A mathematical model for cognitive workload evaluation in smart production systems

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Abstract:

The fourth industrial revolution, as the others, has introduced a new paradigm. This new paradigm refers to the set of digital innovations that are changing the manufacturing systems. The growing adoption of innovative devices in the production process has radically changed operator's work. 'New' operator is required to interact with the new technological devices. This means that the operator is employed in more cognitive than physical task. If on one hand the tasks are changing, on the other ones the existing models, already adopted in workload evaluation, are mainly focused on motor performances rather than cognitive ones. Therefore, in many cases they could not be applied. Further strong limitations are highlighted by scientific literature, on the existing methods adopted for the cognitive workload evaluation, in most of cases the evaluation is strictly related to a specific task, a large number of data samples is required, the data elaboration is quite complex and high computation times are required.

Consistently with the issues above mentioned, the purpose of this paper consists in develop a numerical mathematical model allowing to evaluate the cognitive workload in smart manufacturing systems, in order to quantify the cognitive workload to assign to worker, avoiding a high rate brain occupancy, as well as a high psychological pressure lead to performance reduction in terms of reliability and safety.

The model developed is applied to a full case-study, the results shown the effectiveness of the methodology introduced to predict the cognitive workload and provide a valuable tool for a preliminary evaluation of the human performance in production systems.

Keywords: Cognitive Workload, workload evaluation model, human performance, Smart Operator.

1. Introduction

The fourth industrial revolution introduced new paradigms in manufacturing systems and in industrial systems (Facchini et al. 2020). Manufacturing companies have been encountered different challenges, due to with an increasing level of variability. Variability implies different set of dimensions such as demand, volume, process, manufacturing technology, customer behaviour and supplier attitude; as a result, it has transformed industrial systems engineering domain (Demartini et al. 2017), (Pacchini et al. 2019), (Lucato et al. 2019). Smart systems use cyber-physical systems to provide communication and intelligence for artificial and technical systems (Reiner Anderl 2014). The smart manufacturing systems are based on a digital network where the physical context is closely intertwined with artificial intelligence allowing to monitor and manage the production process at operational and procedural levels. A list of characteristics, technologies and enabling factors for manufacturing systems is provided by Mittal et al. (Mittal et al. 2019).

In this context, information processes aimed at workers are supported by innovative technologies (Damiani et al. 2018). The introduction of smart manufacturing systems led to promote the adaptability, the flexibility, as well as the efficiency of the new manufacturing processes. Indeed, the adoption of more complex automatic machines and innovative robotic cells is required (Villani et al. 2017). Despite the complexity and the automation degree of the machines adopted is increasing, the contribute of workers to the manufacturing process such as control and supervision of the tasks, it is essential. Most of tasks in manufacturing processes, such as set up of machine the parameters, robot re-configuration, process monitoring, and so on, are carried out through the use of computerized human-machine interfaces, in which the human contribution cannot be replaced (Nachreiner et al. 2006).

Consistently with this trend, the increasing adoption of innovative devices in manufacturing process led to radically change the work activities and the 'new' operator is called "Operator 4.0". The concept of "Operator 4.0" is based on the Human-Cyber -Physical Systems plan to promote the cooperation between human and machines. According to Romero et al., the "Operator 4.0" is a skilled operator who performs cooperative work with robots and is also helped by machines (Romero et al. 2016). The changes introduced in industry 4.0 led to a workload shift, from physical to more cognitive tasks, leading operators to perform tasks that require high cognitive demand (Pascual et al. 2019).

In last years, the interest of the scientific community in cognitive or mental workload evaluation in manufacturing applications, it is significantly increased (Morton et al. 2019). Since it is not unlikely that the increasing tasks complexity and the need to operate in more flexible way, will make it harder for the worker to perform the job in a proper way; consequently, it is highly important to accurately measure cognitive load and explore ways to avoid or reduce this load (Gevins & Smith 2003) (Kosch et al. 2018). In general, mental workload is defined as the interaction between the operator and an assigned task (Bommer & Fendley 2018), while cognitive workload is defined as the human information processing load while performing a particular task (Sheridan & Stassen 1979). Information processing load is closely related with the amount of attention that must be directed to a task; therefore, cognitive workload increases with task difficulty (Lively et al. 1993). Humans have only a limited capacity of attentional resources; therefore, performance suffers when subjects are required to simultaneously engage in two or more attention-demanding task (Schneider & Shiffrin 2017), (Intranuovo et al. 2019). This is an important measurement because the cognitive workload provides the awareness to where the human performance is unacceptable when task's demand increases.

In this perspective, recent scientific studies proved that the performance of production systems can be affected by from excessive cognitive workload (Thorvald et al. 2019).

As cited by Bi and Salvendy (Bi & Salvendy 1994b), the traditional task analysis techniques based on continuous monitoring of human behaviour are no longer appropriate. In most of cases, the corresponding evaluation is strictly related to a specific task, and a many data samples are required. Consistently with currently issues, the purpose of this paper consists in develop a numerical mathematical model allowing to evaluate the cognitive workload in manufacturing systems, in order to quantify the cognitive workload to assign to worker, avoiding a high occupancy brain rate, as well as a high psychological pressure leading performance reduction in terms of reliability and safety.

The remainder of this paper is organized as follows: a literature review and the model description are introduced in section 2 and 3, respectively; discussion of results obtained by applying the model a full-case study are in section 4; conclusions of this work are in section 5.

2. Methodologies to assess the cognitive workload

Nowadays many definitions of cognitive workload are available on scientific literature, according to Meshkaty none of them is consistent of quantitative validation and can be applied in different work environment. At general purpose, cognitive workload can be defined a multidimensional variable affected by many factors (Meshkati 1988). Cognitive load is a multi-dimensional variable and not a unitary construct; it covers working memory processes ranging from attention and perception to memory and decision-making (Young et al. 2015). Originally, the concept of cognitive load is evolved from the instructional and educational field, coming together in a cognitive load theory (CLT) (Sweller 1988) (Sweller 1994).

Consistently with the multidimensional nature of the cognitive load concept, cognitive load measures are heterogeneous in nature. In general, the literature converges towards assessing cognitive load based on subjective self-reporting, psychophysiological, performance, and analytical measurements (Young et al. 2015) (Cain 2007) (O'Donell & Eggemeier 1986) (Van Acker et al. 2018) (Wei et al. 2014) (Linton et al. 1989) (Xie & Salvendy 2000) (Patel et al. 2002).

The subjective self-reporting methods include the NASA Task Load Index (NASA-TLX) (Hart & Staveland 1988), Subjective Workload Assessment Technique (SWAT) (Reid et al. 1988), Modified Cooper-Harper Scale (Wierwille & Casali 1983), and many others. The physiological measurements are based on the changes of the physiology parameters of the operator due to change of cognitive workload required by task to be performed; in this category are included oxygen consumption evaluation, heart rate measurement, ongoing Electroencephalography EEG, and so on. The performance measurements include control models, generally adopted for monitoring the evolution of task performance over-time. A review and reappraisal on the current research on the cognitive task analysis methodology is presented by Wei et. al (Wei et al. 2014). The authors provide a classification of the current cognitive task analysis methods and they point out commonalities and differences among all these one.

In 1989, Linton et al. provide a taxonomy on the existing analytical and empirical methodologies to evaluate the cognitive workload (Linton et al., 1989).

Analytical methods are directed at estimating the cognitive load and collect subjective data with techniques such as expert opinion and analytical data with techniques such as mathematical models and task analysis. Bi and Salvendy (Bi & Salvendy 1994a) say that the most prominent analytical models used to assess and predict the cognitive workload are: information theory (Shannon 1948), control theory and queuing theory (Rouse & White 2008). Each model contains a parameters or components that reflect the operator's load or effort required under specified conditions.

3. Materials and method

The model developed in this paper allows to identify the cognitive load imposed on the operator evaluated on the basis on the task's characteristics and human ones. Our idea is that the cognitive load depends on three macro variables: task complexity, capacity to store and retrieve stored information, and information processing strategies.

The developed model is based on the evolution of mathematical model recently introduced by Kumar and Kumar (Kumar & Kumar 2019), that it is focused on evaluating of human efficiency for industry 4.0. Kumar and Kumar (Kumar & Kumar 2019) say that the human efficiency is an outcome of the combined cognitive and physical efficiencies, as follow (eq.1):

$$HE = HCE + HPE \tag{1}$$

where HE is the human efficiency, HCE is the human cognitive efficiency and HPE is the human physical efficiency.

According to Kumar and Kumar (Kumar & Kumar 2019), in the smart manufacturing systems due to, the increasing adoption of adaptive automation movement, the physical tasks are allocated to the machines and no more to the operators. Therefore, the tasks that have to done manually by the operator are negligible if compared with ones that required operator cognitive effort; so, the HPE term can be neglected. Consequently, HE can be evaluated as an outcome of HCE alone, as represented in the equation 2.

$$HE = HCE \tag{2}$$

HCE is given by following equation:

$$HCE = {}^{TE}/_{CL} \tag{3}$$

where the task efficiency (TE) and the cognitive load (CL) are given by the equations 4 and 5, respectively

$$TE = \frac{Total_{tasks} - N_e}{Total_{tasks}} \tag{4}$$

TE is the ratio of the set of tasks performed successfully versus the total number of tasks that operator has to ones. In the eq. 4, N_e identifies the number of errors made in tasks execution, and $Total_{tasks}$ is the overall number of tasks.

$$CL = K \times TR \tag{5}$$

Where CL is the cognitive load; it is defined as the work required to process an information measured in bit, *K* represents a constant that reflects the worker's demographic and psychographic features that can influence the operator's cognitive performance and it can be attributed to the elements such as age, competency, skills, stress level and so on (Patel et al. 2002), and TR is the transmission rate.

As cited by Bi and Salvendy (Bi & Salvendy 1994a), decisions that are made define the tasks and the functions for which the operator is responsible. These decisions define the TR imposed on the operator. It is possible define the TR (eq.6) as the amount of information that must be processed in a prefixed time. The amount of information measured in (bit) can be pattern according to information theory (Park 1987) (Shannon 1948).

$$TR = \frac{log_2(N)}{t} \tag{6}$$

where TR is the transmission rate of information that the operator has to process measured in bit on time, N is the number of equiprobable decision alternatives available, and t is the task time measured in minutes.

The value of the *K*-constant can be identified in accordance to definition of 'resistance', introduced by Patel's model (Patel et al. 2002). Consistently with this approach K-constant is given by equation 7

$$K = {}^{(NASA - TLX_{Score} \times t)}\Big/_{(log_2(N))^2} \tag{7}$$

NASA-TLX is a multidimensional assessment tool that measure perceived workload in order to assess the complexity of a generic task, the methodology is based on the adoption of a test to be filled by the worker. The output is given by a score based on a 100-point scale, that include six weighted subscales consistent with cognitive demand, physical demand, temporal demand, performance, effort and frustration level of the analysed worker (Eggemeier 1981).

NASA-$TLXS_{core}$ shown in equation 7, it is the score of the test obtained by the worker tested, and t is the time required, by same worker, to complete the set of tasks.

In order to summarize the model's abbreviations presented above, the following table is inserted.

Table 1: Definitions of significant abbreviation in developed model

Abbreviation	Term
HE	Human efficiency
HCE	Human cognitive efficiency
HPE	Human physical efficiency
CL	Cognitive load
K	Demographic and psychographic constant
TR	Transmission rate
TE	Task Efficiency
$Total_{tasks}$	Total number of tasks that operator has to perform
N_e	Number of errors made in tasks execution by operator
NASA-TLX_{score}	NASA-TLX_{score} is the NASA-TLX test score obtained by the subjects
t	Task's time
N	Number of equiprobable decision alternatives available to perform the task

4. Experiment setting

As mentioned in Section 1, the increasing adoption of innovative devices and technologies is changing the operator's work. The smart operator is employed in more cognitive tasks, and he/she is asked to process in the unit time more information. N-back task level has become a standardized tool to simulate tasks with different cognitive complexities, especially about in neuroscience cognitive study.

The n-back task is a standardized working memory and attention task with four incremental levels of difficulty (Ayaz et al. 2010).

The tester is define as one who runs the test; they are asked to monitor stimuli (single letters) presented on a computer screen and click a right shift button when a letter on the screen is target or left shift button when a letter on the screen is not target. Two conditions were used to incrementally vary cognitive workload, 0-back and 2 back. In the 0-back condition, participants responded to a single prespecified target letter (e.g., "X"); while in the 2-back conditions, the targets were defined as any letter that was identical to the one presented two trials back. Increasing the number of letters included between two target letters, increase the task's difficulty and complexity, since a higher memory effort is required.

The experiment has been conducted on a sample of students recruited from Polytechnic University of Bari, each test required a session of 5 minutes. The students involved are eight males and six females; they are master's degree students or PhD students in engineering, and the average age is 26.5.

Before starting the n-back task, the subjects to be tested read the instructions and the finality of the experiment. The experiment is conducted in two session, each of them consists of 7 subjects. After the first level of the n-back task is finished, the NASA-TLX score for each subject is known. After a rest period (5 minutes), the subjects start the second task with a different level of the previously session and he/she fill the other NASA-TLX test. The test finished when both n-back tasks and NASA-TLX tests are concluded.

4.1. Results

The NASA-TLX score for each subject, is shown in Table 2.

Table 2: NASA-TLX score

Subject	NASA-TLX Level 0	NASA-TLX Level 2
1	28.33	58.33
2	45.83	53.33
3	31.66	60.83
4	23.33	29.16
5	20.83	40.83
6	15.00	77.5
7	15.83	46.66
8	25.83	47.5
9	5.00	15.83
10	19.16	35.00
11	25.83	55.00
12	18.33	42.5
13	29.16	49.16
14	5.00	29.16

The TR values evaluated in accordance to equation 6, for 0 and 2 level of n-back test, are summarized in table 3.

Table 3 - Transmission Rate (bits/time)

	Transmission Rate
0-Back Task Level	0.2
2-Back Task Level	0.2

For 0-back and 2-back task level, in table 4 and 5 are showed the values of the mean, variance, standard deviation and the coefficient of variation for CL, TE and HCE, respectively.

Table 4: Mean, variance, standard deviation and coefficient of variation

0-Back Task Level	CL	TE	HCE
$\mu_{Lev.0}$	22.08	0.99	0.07
$\sigma^2_{Lev.0}$	105.13	0.00012	0.003
$\sigma_{Lev.0}$	10.25	0.011	0.06
$\varrho_{Lev.0}$	0.46	0.011	0.84

Table 5 - Mean, variance, standard deviation and coefficient of variation

2-Back Task Level	CL	TE	HCE
$\mu_{Lev.2}$	45.77	0.83	0.02
$\sigma^2_{Lev.2}$	224.83	0.0072	0.00011
$\sigma_{Lev.2}$	14.99	0.09	0.01
$\varrho_{Lev.2}$	0.33	0.10	0.49

Figure 1 shows the relationship between the CL and TE for both the task's levels. Furthermore, in the plot is represented the trend for each level, the blue line for 0-back level and the orange one for 2-back level.

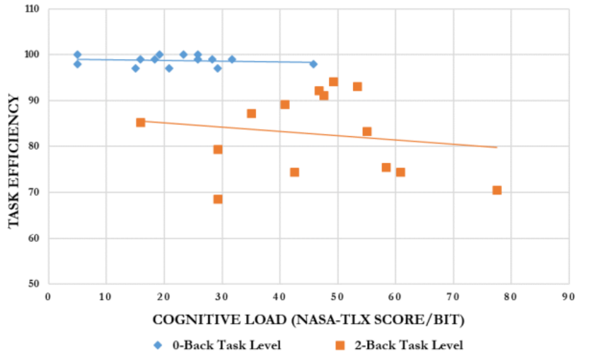

Figure 1 - Field Test of Task efficiency vs. Cognitive Load

Figure 2 shows the relationship between the CL and HCE for both task's levels.

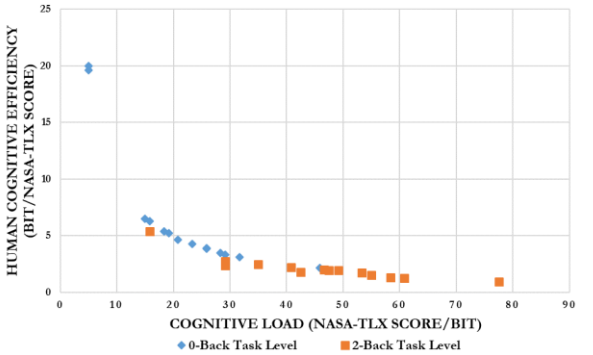

Figure 2 – Human Cognitive Efficiency vs. Cognitive Load for 0-back and 2-level Tasks level

The HCE differences of the subjects interviewed, between 0 level and 2 level, is showed in figure 3.

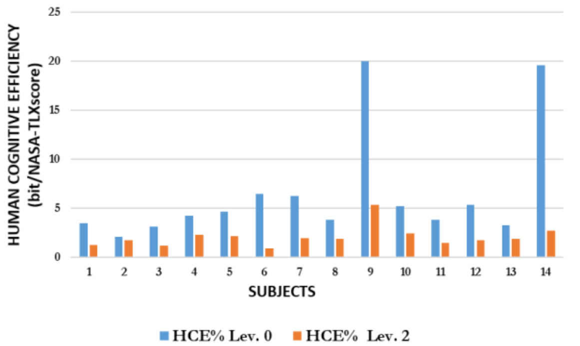

Figure 3 - Field test on Human Cognitive Efficiency

HCE, in function of CL, can be qualitatively described as an iso-task efficiency curve, for a given TE.

Applying the logarithm and then the exponential to eq. eq.3, it is obtained the following equation

$$HCE = e^{(ln(TE)-ln(CL))} \quad (8)$$

In the study conducted, the iso-task efficiency (TE) curve, for 0-level, has been determined by eq. (8) and it is plotted in figure 4.

Where TE is constant (in this case equal to 98%) and represents the subject performance' level required to perform the task.

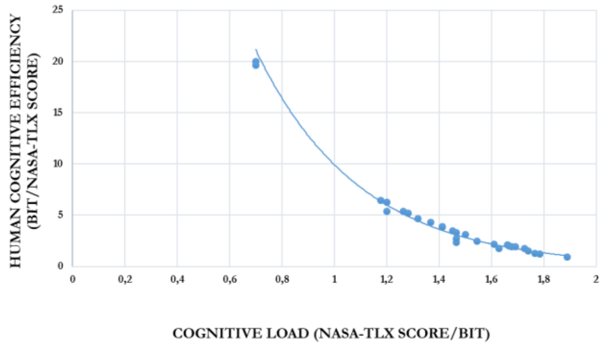

Figure 4- Iso-task efficiency (TE) (0-back task level)

4.2. Discussion

The focus of this study is to assess the cognitive workload through a numerical model. In this study the perceived cognitive load has been simulated through 0-back and 2-back of n-back test. In both cases the number of available decisions is two, consequently the number of bits to elaborate is the same. Task's complexity depends on the ability to store and retrieve the information stored by the subject that performs the task.

Analysing the values in tables 4 and 5, it is observed that the $\mu_{Lev.2}$(CL) increases if compared to $\mu_{Lev.0}$(CL), $\sigma_{Lev.2}$(CL) increases if compared to $\sigma_{Lev.0}$(CL), and ρ(CL), decreases from the level 0 to the level 2. The $\mu_{Lev.0}$(TE) decreases if compared to $\mu_{Lev.2}$(TE) while $\sigma_{Lev.2}$(TE) increases if compared to $\sigma_{Lev.0}$(TE) and so the ρ(TE) value increases from the level 0 to the level 2. The $\mu_{Lev.2}$(HCE) decreases if compared to $\mu_{Lev.0}$(HCE), similarly, $\sigma_{Lev.2}$(HCE) decreases if compared to $\sigma_{Lev.0}$(HCE). Indeed, for more complex task (i.e. from 0-back to 2-back), the increase of expected value of CL is greater than the reduction of the TE. Therefore, the overall human cognitive efficiency is reduced with a lower uncertainty. The average value of CL (tab 4 and 5) increases with increasing of the complexity of the task (0- and 2-back task level). Similarly, the average TE decreases with increasing of the task's complexity. The relationship between CL and TE for both levels (fig. 1) show that at level 0 (blue-line) the performances are almost constant (equal to 100%); while at level 2, the performances are still high but they are characterized by greater variability and higher slope (orange-line). Most of the CL-values at level 0 are localized in the left side of the chart (i.e. low values), while the CL-values at level 2 are localized to the right side (i.e. high values). Furthermore, by relating the TE with CL (fig.1) it is possible observed that the TE depends on the task complexity. For both levels, there are CL overlapping areas (fig.1), but on average a complex task has a greater CL value; although participants sample is small. CL values overlapping is due to that it is evaluated from NASA-TLX values and it is a subjective measurement of perceived cognitive workload by the subject.

The expected value of the HCE decreases in the 2-back task level as shown in tables 4 and 5. It is possible to observe that for more complex task, there is a significantly reduction of HCE (fig. 2 and 3). The uncertainty of HCE decreases when the complexity of the task increases (tab 4 and 5).It is observed that when the HCE decrease, the cognitive load increase (fig. 2).The CL can be considered as an amount of energy required by subject to process one bit of information. The iso-task efficiency curve obtained in the current study (fig. 4) shows the amount of work required to perform the set of tasks by the subjects, keeping the same performance.

5. Conclusion

Study results indicate that the analytical model developed can be adopted to assess the cognitive workload. This model allows to identify the task's complexity and the personal skills. According to the case study conducted, the subject's ability to store and retrieve information is a part of personal skills. For given tasks and for the same number of bits to be processed, the difficulty depends on the subject capacity to memorize the information.

In the current study the workload per bit was estimated for both level of n-back test. The average value shows that the two levels have a different perceived CL. The 2-back level requires more workload per bits than the 0-back level; therefore, the perceived CL is greater for level 2-back. Furthermore, when the CL is low, the subject's performances are higher. In case of the average CL increases, the average performance decreases of 16%. Similarly, increasing the task complexity decrease the uncertainty of HCE. However, the small size of the sample of participants did not allow to point out significant statistical differences between the two levels of the n-back test. Despite of, the average values show differences between the two n-back levels.

However, the developed model can be used to predict the perceived cognitive workload and evaluate the operator characteristics in any situation and in any work environment. From a managerial point of view, the developed model can be used to assign operators to tasks, avoiding that a specific operator is assigned a task that he/she is unable to perform. Avoiding a high operator's rate brain occupancy, which leads a decreasing operator's performance.

Future research should be required to validate this model across a larger sample of participant and across different tasks complexity. Additional research should also be focussed on researching at different types of tasks and how the K constant value varies by the different type of tasks.

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