The Entropic Complexity of Human Factor in Collaborative Technologies

Sotirios Panagou[1](✉), Fabio Fruggiero[1], W. Patrick Neumann[2], and Alfredo Lambiase[3]

[1] School of Engineering, University of Basilicata, 85100 Potenza, Italy
sotirios.panagou@unibas.it

[2] Department of Mechanical and Industrial Engineering, Ryerson University, 350 Victoria Street, Toronto, ON M5B 2K3, Canada

[3] Department of Industrial Engineering, University of Salerno, Fisciano, SA, Italy

Abstract. In recent years manufacturing and assembly lines are undergoing workplace changes with a scope to adapt to the Industry 4.0 (I4.0) design principles. Automation of manufacturing, collaborative robots (cobots), interconnection of cyber physical systems (CPS), cloud computing, big data analytics and Augmented/Virtual reality (AR/VR) are some of the technologies that are being introduced in industry. Human operators are required to adapt and integrate into those new environments. Human operators should be flexible in their work-tasks, upgrade their skillset and be able to act as a safeguard entity in this complex and dynamic environment. A recent shift in paradigms, the Industry 5.0 concept, focus on the sustainability of the human factor inside the technologies that I4.0 framework introduced, and relates to the ageing workforce issue and the change in individuals' capabilities. Productivity and safety of the ageing operators in the new workplace environment is causally related to their capabilities. In this research paper, we (i) study the interactions of human operator inside the "smart" workplace and (ii) develop a model using the entropy concept of statistical mechanics. This model can be utilized in the evaluation of human factor inside the complex environment by computing the probability of error based on human operator capabilities.

Keywords: Entropy · Complex · Collaborative · Human factor · Ageing workforce · Statistical mechanics

1 Introduction

The main theme of I4.0 is automation in the industrial chain of operations such as in manufacturing lines, logistics, supply chains and maintenance. For the workplace to change according to this thematic, it must follow the design principles of interoperability, virtualization, decentralization, real-time capability, service-orientation, modularity and sustainability. The emerging Industry 5.0 theme [1] focuses in using those technologies to assist the human operators inside the workplace. Those principles introduce smart technologies inside the workplace environment that human operators should learn to

N. L. Black et al. (Eds.): IEA 2021, LNNS 221, pp. 503–510, 2021.
https://doi.org/10.1007/978-3-030-74608-7_62

cooperate and interact with (Fig. 1). AR/VR tools (that can assist in work-tasks with information regarding the tasks, potential or critical issues), cyber systems (such as RFID, cloud computing), human-robot communication or machine-machine communication and cobots are some of the smart technologies that human operators should learn how to cooperate and work with to meet product requirements. Real-time data concerning process evaluation, product process, and synchronization status will be conveyed to human operators who in turn should be able to evaluate as useful information, critical information or as simple information and act upon, react on arising/critical situations or ignore. A concern in this scenario is the rising trend of ageing workforce and the new demands these technologies place on that workforce.

The ageing workforce issue is recognized and acknowledged by government officials and global economic institutions [2]. In a report published by EU-OSHA in 2019, the proportion of workers aged over 55 accounts in roughly a quarter of the overall human workforce (from 21% in 2014 to close to 26% in 2019), where the younger workforce percentage fall from 35% in 2005 to 30% in 2015. Older workers in manufacturing and industry in general faces new challenges due to the evolution and introduction of new smart technologies inside the workplace and raises the question of how vulnerable in comparison with their younger counterparts the older workers are due to decline of their capabilities [3]. The decline of those capabilities can lead to increased errors, loss of performance and a probability of safety accidents. Although human errors (HEs) have been classified through research and methods (such as THERP, [4]), and through human reliability analysis (HRA) which study human error probability due to human factors [5], age is not taken into consideration as a factor that influences error and performance. This gives rise to the question of how can we evaluate those declining capabilities due to age in the I4.0 context and benefit from it.

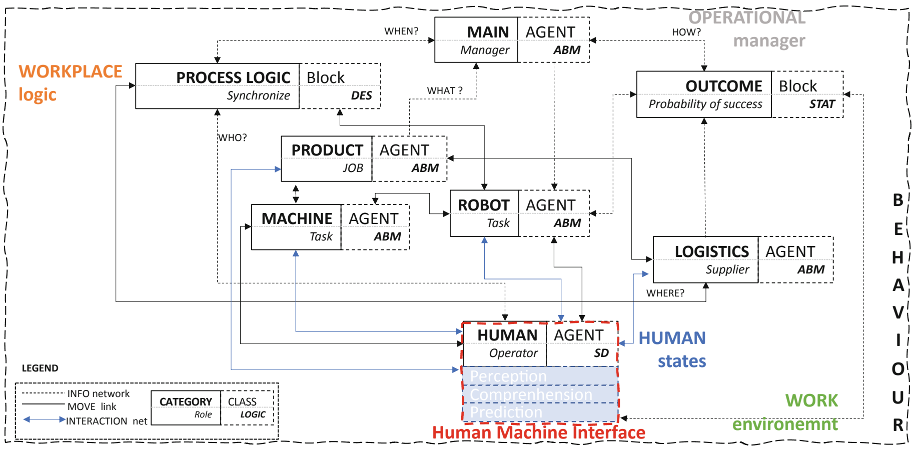

Fig. 1. "Smart" workplace. Human operator in his working environment interacts with machine, based on workplace logic indicated by operational management. Interaction and environment affect behavior and states of human operators.

The aim of our research is to study how human workers interact with their workplace environment and how they are affected by it. The statistical mechanic concept of entropy was used to develop a computational method in estimating the probability of human error. Entropy in statistical mechanics is considered as the measurement of a system's disorder, randomness, or uncertainty and can be used in various and diverse fields. In our work, entropy is used as a tool to quantify the uncertainty of an outcome from a process or the uncertainty of the system. In that regard, identifying the rules and variables that govern and define the system, such as the emotion of human operators, fatigue, cognitive load and motor resilience is necessary and requires the understanding of their connection to the macro-states of the systems (Physical, Behavior, Mental, Psychosocial); the entropy concept can be used to analyze the system and draw the connections between those states. In that regard, entropy is utilized as an asset in the understanding of human operators' reactions and behaviors inside the workplace environment. In this report, Sect. 2 address the changes in the human-robot interaction inside the workplace based on I4.0 collaborative theme, Sect. 3 address the initial formulation of the probability of error based on the macro states of our system, followed by Sect. 4 in which a brief discussion is presented based on results from testing the formula on initial data of our work.

2 Industry 4.0 Collaborative Workplace Scenario

Human robot collaboration – cobotics – in the workplace is a fundamental theme in the Industry 4.0 framework [6]. It requires an intense workplace transformation that aims in an environment that consists of connected people, processes, services, systems, and big data using Internet of Things (IoT). The goal is by using the collected data and information from those connections, to achieve an ecosystem of innovation and human-robot collaboration. Several technologies and tools are considered vital for this transformation: Cloud computing and platforms, big data analytics in cooperation with artificial intelligence (AI), cognitive computing and data analysis, mobile and RFID technologies, human to machine communication, advanced robotics and cybersecurity. The CPS are used as the main tool used to enable human operators to monitor changes inside the workplace, react to critical situations and direct communication with the end-customer (feedback, order placement, market needs). CPS assist in the information exchange between all the links of the market chain (between shop floors), maintenance and warehouse management which aims in operational efficiency and cost reduction. In general, the waste of production cycle is reduced. Digitization along with cloud computing create transparency and efficiency in the human-robot collaboration. Cybersecurity is vital in data security and creating trust between human operators and cobots, and prevention of unauthorized use/access or illegal attempt of access, malicious use of the information or workplace safety risks.

In this complex and dynamic workplace, human operators remain an integral part, as human expertise in many areas is an invaluable asset for management (such as production, customer requirements and development of new trends). In this workplace, human workforce interacts dynamically with the entities (cobots, CPS, AR tools) that are part of the workplace through information exchange and physical interactions (Fig. 2). Human operators interact with cobots and CPS in their work tasks; production and quality assurance of product, safety entity inside the workplace and maintenance. In this scenario, operators receive real-time data from sensors, CPS, AR/VR tools, from logistic entities or from management for maintenance status, possible arising situation, error, simple status information and product requirements. The operator in turn, need to react to information that need his attention, take quick decisions, respond, or not act at all depending on the status of information he receives. Those interactions and the decisions that need to be made affect the demand on human operators' perception, emotions, fatigue, cognitive load and motivation.

Human operators have limitations to their abilities and are affected by several issues. Workplace changes, lack of social interaction, cognitive capacity, emotion-driven decisions in certain cases and are prone to errors when their fatigue reaches certain levels. Training of human operators can prove effective in minimizing risks and safety concerns but overcoming all the weaknesses in the design of systems and workplaces requires further measures. The needs of human operators from the side of system operations must be addressed as well. In the human robot interaction for example, cobots can be designed to create trust and meet the needs, preferences and capabilities of the human operators. To this end, we designed a simple input-output human-robot interaction map based on the following principles. Human perception and age group plays a major role on how human operators react to their environment (Fig. 3). Perception of the environment then affects the mental state, behavior, and psychosocial state of the human operator. Physical interaction while in a state of emotional discomfort can affect productivity or lead to safety risks. Although technological advances in ergonomic designs can smooth the interaction and perception of cobots, the probability of human-system interaction error is affected by more variables. Age is a variable that needs to be addressed.

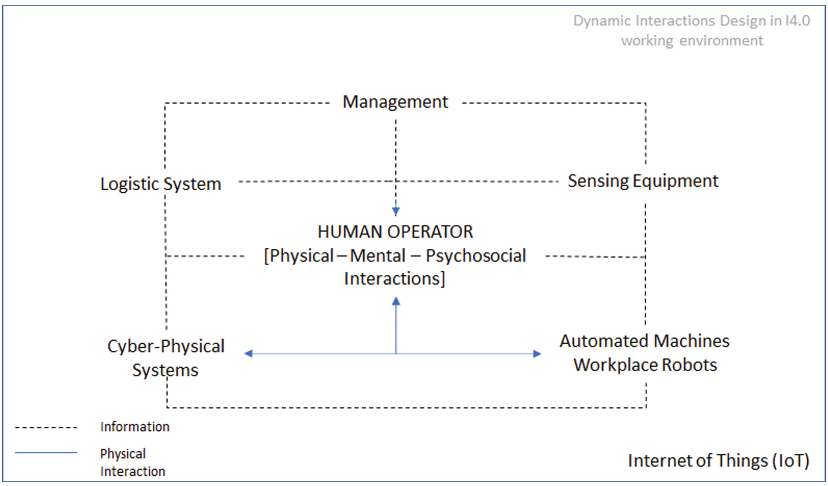

Fig. 2. Dynamic Interactions inside I4.0 workplace (Information data is exchanged between every agent inside workplace).

Elder workers as a term refers to employees over the age of 55 years. Furthermore, the term ageing worker/operator is used to signify when changes start to occur in a significant way in the working capacity after a certain age (usually after age 30) and will become critical in the span of the next 15–20 years if the work demands of the person do not decrease. Physical injuries tend to hinder those workers if their working tasks are heavily physical [7, 8]. Moreover, decision making becomes slower and environment changes impact older workers more than their younger counterparts [9, 10]. Despite the decline of certain capabilities, older workers are considered valuable due to the work experience and skills they possess. Their knowledge is valuable to the organization and they can transfer that knowledge to their younger counterparts [11, 12]. Older workers tend to be better prepared and use their safety equipment more effectively than their younger counterparts [13]. Furthermore, they are more autonomous and can quickly identify situations before they become critical [14]. In that extent, management and decision-making of organizations can use the knowledge of those workers either by training them for management positions or by using job scheduling and work tasks to lower the load the demands placed on workers, and by introducing to their workplace ergonomic designs for safety and assist in work tasks. Knowing the advantages and disadvantages of older workers, assisted in the development of the model to quantify the probability of error.

3 Entropy Concept and Human Factor

Entropy is a probabilistic measurement of the uncertainty of a system based on its states. If the probability of a certain state is equal to 1, then we have certainty, and the entropy is not defined. Human operators can be defined as a natural system. It is defined by macro states that categorized as psychosocial (PS), mental (M), behavior (B) and physical (PH). Each state affects the system and is affected by it. Furthermore, those states affect and are affected by each other. Each state is defined by several parameters and variables. The human operator at a workplace scenario is characterized by traits that are summarized as: (i) the dynamic and complex interactions between human and machine inside the workplace are the dynamics of the workplace system and affect the human through perception, (ii) initial conditions of the system are the human operator state and the machine state, (iii) initial condition of the human operator are non-consequential in the time evolution (work-shift) of the system and (iv) the probabilities of the system states are measurable.

In the human-robot interaction (Fig. 1), humans perceive the workplace (environment, operational concepts, machine and logic), thus affecting their psychosocial state. Motivation is affected by the perception and interaction, which is affecting the Skill-Rule-Knowledge based decision making of the operator and thus his behavioral state. Fatigue affects the cognitive load of the operator (linked with his mental state) and motor resilience (linked with his physical state and is linked with the training experience and ergonomics of the workplace). The above variables affect and are affected by all states of human operators. The above are part of the foundational principles of our formulation, which can be stated by the following: the human operator as a system (i) has four states, which are Psychosocial (PS), Mental (M), Behavior (B), Physical (PH) and (ii)

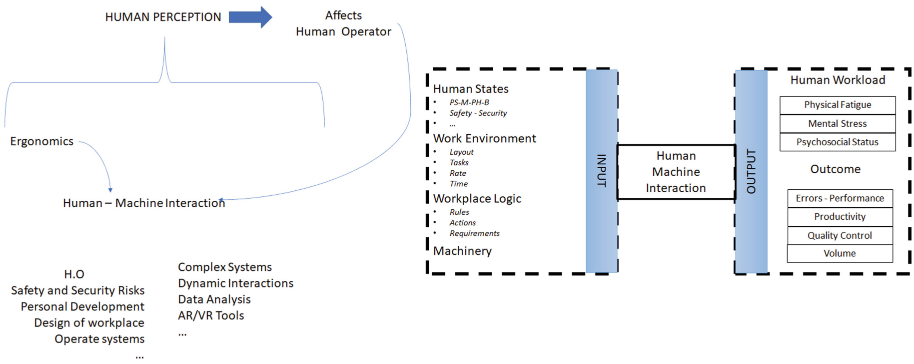

Fig. 3. Human-Machine Interaction Environnent. Left scheme represents how perception affects human operators and right scheme depicts the input-output of the h-r-i environment. (Ps-Psychosocial, M-Mental, PH-Physical, B-Behavior).

is affected by the age criteria. With those principles and the parameters set above the probability of error can be calculated by:

$$hfpe = exp\left[-\frac{(PHxM)}{(PSxB}\right]^{a} \quad (1)$$

The HFPE notation stands for human factor probability of error. Each state and parameter have its own weight determined by the individuals' operators' parameters and can be seen in Fig. 4.

$$PS = w_{PS} xf(I, EM, P) \quad (2)$$

$$M = w_{M} xf(F, C) \quad (3)$$

$$B = w_{B} xf(SRK, M) \quad (4)$$

$$PH = w_{PH} xf(Erg, MR, TE) \quad (5)$$

LEGEND

Acronyms	Description
I	Interaction
EM	Emotion
P	Perception
F	Fatigue
C	Cognition
SRK	Skill Rule Knowledge
M	Motivation
Erg	Ergonomics
MR	Motor Resilience
TE	Training Experience

Fig. 4. Computational equation of states with weights determined by individuals' parameters.

In Eqs. (2) to (5), the states with their weights and variables are set. Factor a in Eq. 1 symbolizes the age index which for this initial study we set to 1 for young workers and −1 for older workers. To demonstrate the application of the proposal (Eq. 1), we used the Constrained Non-Informative prior (CNI) distribution [15]. Entropy, in our case, can be defined as the expectation on the logarithm scale of the HFPE distribution. We excited the HFPE state in order to have overall mean and variance of possible configurations. This means we are investigating configurations where states mutual influence affects the overall HFPE. The statistical "moment" method is then applied to fit the approximate mean and variance to a beta distribution. To investigate the stability in error probability we plotted the HFPE over cases of the percentile variation of beta distribution (Fig. 5):

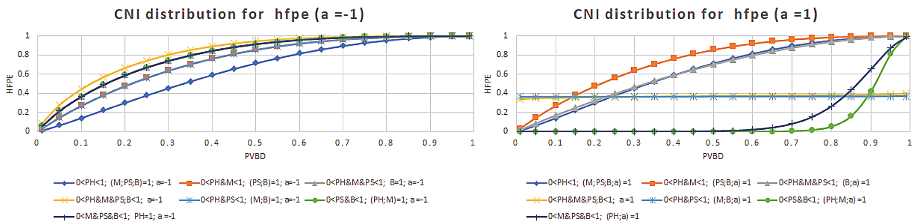

Fig. 5. CNI distribution of HFPE-PVBD (percentile variation of beta distribution) for old workers (a = −1) and young workers (a = 1).

The results of our test show how the probability of error changes based on how "controllable" the states are, level of control varies from 1 (control) to 0 (no-control). It reports, the span of uncertainty distribution. The model was tested for both younger and older workers. Younger workers have better stability, even when control status of one or more of their states is close to 0.

4 Discussion

In this work, the changes in human-robot interaction (HRI) due to the advancement of Industry 4.0 technologies, such as CPS and IoT, is presented. Integration of human operators, and older workers in particular, is essential in the advancement to the new workplace environment. The statistical mechanics concept of entropy was used to determine the connections between the input variables of the HRI. A formula was developed to compute the probability of error, based on the notion that human factor is a system consisted by four states, Mental, Psychosocial, Physical, Behavior. Weights are adjusted to those states, based on individuals' attributes. CNI distribution was used for risk assessment based on Eq. 1. The constrained non informative distribution implies that we know the posterior expected values and it does not limit the application of causal diagram or Bayesian methods. For the controllability of HFPE we require a set of rules and interaction analysis those could be mapped in a particular risky scenario with doubtful generalization. Results from the CNI distribution, show the areas where older workers and their younger counterparts are more prone to errors. There are states-based situations where controllability for young workers is inopportune (we cannot present probability of error that is more oriented to a uniform shape). On the counterpart, an older worker will report leptokurtic distribution of error. The cyber physical system of cobots assessment can excite the causal loop relations in state of human factors. These will report performances and error probability as per the constrained non informative distribution related with the maximum entropy. The future agenda of our study is to conduct a larger scale validation, using different states of control in different workplace scenarios with various ergonomic designs, robotics and AR/VR tools.

References

1. Breque, M., De Nul, L., Petridis, A.: Industry 5.0. towards a sustainable, human-centric and resilient european industry. Publications Office of the European Union, Luxembourg (2021)
2. EU-OSHA: Third European survey of enterprises on new and emerging risks. Publications Office of the European Union, Luxembourg (2019)
3. Di Pasquale, V., Miranda, S., Neuman, P.W.: Ageing and human-system errors in manufacturing: a scoping review. Int. J. Prod. Res. **58**(15), 4716–4740 (2020)
4. Swain, A.D., Guttmann, H.E.: Handbook of human-reliability analysis with emphasis on nuclear power plant application. Final report. No. NUREG/CR-1278. Sandia National Labs (1983)
5. Boring, R.L., Hendrickson, S.M.L., Forester, J.A., Tran, T.Q., Lois, E.: Issues in benchmarking human reliability analysis methods: a literature review. Reliab. Eng. Syst. Saf. **95**(6), 591–605 (2010)
6. Fruggiero, F., Lambiase, A., Panagou, S., Sabattini, L.: Cognitive human modeling in collaborative robotics. Procedia Manuf. **51**, 584–591 (2021)
7. Neumann, P.W., Winkel, J., Palmerud, G., Forsman, M.: Innovation and employee injury risk in automotive disassembly operations. Int. J. Prod. Res. **56**(9), 3188–3203 (2018)
8. Verma, S.K., Lombardi, D.A., Chang, W.-R., Courtney, T.K., Brennan, M.J.: A matched case-control study of circumstances of occupational same-level falls and risk of wrist, ankle and hip fracture in women over 45 years of age. Ergonomics **51**(12), 1960–1972 (2008)
9. Gilles, M.A., Guélin, J.-C., Desbrosses, K., Wild, P.: Motor Adaptation capacity as a function of age in carrying out a repetitive assembly task at imposed work paces. Appl. Ergon. **64**, 47–55 (2017)
10. Nardolillo, A.M., Baghdadi, A., Cavuoto, L.A.: Heart rate variability during a simulated assembly task: influence of age and gender. In: Proceedings of the Human Factors and Ergonomics Society, pp. 1853–1857, October 2017
11. Guvernator IV, G.C., Landaeta, R.E.: Knowledge transfer in municipal water and wastewater organizations. EMJ – Eng. Manag. J. **32**(4), 272–282 (2020)
12. Massingham, P.R., Massingham, R.K.: Does knowledge management produce practical outcomes? J. Knowl. Manag. **18**(2), 221–254 (2014)
13. Lombardi, D.A., Verma, S.K., Brennan, M.J., Perry, M.J.: Factors influencing worker use of personal protective eyewear. Accid. Anal. Prev. **41**(4), 755–762 (2009)
14. Fruggiero, F., Fera, M., Iannnone, R., Lambiase, A.: Revealing a frame to incorporate safe human behavior in assembly process. IFAC PapersOnLine **51**(11), 661–668 (2018)
15. Atwood, C.L.: Constrained noninformative priors in risk assessment. Reliab. Eng. Syst. Saf. **53**(1), 37–46 (1996)