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An analytical framework for assessing cognitive capacity and processing speed of operators in industry 4.0

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Abstract

The fourth industrial revolution introduced a new paradigm in manufacturing systems. The digital network is at the basis of the smart manufacturing and the physical context is strictly related to the artificial intelligence. This new manufacturing context drastically changed the role of the operator since the increasing adoption of innovative devices in manufacturing process modified the work activities and the operator is employed in more cognitive than physical tasks.
Therefore, the purpose of this paper consists in developing an analytical framework to assess the human cognitive capacity occupancy and the human processing time of correct information known as the quality performance.
The analytical framework presented allows to assess the human mental workload imposed by the task and how the processing speed of correct information changes when quality performance varies.

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Keywords: human cognitive capacity occupancy; mental workload; human information processing speed; smart production system

1. Introduction

The fourth industrial revolution, better known as Industry 4.0, introduced new paradigms in industrial systems [1] and manufacturing systems [2]. Qu et al. [3] define a Smart Production System as "an intensified application of advanced intelligence systems which enable the rapid manufacturing of new products, dynamic response to product demand, and real-time optimization of manufacturing production and supply chain networks. Meanwhile, SMSs are

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new platforms which integrate the products, operations, and business systems spanning factories, distribution centers, companies, and the entire supply chains under the knowledge-rich environment. In SMSs, all aspects of manufacturing are connected, intake of raw materials to the delivery of finished smart products to customer". Smart systems are based on wide-scale automatization, connectivity and can contain the use of AI-driven technology [4], [5]. Internet of things (IoT) is used in smart systems to create cyber-physical systems [6], in order to provide communication and intelligence for artificial and technical systems [7] ensuring an energy efficient management allowing to minimize the environmental impact of the innovative technologies [8]. The digital network is at the basis of the smart manufacturing [9]; the physical context is closely intertwined with artificial intelligence allowing to monitor and manage the production process at operational and procedural levels. The introduction of smart manufacturing systems led to promote the adaptability, the flexibility as well as the efficiency of the new manufacturing processes. It is known that some jobs involving simple and repetitive task will disappear in favour of robots and co-bots [10]. For example, an assembly worker performing a task is constantly exposed to situation with varying mental demands, since it is required to operate more and more in a flexible way and to adjust his or her skills to change job demands and technology [11]. This new manufacturing context changed drastically the role of the operator, since the increasing adoption of innovative devices in manufacturing process led to radically change the work activities and the 'new' operator, named "Operator 4.0" [12]. Operator 4.0 is employed in more cognitive than physical tasks [13], and he/she has to process more information. This information load is known as mental load [14]. Indeed, from a cognitive ergonomics point of view, it is most important to assess mental workload in order to reduce or avoid high load imposed on the operator [15,16].

Literature review shows that there are many studies on physical ergonomics, but limited studies on cognitive one. Physical ergonomics is focused on reducing operator discomfort and fatigue in order to increase the throughput [17,18], while cognitive one is focused on the quality of the work [19]. However, smart manufacturing system changed the operator activities from tasks that involve the manual and physical activity in much more cognitive ones. Indeed, the traditional task analysis techniques based on continuous monitoring of human behaviour are no longer appropriate to assess the mental workload [20]. In 1991, Hart defined the concept of "optimal" workload as "a situation in which the operator feels comfortable, can manage task demands intelligently, and maintain good performance" (Hart 1991).

As a result, the aim of this paper consists to develop an analytical framework to evaluate the human cognitive capacity occupancy rate and the operator processing speed of correct information at given quality performance.

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

2. Theory background

Cognitive ergonomics studies the interaction between tools and users; the cognitive process of understanding, the use of the knowledge and the reasoning are emphasized [21]. The cognitive ergonomics is the ergonomics of the mental process, it is based on the study of how work affects the mind and how mind affects the work [22].

Mental workload is generally defined as the interaction between operator and tasks [23], it represents the operator information processing load while performing an assigned task [24].

Nowadays mental workload can be defined in general as a multidimensional variable affected by many factors, since none of the definitions of mental workload available in scientific literature is consistent to quantitative validation [25]. Mental load is a multidimensional construct and not a unitary one; it involves working memory processes ranging from attention and perception to memory and decision-making [26].

However, mental workload represents the task demands and is influenced by the brain's capability to process information, in the same way the physical workload is influenced by the energy demand upon the muscles [27]. Hart and Staveland [28] define the mental workload as the individual cost incurred, given their capacities, while performing a task with a particular level of performance required. The measure of mental workload provides awareness of when the operator performance become unacceptable with task demand increasing. When the number or the difficulty of the tasks increase and the time available to accomplish the task decreases, the mental workload increases [29]. In order to provide safe and efficient operations of complex systems, the mental workload required by the workers should not exceed their capacity [30]. Indeed, the literature shows that the concept of mental workload is associated with the difference between the amount of resources available by the subject and the amount of resources needed to accomplish the task. When the task's resources exceed the subject's resource, the subject could not perform the task [31]. Humans have a limited capacity of attentional resources: when they are required to simultaneously engage in two or more attention-demanding tasks, the performance suffers [32], [33].

3. Methodology

In Kumar and Kumar [34] a framework to evaluate human efficiency through a cognitive load and task efficiency measure is proposed. The authors state that when the cognitive load increases or the task efficiency decreases, the human efficiency decreases.

In 1994, Bi and Salvendy [35] developed an analytical model to analyses the cognitive tasks in dynamic systems. According to the authors, mental workload is a system's objective demand independent of subjective factors. The mental workload is modelled by the authors as follows:

$$H_{owl} = \frac{TL}{K_e \cdot K_{or}} \leq H_{owl,\lim} \tag{1}$$

where H_{owl} is the mental workload imposed on the subject expressed in bits per second, TL is the task load expressed in bits per second, K_e is the parameter evaluating the environmental factors, K_{or} is the parameter evaluating the organizational factors, and $H_{owl,lim}$ is the mental workload threshold expressed in bits per second. A scale ranging from 0 to 1 can be defined for K_e and K_{or}. When

$$K_e = K_{or} = 1 \tag{2}$$

the system is providing subject with satisfied stimuli and an ideal environment. When

$$K_e = K_{or} \to 0 \tag{3}$$

people cannot work properly. The authors do not determine mental workload threshold value, but they say that it can be obtained through empirical studies.

Our model is based on Bi and Salvendy model [35] for assessing the mental workload. In the model proposed in this paper, the TL is given by the equation 4; it represent the task's amount of information, calculated according to information theory [36,37], that they must processed in a given range time.

$$TL = \frac{\log_2(N)}{T} \tag{4}$$

where T is the total time available to complete the set of tasks, and N is the number of alternative decisions.

Human cognitive capacity occupancy (HCCO) is a rate of consumption of operator brain's capacity; it represents the cognitive occupation of the subject. HCCO (eq.5) is obtained by dividing eq.1 by $H_{owl,lim}$

$$HCCO = \frac{H_{owl}}{H_{owl,\lim}} \leq 1 \tag{5}$$

Human cognitive capacity reserve (HCCR) is a rate of cognitive reserve of operator's brain capacity. HCCR is obtained by the equation 6

$$HCCR = 1 - HCCO \tag{6}$$

As far as concern H_{owl}, in scientific literature are available tests providing subjective measure of the perceived workload of subjects involved in cognitive oriented tasks. One of the most adopted is the NASA-TLX. The test consists of a multidimensional scale and provides an overall score of the perceived workload in a 0-100 scale based on the weighted average of six subscales consistent with cognitive demand, physical demand, temporal demand, performance, effort, and frustration level. The subject is provided of a brief description for each subscale and is asked to rate them in a 0-100 range with reference to the task previously accomplished [38].

$H_{owl,lim}$ represents the maximum amount of mental workload (bit/s) a subject is able to process. In case of H_{owl} exceeding $H_{owl,lim}$, the subject won't be able to perform the assigned task in the available time window. The evaluation of $H_{owl,lim}$ requires ad-hoc experimental tests. Nevertheless, in this paper, $H_{owl,lim}$ values have be calculated by means of a linear regression analysis based on H_{owl} and NASA-TLX values obtained from experimental data. $H_{owl,lim}$ values have been calculated considering the maximum score (100) of the NASA-TLX.

For a given task load ($TL = cost$), when the boundary conditions decrease ($K_e = K_{or} \to 0$), HCCO increases and HCCR decreases. This means that the external stimuli can lead to increase the numbers of bits that the operator has to process in a given time.

In order to evaluate the operator's time required to correctly process the information, it is possible to model the concepts of human information processing speed (HIPS) and task information processing speed (TIPS); the relationship between HIPS and TIPS is expressed by the equation 7:

$$HIPS \cdot TIPS = TE \tag{7}$$

where HIPS (sec/bit) is the speed in processing of 1 bit of correct information by the operator, TIPS (bit/sec) is the task information processing rate at required speed, and TE is the task efficiency expressed by the following equation according to the definition of Kumar & Kumar [34]. TE represents the probability to perform the task correctly, and it could be evaluated as the ratio of the set of tasks performed successfully versus the total number of tasks performed ($Total_{tasks}$).

$$TE = \frac{Total_{tasks} - N_e}{Total_{tasks}} \tag{8}$$

In equation 8, N_e identifies the number of errors made in tasks execution. TE expresses the process quality and represents the ratio between the amount of bits correctly processed by the operator and the total amount of bits that the operator must process. TE values range in a [0;1] interval.

This means that low HIPS values can be required to meet high TIPS values at a given process quality. However, low HIPS values and high TIPS values can cause low process quality. The ideal case occurs when $TE = 1$ (eq. 10), in this case the operator's performance is equal to 100% and this implies that the bits processed (per unit time) by the operator equals the bits required by the task; therefore, the information processing speed of the operator (HIPS) is equal to the inter arrival time of information to be processed (task execution time).

$$HIPS_{TE=1} = \frac{1}{TIPS} \tag{9}$$

TIPS is the arrival rate of bits to be processed; therefore, TIPS is the mental workload imposed on the operator (eq. 10)

$$TIPS = H_{owl} \tag{10}$$

and relation (7) becomes:

$$HIPS = \frac{TE}{H_{owl}} \tag{11}$$

When the operator reaches his or her maximum perceived mental load at a given quality performance, the eq.11 becomes:

$$HIPS_{max} = \frac{TE}{H_{owl,lim}} \tag{12}$$

Whit the same TE values, being $H_{owl} \leq H_{owl,lim}$, it follows that $HIPS_{max}$ is less than or equal to HIPS. Since the bits to be processed by the operator per unit time are at most equal to the bits required by the task, when $H_{owl} = H_{owl,lim}$ the operator will have to process 1 bit of information in less time. $HIPS_{max}$ represents the operator's maximum speed in correctly processing information.

The optimal condition occurs when $TE = 1$, in this case the time to correctly process information by the operator is equal to the time available to accomplish the task. (eq. 13)

$$HIPS_{TE=1,max} = \frac{1}{H_{owl,lim}} \tag{13}$$

4. Case study

In the period November 2019 - January 2020, in the Laboratory of Industrial System Engineers (LISE) at the Polytechnic University of Bari (LISE, https://research.poliba.it/laboratories/lise) experiments have been carried out in order to assess mental workload of subjects involved in tasks of increasing complexity. For each subject, starting from the perceived mental workload evaluated by means of the NASA-TLX, the $H_{owl,lim}$ value has been obtained.

Different subjects (Master's degree and PhD students with an age between 24 and 32 years old, see table 1) have been asked to accomplish tasks of different complexity. Tasks were simulated by means of the n-back test. N-back test has become a standardized tool to simulate tasks with different cognitive complexities; it consists of standardized working memory and attention tasks with four incremental levels of difficulty [39].

A sequence of stimuli (letters on a computer screen) are showed to the tester (subject who runs the test). The task consists of indicating, by digit the right shift button on a keyboard, when the current stimulus matches the one observed n steps earlier in the sequence; in case of mismatching stimuli, the tester has to digit the left shift button. Increasing the number of letters included between two target letters, increases the difficulty of the task and the mental effort required to accomplish it. Two conditions of n-back test were used to incrementally vary task's complexity: 0-back and 2-back. In the 0-back condition, participants responded to a single target letter (i.e., "X"); while in the 2-back conditions, the targets were defined as any letter that was identical to the one presented two trials back.

The experiment has been carried out on a sample of students recruited at Polytechnic University of Bari; each test required 15 minutes. The students involved were both male and female; they were master's degree students or PhD students in engineering, and the average age was 27.2. Before starting the n-back test, the subjects to be tested read the instructions and the goal of the experiment. The experiment was conducted in two sessions, each of them consisting of 7 subjects. Each subject performed both levels of n-back test, and for each level he/she filled out the NASA-TLX. Between one level and the next, the subject had a rest period 5 minutes. The test ended when both tasks were accomplished by the subjects.

4.1. Results

The weight of the six subscales of NASA-TLX, presented in Section 3, have been determined for the 0 level and the 2nd level by pair-wise comparison of subscales; for both levels the weight associated with the physical demand is equal to zero [40].

In the 0-back task level the number of available decision alternatives is two, whether the letter shown on the screen is a target or not. In the 2-back task level the number of available alternative decisions is the sum of comparisons of the letter on the screen and the letter memorized two times before plus two letters memorized in the working memory. The number of available alternative decisions

associated with the letter memorized in the working memory is equal to twenty-six. This amount correspond to the letters of english alphabet according to [41].

In the 0-back level task one hundred subtasks (one subtask corresponds to one letter showed on the screen) must be performed, while in 2-back level task one hundred and two subtasks must be performed. The time set for each subtask was 3 seconds. In case the subject did not react within this time limit, an error was associated to the subtask.

For sick of simplicity, K_e and K_{or} values were setting equal to 1 for both levels. K_e and K_{or} values are independent by the subject and depend only by boundary conditions. Since the boundary conditions in the experimental sessions are the same for the two test levels performed, and K_e and K_{or} values affects in the same way H_{owl} for both levels, they have been considered unitary. The H_{owl} values evaluated in accordance with eq.1, for zero and two level of n-back test, are summarized in table 1.

Table 1. H_{owl} values (bits/seconds).

	H_{owl}
0-Back Task Level	0.33
2-Back Task Level	3.47

$H_{owl,lim}$ value for each subjects is obtained by means of a regression analysis based on NASA-TLX values and H_{owl} values. The $H_{owl,lim}$ values are summarized in table 2.

Table 2. $H_{owl,lim}$ values (bits/seconds).

Subject	$H_{owl,lim}$
1	6.44
2	12.40
3	6.95
4	-30.84
5	11.68
6	4.07
7	8.66
8	10.38
9	28.24
10	17.77
11	8.50
12	8.45
13	8.41
14	14.97

The $H_{owl,lim}$ value of the subject n. 4 was not admissible and has been eliminated. The reason was in the incorrect NASA-TLX test filled (the subject rate at the maximum value the subscale “physical demand”).

HCCO and HCCR are determined for each subject, respectively with eq. 5 and 6. For 0-back and 2-back task level, table 3 and 4 show the values of the mean (μ), variance (σ^2), standard deviation (σ), and the coefficient of variation (cv) for HCCO and HCCR, respectively.

Table 3. Mean, variance, standard deviation, and coefficient of variation.

HCCO	0-Back Task Level	2-Back Task Level
μ	0.0370	0.3830
σ^2	0.0003	0.0339
σ	0.0180	0.1840
cv	0.4810	0.4810

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

HCCR	0-Back Task Level	2-Back Task Level
μ	0.9630	0.6170
σ^2	0.0003	0.0339
σ	0.0180	0.1840
cv	0.0183	0.2990

For 0-back and 2-back task level, the values of the mean (μ), variance (σ^2), standard deviation (σ), and the coefficient of variation (cv) for HIPS are showed on table 5.

Table 5. Mean, variance, standard deviation, and coefficient of variation for HIPS (sec/bit).

HIPS	0-Back Task Level	2-Back Task Level
μ	2.9580	0.2420
σ^2	0.0010	0.0005
σ	0.0323	0.0230
cv	0.0110	0.0930

By adopting a logarithmical scale to equation 12, the iso-performance curve can be obtained by the equation 14

$$HIPS_{max} = e^{\left[\ln(TE)-\ln\left(H_{owl,lim}\right)\right]} \tag{14}$$

Figure 1 shows the iso-performance curves, for a quality performance value of 100% (ideal case (a)) and 60% (b).

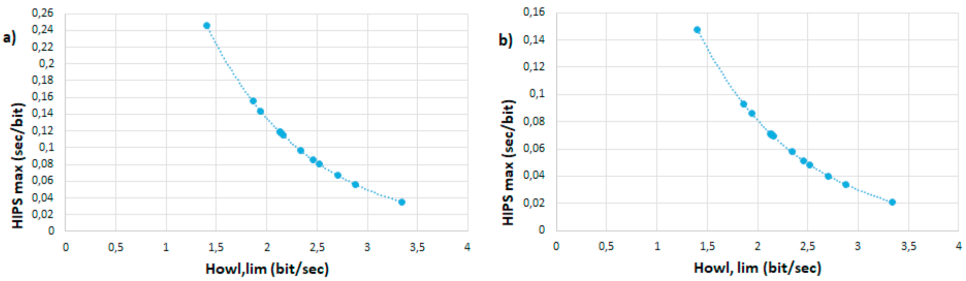

Fig. 1. a) Iso-performance curve (ideal case) b) Iso-performance curve (quality performance equal to 60%)

4.2. Discussion

The focus of this study is to assess the human cognitive capacity occupancy and the human processing time of correct information when the quality performance is known. In this study the perceived mental load has been simulated throughout two tasks (0-back and 2-back level) of different cognitive complexity of the n-back test.

For each level, the number of available decisions has been determined, and the corresponding number of bits to be elaborated in the given time has been calculated (TL). The imposed human mental workload is an objective demand

and depends on the environmental and organizational parameters and on the complexity of the task that the subject must perform.

$H_{owl,lim}$ value has been calculated for each subject and it is summarized in table 2; it is possible observe how vary the maximum amount of information per unit time that can be processed by the subjects.

Analysing the values in table 3 it has been observed that the $\mu_{Lev.2}$(HCCO) is about ten time the $\mu_{Lev.0}$(HCCO); in 0 level of n-back the average HCCO value is about 4%, while in 2nd level it is about 40%; this means that the cognitive effort in 0 level is almost negligible. The $\sigma_{Lev.2}$(HCCO) is about one hundred time the $\sigma_{Lev.0}$(HCCO); this shows that with task complexity increasing, grows up the variability around the average HCCO value. The cv(HCCO) is the same for both level and it is equal to 0.481. Analysing the values in table 4 it has been observed that the $\mu_{Lev.2}$(HCCR) is about 1.5 time the $\mu_{Lev.0}$(HCCR); the average HCCR value is about 96% in 0 level of n-back, while is about 60% in 2nd level. This means that in 0-back task level, the subjects have at their disposal almost the entire cognitive capacity. The $\sigma_{Lev.2}$(HCCR) is about one hundred time the $\sigma_{Lev.0}$(HCCR), and these values are equal to the HCCO standard deviation values. The $cv_{Lev.2}$(HCCR) is bigger than $cv_{Lev.0}$(HCCR); this means that the HCCR values are more variable in 2nd level if compared with ones in 0 level. Table 4 and 5 show that HCCO and HCCR values of variance and standard deviation are smaller in 0-level if compared with ones in 2-level, respectively. This mean that HCCO and HCCR values are mostly concentrated around the average value in 0-level. Therefore, the average HCCO value increases with the the increase of the complexity of the task load, with the same boundary conditions. This means that when a task to perform is more complex, the HCCO will be greater than for a simpler task. The HCCO and HCCR values allow to understand if the operator is full or he/she can perform other tasks that involve more cognitive demand.

Analysing the values in table 5 it is observed that $\mu_{Lev.0}$(HIPS) is about twelve time the $\mu_{Lev.2}$(HIPS); this shows that the average time to process 1 bit of correct information by the subject is greater in 0-back than 2-back. The average HIPS value decreases from the level 0 to level 2 for two reasons; the first is that human performance decrease with the increase of the task complexity, and the second is that the given time to perform the subtasks in each level is the same, but the amount of information that the subject has to process is greater in the 2nd level, considering the same boundary condition in the two levels. The HIPS standard deviation values are of the same order of magnitude in both levels; this mean that in both level the variability around the average HIPS value is almost the same. The $cv_{Lev.2}$(HIPS) is about eight time the $cv_{Lev.0}$(HIPS); the HIPS value in 2nd level is more variable than one in 0 level.

The iso-performance curves obtained in the current study (fig. 1) show the subject's maximum processing speed of 1 bit of correct information. The iso-performance curves show how high value of $HIPS_{max}$ is required when a lower value of $H_{owl,lim}$ occurs. Figure 1 shows the iso-performance curve for a quality performance equal to 100% (a) and 60% (b). The comparison between figure 1a and 1b show that for the same value of $H_{owl,lim}$, when the quality performance required decreases the $HIPS_{max}$ value decreases. This means that the subject will spend less time to process one bit of correct information. The iso-performance curve permits to evaluate in a qualitative way the maximum processing speed of 1 bit, when the level of performance to perform the set of task and the $H_{owl,lim}$ value are known.

5. Conclusion

The results of this study indicate that the analytical framework developed can be adopted to assess both the human cognitive capacity occupancy (HCCO) and the human information processing speed (HIPS) of the operator, that is the operator's time used to process 1 bit of correct information for a given quality performance. In this study the mental workload for 0-back and 2-back task level are estimated. The H_{owl} values show that the 2-back task level requires to process more bits per second than 0-back task level. The developed concepts of HCCO and HCCR allow to understand if the operator capacity is full or he/ she can perform other tasks that involve more cognitive demands.

Moreover, the analytical framework presented in this study allows us to assess the maximum amount of time used to process 1 bit of correct information by the subject based on the quality performance required and the imposed mental workload. The analytical framework developed is robust and it can be applied in smart factory systems.

Going forward, this study can be applied to a larger sample of participants and the subjects could perform more tasks with different cognitive loads; for instance, designing an experimental session where the subjects will have to carry out multiple levels of the n-back test. Experimental sessions will be designed in order to better estimate the relation between H_{owl} and NASA-TLX, an to evaluate (by increasing the test level or reducing the available time)

$H_{owl,lim}$ values for subject of different age and sex. Moreover, the analytical approach could be applied and tested in experimental sessions simulating an assembly line.

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