factory 4.0) of production systems. The vision of Next Generation BASs is that while they will still rely on the guidelines of ‘anthropocentric production systems’ [5], they will moreover feature ‘adaptive automation’ [7–9] for the dynamic allocation of control over manufacturing and assembly tasks to a human operator and/or a machine for the purpose of

optimising overall production system performance. This will be done considering [10, 11]: (a) sustainable technical and economic benefits for the manufacturing enterprise (e.g. improved quality, increased responsiveness, shorter throughput times, easier planning and control of production processes, increased capacity for innovation and continual improvement) and (b) social-human benefits for the workforce (e.g. increasing quality of working life, higher job satisfaction through meaningful tasks, greater personal flexibility and adaptation, improved ability and skills of shop-floor personnel).

Based on the previous context, we define *Human Cyber-Physical Systems (H-CPS)* as systems engineered to: (a) improve human abilities to dynamically interact with machines in the cyber- and physical- worlds by means of ‘intelligent’ human-machine interfaces, using human-computer interaction techniques designed to fit the operators’ cognitive and physical needs, and (b) improve human physical-, sensing- and cognitive-capabilities, by means of various enriched and enhanced technologies (e.g. using wearable devices). Both H-CPS aims are to be achieved through computational and communication techniques, akin to adaptive control systems with the human-in-the-loop.

The *Adaptive Automation (AA)* movement [7, 8, 12, 13] aims at optimising human-machine cooperation to efficiently allocate labour (cognitive & physical) and distribute tasks between the automated part and the humans in the workstations of an adaptive production system [13]. AA allows the human and/or the machine to modify the level of automation by shifting the control of specific functions whenever predefined conditions (e.g. critical-event, measure-based and/or modelling-based) are met [14]. The ultimate AA goal is the achievement of human-automation symbiosis by means of adaptation of automation & control across all workstations of a human-centred and adaptive production system in order to allow a dynamic and seamless transition of functions (tasks) allocation between humans and machines that optimally leverages human skills to provide inclusiveness and job satisfaction while also achieving production objectives.

Human-in-the-loop (HITL) feedback control systems are defined as systems that require human interaction [15]. HITL control models offer interesting opportunities to a broad range of H-CPS applications, such as the ‘Operator 4.0’. HITL control models can help to supervise an operator’s performance in a human-machine interaction, and (a) let the operator directly control the operation under supervisory control, (b) let automation monitor the operator and take appropriate actions, or (c) an hybrid of ‘a’ and ‘b’, where automation monitors the operator, takes human inputs for the control, and takes appropriate actions [15]. HITL control models, although being challenging due to the complex physiological, sensorial and cognitive nature of human beings, are an important enabler for ‘human-automation symbiosis’ achievement.

3 Human-Automation Symbiosis: Intelligent Hybrid Agents

In this section, the strategy to attain *human-automation symbiosis* in manufacturing work systems is explored through a discourse of ‘adaptive automation’ and ‘intelligent multi-agent systems’ as the bases for a sharing and trading of control strategy [14].

An *intelligent agent* is an entity (human, artificial or hybrid) with the following characteristics [16]: (a) *purposeful* - displays goal-seeking behaviour, (b) *perceptive* - can

observe information about the surrounding world and filter it according to relevance for orientation, (c) *aware* - can develop situational awareness that is relevant for the agent's purpose, (d) *autonomous* - can decide a course of action (plan) to achieve the goal, (e) *able to act* - can mobilise its resources to act on its plan; these resources may include parts of the self or tools at the autonomous disposal of the agent, and resources for physical action or information gathering/processing, (f) *reflective* - can represent and reason about the abilities and goals of self and those of other agents, (g) *adaptable* and *learning* - can recognise inadequacy of its plan and modify it, or change its goal, and (h) *conversational* and *cooperative* - can negotiate with other agents to enhance perception, develop common orientation, decide on joint goals, plans, and action; essentially participate in maintaining the 'emergent agent' created through joint actions of agents. Note that this classification of agent functions may be interpreted as the ability to perform the Observe, Orient, Decide and Act (OODA) Loop of Boyd [17, 18], developed as a theory to explain the conditions and functions of successful operation, and therefore this classification may be used to direct the engineering and development of intelligent agents [16], which, as we shall see below, are expected to be 'adaptive' and 'hybrid' in nature.

Human agents, under certain circumstances, and in defined domains of activity, are able to act as intelligent agents (e.g. able to perform complex assembly sequences and operations in a flexible production line). However, once the assumptions are no longer true (e.g. due to a heavy physical, sensorial and/or cognitive workload), the quality of *agenthood* deteriorates; thus the human does no longer have the ability to perform one or several functions that are normally attributed to an intelligent agent. Consequently, the question is: how to reconstitute human agenthood by extending human capabilities (physical, sensorial and/or cognitive) through automation-aided means?

Similarly, *artificial (machine) agents*, under certain circumstances and in defined domains of activity can act as intelligent agents (e.g. they are able to perform repetitive and routine tasks in a high volume production line, make decisions based on learnt patterns, etc.). Nevertheless, once the assumptions are no longer true (e.g. the need (ability) to improvise and use flexible processes to reduce production downtime due to an error), the quality of *agenthood* deteriorates; thus the machine does no longer have the ability to perform one or several functions that are normally attributed to an intelligent agent. Therefore, the question is: how to restore machine agenthood by extending the machine's capabilities through human-aided means?

Hybrid agents are intelligent agents established as a symbiotic relationship (human-automation symbiosis) between the human and the machine, so that in situations where neither would display agenthood in isolation, the symbiotic hybrid agent does. In this research, the vision is that at any time a human (the 'Operator 4.0') lacks some of these *agenthood* abilities, such as due to heavy physical, sensorial and/or cognitive workload, automation will extend the human's abilities as much as necessary to help the operator to perform the tasks at hand, according to the expected quality of performance criteria. Thus, it is proposed to implement *hybrid agents*, as a form of 'adaptive automation', in order to sustain *agenthood* by determining whenever and wherever the operator requires augmentation (e.g. using *advanced trained classifiers* to recognise this need [19]), and prompting the appropriate type and level of automation to facilitate optimal operator performance. An important objective is that the level of

this extension need not be a ‘design time’ decision, but should be able to be dynamically configured as needed. Furthermore, the ‘hybrid agents’ view of the Operator 4.0 is a component of the solution to preserve the operator’s *situation awareness* [20], as the status, experience and information processing capability of the operator can cause loss of agenthood and consequent decision-making errors, thus the need for ‘symbiotic technical support’. Work on *affective computing* [21] showed that the task allocation and adaptation between humans and machines/computers supporting them is not a trivial task and should involve sensory assessments of humans’ physical and cognitive states in order to be efficient.

For the purpose of comparison, in the case of an Operator 3.0 (*cf.* human-robot collaboration), the design time decision would be determined by the required capability of the manufacturing or assembly operation (e.g. speed, accuracy, capacity, reliability, etc.), which then would decide (based on technical, economic, social and human benefits) the level of automation of the process, as well as the accompanying skills and abilities required by the human role. In contrast, in the case of an Operator 4.0, automation level would be determined in less detail at design time, allowing an initial detailed procedure and much automated support (e.g. in case of a novice or new-to-the-task operator), while providing ‘on the fly’ solutions that develop together with the individual operator’s skills. Apart from achieving job satisfaction and a variety of desired process ‘ilities’ [22], such dynamic allocation of different levels/extent of automation fosters the use of human skills and abilities. This includes the creation of favourable conditions for workforce development and learning, the improvement of human-robot collaboration and tacit knowledge development, as it is well known that in many (although not all) tasks acting based on tacit knowledge are much more efficient and effective than following predetermined procedures.

Emergent agents are virtual entities, who exist as a cooperative and negotiated arrangement between multiple agents of either kind above (sometimes on multiple levels of static or dynamic aggregation), whereupon two human agents, or a human and a machine/robot, or two machine/robot agents, or more than two agents of any of these types, form a ‘join entity agent’ that from the external observer’s viewpoint acts as a single intelligent agent. It is expected that an Operator 4.0 will have the ability to be part of an intelligent group of agents with appropriate functionality for the formation, operation, transformation and dissolution of these groups. Note that it is not necessary for every agent to have the same level of contribution to such self-organising ability; agents may specialise in certain tasks and assume different roles in the lifecycle of the emergent agent.

4 The Operator 4.0: Aiding for Enhanced Workers Capabilities

A *capability* is the “measure of the ability of an entity (e.g. department, organisation, person, system) to achieve its objectives, especially in relation to its overall mission” [23]. In the case of human beings, this involves having the resources and the ability to deploy their capabilities for a purpose.

4.1 Automation Aiding for Enhanced Physical Capabilities

A *physical activity* is any bodily movement produced by skeletal muscles that requires energy expenditure. We define *physical capability* as the operator's capacity and ability to undertake physical activities needed for daily work, and can be characterised by multiple attributes, including the description of the physical function (e.g. ability to lift, walk, manipulate and assemble) together with its non-functional properties (e.g. speed, strength, precision and dexterity), as well as the description of the ability in terms of maturity- and expertise-level. The agent's activity supported is that of (physically) acting, i.e. the 'A' in the OODA loop.

For example, the operator may be: (a) 'procedure following - novice' with no autonomy over the details of the operation and under supervision along the whole procedure, (b) 'procedure following - advanced' with limited operational autonomy and less supervision across the procedure, or (c) 'expert' - featuring internalised tacit knowledge (know-how) and autonomy towards improving the operation, where only the operation's outcome is supervised. The vision of Operator 4.0 acknowledges that capabilities are not static, but they evolve over time, as well as change depending on context (e.g. the operator may be tired or rested, new- or accustomed- to-the-task), therefore physically aiding an Operator 4.0 assumes that one can assess the physical capabilities in a dynamic and timely fashion, preferably in real-time. Some assessment tools for testing an operator's physical capabilities may include: (a) *Physical Abilities Tests (PATs)* [24, 25] capable of matching the physical abilities of an operator with the physical demands of a job (or operation) up-front to its allocation (e.g. such methods are getting increased attention in the defence community); and (b) *Advanced Trained Classifiers (ATCs)* [26], based on a variety of machine learning techniques, to measure (test) in real-time the operator's physical performance and dynamically identify when an assisted/enhanced operation is necessary in an unobtrusive manner, relying on physiological measures (*cf.* ergonomics [27]). This is done in order to actively determine when an operator actually requires assistance and subsequently prompt the appropriate type and level of physical (aided) capability to facilitate optimal physical performance by the operator. Moreover, PATs may be useful for job role allocation and/or for determining training needs (e.g. how to handle lifting, posture correction, etc.), while ATCs may be advantageous for reducing the chances of accidents due to tiredness or of injuries due to repetitive strain, or to improve product quality by reducing errors and re-work.

4.2 Automation Aiding for Enhanced Sensing Capabilities

A *sensorial* capability is the operator's capacity and ability to acquire data from the environment, as a first step towards creating information necessary for orientation and decision-making in the operator's daily work [28]. There are two components to sensing: (a) the physical ability to collect data from the environment (by vision, smell, sound, touch, vibration), and (b) the ability to selectively perceive it (as we know that a very low percentage of the data generated by the physical sense of an operator enters the short-term memory and is made available for processing). It is known that an

operator is selectively filtering out what he/she does not consider important: “of the entire amount of new information generated by our environment, our senses filter out >99% of signals before they reach our consciousness” [29]. It is also known that this filtering is not a conscious process. Therefore, OODA is not a simple loop; there is information that flows to make an operator perceive selectively what his/her brain considers important (i.e. what data are useful for analysis and decision-making). This selectivity is acquired by the operator through learning. As a consequence, there are two points where the operator’s sensing abilities are subject to assessment and where these abilities may need improvement, as further described.

The first potential sensory improvement is the creation of new- or augmentation- of existing senses (e.g. by way of using sensor devices to collect, convert, aggregate signals that would not be accessible for the operator, either due to physical accessibility of the data source, general human limitations, or due to individual personal limitations). Also, due to the different levels of sensitivity of humans across senses, transforming one signal to another form may increase the ability of the human to identify information within the data (e.g. transforming temperature to visible colour, vibration to audible spectrum sound, or using data aggregation, can enable the human to make use of otherwise inaccessible data). The second type of sensory limitation is more difficult to overcome if it is to be done exclusively at sensor level. This is because information feedback produced by analysis (orientation) and decision-making must be used to filter out unwanted data (i.e. containing irrelevant information) and to sensitise selective perception to smaller signals, which may carry relevant information.

Some assessment tools for testing an operator’s sensorial capabilities may include: (a) *Sensorial Abilities Tests (SATs)* [30] capable of matching the sensorial abilities of an operator with the sensorial demands of a job (or operation) up-front to its allocation. This is not a trivial task, because even though the sensorial abilities of an operator can be tested (such as by using simple vision and hearing tests), sensing successfully in the situation (i.e. registering/perceiving signals necessary for analysis and orientation) is also dependent on the nature and level of prior experience of the operator as previously explained.

It is therefore expected that the solution to selective perception deficits is not simply providing operators with ‘bionic ears and eyes’ (even though in some situations that may be sufficient), but in using the ‘emergent agent’ model, where the machine agent has its own intelligence in terms of analysis and orientation, and the ability to reason about the human agent’s needs and decision what data to present for the human’s needs and when.

The traditional limitation for decision-making has been scarcity of information, requiring human (and machine) agents to make decisions in light of insufficient data about the operations. With the proliferation of sensor devices (the so-called ‘Internet of Things’) this situation could change, but only if sensor agents are made intelligent in terms of what data to register and transmit to other agents.

New algorithms are needed for cooperative and collaborative learning of situations for collective sense-making and decision-making by sensor agents (including agent networks). This is so that the situational knowledge base of participating agents can be utilised to adaptively filter unwanted data and to ‘zoom-in’ to enhance faint but relevant signals, as well as negotiate signal bandwidth for priority communication. Part of this

situation recognition may be implemented by machine learning techniques, such as (b) *Advanced Trained Classifiers (ATCs)* [26], where part of an intelligent sensor agent may use machine learning to support human-automation symbiosis and to learn about the individual operator and that operator's behaviour in action, to actively determine when an operator actually requires assistance, and to subsequently prompt the appropriate type and level of sensing (aided) capabilities to facilitate optimal sensing performance by the operator.

4.3 Automation Aiding for Enhanced Cognitive Capabilities

A *cognitive capability* is the operator's capacity and ability to undertake the mental tasks (e.g. perception, memory, reasoning, decision, motor response, etc.) needed for the job and under certain operational settings [31]. In the OODA model, these cognitive tasks are to 'Orient' and to 'Decide', together amounting to a mental workload, decision-making, skilled performance, human-computer interaction, maintaining reliability in performance, dealing with work stress whether in training or in the job.

As the Factories of the Future become increasingly dynamic working environments (*cf.* Industry 4.0) due to the upsurge in the need for flexibility and adaptability of production systems, the upgraded shop-floors (*cf.* Factory 4.0) call for *cognitive aids* that help the operator perform these mental tasks, such as those provided by augmented reality (AR) technologies or 'intelligent' Human-Machine Interfaces (HMI) to support the new/increased cognitive workload (e.g. diagnosis, situational awareness, decision-making, planning, etc.) of the *Operator 4.0*. It can be expected that this aid would increase human reliability in the job, considering both the operator's well-being and the production system's performance.

Some assessment tools for testing an operator's cognitive capabilities may include: (a) *Cognitive Abilities Tests (CATs)* [32] capable of matching the cognitive abilities of an operator with the mental demands and cognitive skills needed for performing a job (or operation) up-front to its allocation; and (b) *Advanced Trained Classifiers (ATCs)* [26] based on various machine learning techniques, to measure (test) in real-time the operator's cognitive performance and dynamically identify when an assisted/enhanced action is necessary, and do so in an unobtrusive manner, relying on cognitive load measurements (*cf.* cognitive ergonomics [33]).

5 Conclusions and Further Work

Industry 4.0 would be inconceivable without human beings. Hence, human-automation symbiosis by means of H-CPS and AA aims to take into account established principles of the design of operator-friendly working conditions [34] for aiding the workforce [35], such as: (a) *practicability*, considering compliance with 'anthropometric' and physical, sensorial and cognitive norms in the design of a work system; (b) *safety*, bearing in mind in the design of work systems embedded security and safety measures to avoid accidents; (c) *freedom from impairment*, by providing automation-aided means to compensate various individual (human) limitations and thus keep with the physical,

sensorial and cognitive quality performance of the job; and (d) *individualisation and personalisation of the working environment* thanks to adaptive systems (*cf.* AA) that support the operator as an individual and promote learning (e.g. by means of sharing and trading of control strategy [14]).

The development of ‘human-automation symbiosis’ in work systems [6, 36] offers advantages for the social sustainability of the manufacturing workforce in *Industry 4.0*, in terms of improving operational excellence, safety and health, satisfaction and motivation, inclusiveness, and continuous learning. Hence, the purpose of H-CPS and AA in this research is to support the *Operator 4.0* to excel in the job by means of automation-aided systems that aim to provide a sustainable relief of physical and mental stress and contribute to the development of workforce creativity, innovation and improvisational skills, without compromising production objectives.

Further work aims to explore ‘intelligent’ human-machine interfaces and interaction technologies, and adaptive and human-in-the-loop (HITL) control systems to support the development of ‘human-automation symbiosis’ work systems for the *Operator 4.0* in the Factory of the Future.

References

1. BCG Group: Report on Man and Machine in Industry 4.0 (2015)
2. European Factories of the Future Research Association (EFFRA) Roadmap 2020
3. Tzafestas, S.: Concerning human-automation symbiosis in the society and the nature. *Int. J. Fact. Autom. Robot. Soft Comput.* **1**(3), 6–24 (2006)
4. Camarinha-Matos, L.M., Rabelo, R., Ósorio, L.: Balanced automation. In: Tzafestas, S.G. (ed.) *Computer-Assisted Management and Control of Manufacturing Systems*, pp. 376–413. Springer, London (1996)
5. Kovács, I., Brandão-Moniz, A.: Issues on the anthropocentric production systems. In: Camarinha-Matos, L.M., Afsarmanesh, H. (eds.) *Balanced Automation Systems: Architectures and Design Methods*, pp. 131–140. Springer, New York (1995)
6. Romero, D., Noran, O., Stahre, J., Bernus, P., Fast-Berglund, Å.: Towards a human-centred reference architecture for next generation balanced automation systems: human-automation symbiosis. *Adv. Prod. Manag. Syst.* **460**, 556–566 (2015)
7. Hancock, P.A., Chignell, M.H.: Adaptive control in human-machine systems. In: Hancock, P.A. (ed.) *Human Factors Psychology*, pp. 305–345. Elsevier Science Publishers, North Holland (1987)
8. Hancock, P.A., Jagacinski, R.J., Parasuraman, R., et al.: Human-automation interaction research: past present and future. *Ergon. Des.* **21**(2), 9–14 (2013)
9. Sheridan, T., Parasuraman, R.: Human-automation interaction. *Hum. Factors Ergon.* **1**(1), 89–129 (2006)
10. Kidd, P.: *Organisation People and Technology in European Manufacturing*. CEC, FAST, Brussels (1992)
11. Lehner, F.: *Anthropocentric Production Systems: The European Response to Advanced Manufacturing and Globalization*. CEC, Brussels (1992)
12. Kay, M.: Adaptive automation accelerates process development. *Bioprocess Int.* **4**(4), 70–78 (2006)

13. Calefato, C., Montanari, R., Tesauri, F.: The adaptive automation design. In: Asai, K. (ed.) *Human Computer Interaction: New Developments*, pp. 141–154. InTech, Rijeka (2008)
14. Inagaki, T.: Adaptive automation: sharing and trading of control. In: *Handbook of Cognitive Task Design*, pp. 147–169 (2003). Chapter 8
15. Munir, S., Stankovic, J.A., Liang, C-J.M., Lin, S.: Cyber-physical system challenges for human-in-the-loop control. In: *Feedback Computing* (2013)
16. Kasabov, N.: Introduction: hybrid intelligent adaptive systems. *Int. J. Intell. Syst.* **6**, 453–454 (1998)
17. Boyd, J.R.: *The Essence of Winning and Losing* (1996). www.dnipogo.org
18. Osinga, F.P.B.: *Science, Strategy and War: The Strategic Theory of John Boyd*. Eburon Academic Publishers, Delft (2005)
19. Willson, G.F., Russel, C.A.: Performance enhancement in a UAV task using psycho-physiologically determined adaptive aiding. *Hum. Factors* **49**(6), 1005–1019 (2007)
20. Endsley, M.R.: Towards a theory of situation awareness in dynamic systems. *Hum. Factors* **37**(1), 32–64 (1995)
21. Picard, R.W.: *Affective Computing*. MIT Press, Cambridge (1997)
22. Ricci, N., Fitzgerald, M., Ross, A.M., Rhodes, D.H.: Architecting systems of systems with Ilities: an overview of the SAI method. In: *Conference on Systems Engineering Research* (2014)
23. Capability (General) Business Dictionary. <http://www.businessdictionary.com> (2016)
24. Committee on Measuring Human Capabilities: *Measuring Human Capabilities: An Agenda for Basic Research on the Assessment of Individual and Group Performance Potential for Military Accession* (2015)
25. Champion, M.A.: Personnel selection for physically demanding jobs: review and recommendations. *Pers. Psychol.* **36**, 527–550 (1983)
26. Woźniak, M., Graña, M., Corchado, E.: A survey of multiple classifier systems as hybrid systems. *Inf. Fusion* **16**, 3–17 (2014)
27. Lee, J.D., Seppelt, B.D.: Human factors and ergonomics in automation design. In: Salvendy, G. (ed.) *Handbook of Human factors and Ergonomics*, pp. 1615–1642. Wiley, Hoboken (2012). Sensory activity
28. Attwood, D., Deeb, J., Danz-Reece, M.: Personal actors. In: Tooley, M. (ed.) *Design Engineering Manual*, pp. 234–247. Elsevier, New York (2010). Chapter 6.1
29. Simon, H.: Artificial intelligence as a framework for understanding intuition. *J. Econ. Psychol.* **24**, 265–277 (2003)
30. Stone, H., Bleibaum, R., Thomas, H.A.: *Sensory Evaluation Practices*, 4th edn. Elsevier, Amsterdam (2012)
31. Carrol, J.B.: *Human Cognitive Abilities*. Cambridge University Press, Cambridge (1993)
32. Hutton, R.J.B., Militello, L.G.: Applied cognitive task analysis (ACTA): a practitioner’s toolkit for understanding cognitive task demands. *Ergonomics* **41**(11), 1618–1641 (1998)
33. Falzon, P., Gaines, B.R., Monk, A.F.: *Cognitive Ergonomics: Understanding, Learning, and Designing Human-Computer Interaction*. Academic Press, Cambridge (1990)
34. Hacker, W.: *Allgemeine Arbeitspsychologie: Psychische Regulation von Wissens Denk und körperlicher Arbeit*, 2nd edn. Verlag Hans Huber, Bern (2005)
35. Bailey, R.W.: *Human Performance Engineering*, 2nd edn. International Prentice-Hall, London (1996)
36. Kaber, D.B., Riley, J.M., Tan, K., Endsley, M.R.: On the design of adaptive automation for complex systems. *Int. J. Cogn. Ergon.* **5**(1), 37–57 (2001)