A model for balancing the cognitive ergonomic risk of operators in assembly lines

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Abstract: In manufacturing industries, employee performance and industry productivity are affected by many factors related to line efficiency and workforce well-being. The new technologies and the Industry 4.0 paradigms lead to a change in the operator's role. According to recent scientific studies, in the next years, workers will be employed more in cognitive than in physical tasks due to the increasing adoption of innovative and autonomous devices in the manufacturing process. Operators are exposed to physical and cognitive overload risks, in particular in assembly lines. To this concern, one of the most used methods in the operative phase consists of job rotation. It is a wide applicated method to reduce operators' physical fatigue, ensuring high production performances. Regarding cognitive fatigue, the design and schedule of human-based assembly systems require a joint balancing between production system performance and operator's well-being. A model that schedules job rotations, minimizing the cognitive ergonomic risk of assembly line operators, is developed. Consistent with the paper aim, the authors propose a mixed-integer nonlinear programming model allowing the balance of each operator's cognitive workload, meeting the production rate of an assembly line. The mental workload is evaluated using the Cognitive Load Assessment for Manufacturing (CLAM) method. Results show the model effectiveness in identifying the job rotation schedules that achieve cognitive ergonomic risk minimization and productivity goals.

Keywords: Human Performance; cognitive load; cognitive ergonomic risk balancing; job rotation schedule

I. INTRODUCTION

Millions of people in the world are affected by mental health problems at work [1]. Common mental disorders (e.g. anxiety, bipolarity, acute stress) in about 17.6% of the global working population are present [2]. Recent surveys [3] and reviews [4], [5] pointed out that inappropriate work organisation and excessive working demands are the primary cause of these disorders. Financial implications for companies and governments are related to stress and psychological risks. In Europe, about 617 billion euros per year is the cost due to mental illness symptoms, including employers' expenses (i.e., absenteeism, presenteeism, turnover and loss in productivity) and social distress [6]. The smart factory of the future aims not only to optimize processes and their sustainability but also to give the worker a central role in this scenario. In this context, preserving workers' well-being plays a role of paramount importance [7], [8]. On the one hand, the latest global policies lead to an increased focus on workers' wellness and safety [9]. On the other hand, the new technologies lead to an increase in cognitive workload in manufacturing systems considered "human-centred", where human operators interact with intelligent devices all around [10]. Consistent with this trend, the interest in human cognitive factors related to manufacturing systems has increased in recent years [11].

Moreover, recent research show a strong relationship between musculoskeletal disorders (MSDs), affecting almost 50% of human workers [12], and psychological disorders [13]. In many cases, the human motor tasks evaluated according to the well-known Fitts' law were re-adjusted, including the psychomotor aspects [14]. Therefore, an overall ergonomic evaluation cannot ignore cognitive workloads [15].

In light of these considerations, the study of methodologies to assess the human cognitive factors have to integrate the well-known methods of physical factors assessment [16], [17].

Thorvald and Lindblom [19] define cognitive workload as the mental effort required by the human cognitive system to perform a specific task. According to Sweller et al. [18], the cognitive workload depends on the working memory resources and the amount of information to be processed to perform an assigned task. Consistent with these considerations, the more common cognitive processes in the production systems are perception, decision-making, problem-solving, attention, and memory. Similarly, the cognitive workload is defined as the human response to the external stimuli due to task complexity, production demand, and work environment [19].

According to Kalakoski et al. [20], cognitively straining conditions can affect task performance and system productivity. When an operator manages too much information, a phenomenon, identified as the "information overload problem", occurs. The manual assembly line is considered an industrial process with frequent cognitive demands variability [21], and the information overload problem frequently happens [22]. In [23], a holistic information-based model is developed to estimate the performance time of operators of different ages and sex involved in cognitive or motor tasks. The effectiveness of the model is validated in a real full-case study.

Currently, in scientific literature, there is a lack of studies regarding cognitive ergonomics in industrial systems. Although the cognitive load is widely investigated in psychology, there are very few applications in the industrial context [24], [25]. Therefore, methodologies that evaluate the cognitive ergonomic risk and ensure a high production rate in manual assembly lines are not deeply investigated.

This work aims to develop a model that schedules a job rotation, minimizing the cognitive ergonomic risk of operators involved in assembly lines. Consistent with this end, the authors propose a mixed-integer nonlinear programming model that balances the cognitive workload of each operator, meeting the production rate of an assembly line. Risk and its acceptability are evaluated using the Cognitive Load Assessment for Manufacturing (CLAM) method [26]. The balance of the cognitive workload is achieved by minimizing the coefficient of variation of the average CLAM index.

The remainder of this paper is organized as follows: a theoretical background on the existing methods for the cognitive workload evaluation and the CLAM method are introduced in sections 2 and 3, respectively; the model developed is introduced in Section 4; a numerical case study and the discussion of the results achieved are described in section 5. Finally, conclusions and further research are in section 6.

II. COGNITIVE WORKLOAD EVALUATION

High cognitive demand can affect the operator's mental health and his/her performance; this implies an increasing interest in Cognitive Load Theory (CLT). According to recent studies, CLT investigates the interaction between cognitive structure, information and its implication [18].

A growing body of literature developed models to assess the human cognitive workload [27]. Mental load, mental effort, performance, and stress level are used as measurable dimensions to describe the cognitive workload [28]. Cognitive workload measurements can be divided in three main categories: subjective, performance-based, and physiological measures:

- Subjective measures: the subject's cognitive workload is evaluated using a set of questionnaires or different rating scales. Consistent with this end, a survey is conducted when the subject(s) has(have) completed an assigned task to evaluate the cognitive effort perceived during the task execution. The output of the survey provides a Task Workload Index (TWI) in a given range, depending on the methodology adopted. The subjective methods include the NASA Task Load Index (NASA-TLX) [29], the Subjective Workload Assessment Technique (SWAT) [30], the Modified Cooper-Harper Scale [31], and many others.
- Performance-based measures: the performance measures include control models, generally adopted for monitoring the evolution of task performance over time; included in this category are completion time, reaction time or the number of errors as drivers to quantify the cognitive workload.
- Physiological measures: the cognitive workload is evaluated on changes in the physiological parameters of the subject due to a change of cognitive demand required by the task to be performed. This category includes oxygen consumption evaluation, heart rate measurement, ongoing Electroencephalography (EEG), and others.

Unfortunately, most of these techniques are not applicable in the industrial work environment since they require expensive and impractical equipment that may be uncomfortable for the worker during the task(s) execution.

According to the experiences reported in the scientific literature, the above-mentioned cognitive workload measurements can be used exclusively by experts and, in most cases, do not provide an immediate output.

III. COGNITIVE LOAD ASSESSMENT MANUFACTURING METHOD

The purpose of the CLAM method consists of assessing the cognitive workload of the operator in accomplishing a manufacturing task [26]. The CLAM method supports the workstation design to reduce the cognitive workload. It is developed to quickly assess cognitive workload connected to tasks and designed workstation. The CLAM method can be applied by adopting a free online tool (http://www.clam.se/tool.html).

The CLAM method consists of 11 factors of evaluation, all using common terminology from the manufacturing industry. All factors are assessed on a scale from 0 to 8, where the higher assessment indicates a more cognitively challenging task (figure 1).

INTERVAL	ASSESSMENT
6-8	High cognitive workload
4-6	Moderate cognitive workload
2-4	Low cognitive workload
0-2	Very low cognitive workload

Fig. 1 The scoring levels of cognitive workload in CLAM.

The 11 evaluated factors are divided into two categories identified as task- and workstation- based. A weight, included in the range between 0-1, is assigned to each factor, as shown in brackets. A brief description of each factor is shown below:

- Task-based factors

Saturation (0.17): indicates how much of the available time is occupied by work tasks. It is measured by the percentage of the planned busy time.

Variant flora (0.11): estimates the level of product variation on a workstation. It is measured by the percentage of the same products considering all available variants.

Level of difficulty (0.07): estimates the physical and cognitive effort to perform a task. It is measured from a subjective perspective.

Production awareness (0.07): indicates how much attention the task requires. It is measured from a subjective perspective.

Difficulty of tool use (0.02): relates to the type of tools used with their subjective complexity. It is measured from a subjective perspective.

- Workstation-based factors

Number of tools used (0.01): indicates the number of tools used.

Mapping of workstation (0.13): indicates the correspondence between the workstation layout and the assembly sequence. It is measured from a subjective perspective.

Parts identification (0.11): indicates the presence or absence of alternative parts for the finished product assembly.

Information cost (0.12): indicates the physical or cognitive effort required to identify the information, i.e., if the information is easily accessible or not. It is measured from a subjective perspective.

Quality of instruction (0.11): indicates the quality of the instructions provided to the worker to accomplish the task. It is measured from a subjective perspective.

Poke-a-yoke (0.07): indicates the presence or absence of poke-a-yoke solutions or other types of constraints. It is measured from a subjective perspective.

IV. MODEL DESCRIPTION

A mixed-integer nonlinear programming model is proposed to balance the cognitive ergonomic risk in an assembly line. Consistent with the aim of the paper, differently aged and skilled operators were involved on a single product assembly line. All operators are assumed to be constantly exposed to tasks, considering a different cognitive demand for each workstation (WS). The cognitive workload increases with the increasing flexibility required by each task. In other words, the operator's capability to perform assigned tasks by adopting different approaches leads to higher cognitive demands [32], [33].

The work shift is divided into a given number of time slots (K), and the operators are assigned to the WSs in each time slot. The operator's cognitive ergonomic risk (ER), evaluated according to the CLAM method, is affected by the time required to perform the task on each WS. It is assumed that the operators assigned to each WS can rotate at the start of each time slot. The time required for the job rotation is assumed constant and identical for all the workstations, which leads to a slight reduction in productivity.

The constraints ensured by the model are summarized below:

a. The number of units to be assembled in a work shift.

b. The operating time of the operator for each WS.

c. The cognitive workload of each WS, that cannot exceed 8 (maximum threshold level evaluated adopting the CLAM method).

The variables of the model are represented by the binary variables $x_{i,j,k}$, where the index i identifies the i-th operator among the total number of operators n, the index j identifies the j-th WS among m workstations and the index k identifies the time slot in K time slots. Consequently, $x_{i,j,k}$ is equal to one if the i-th operator is assigned to the j-th workstation during the k-th time slot and equal to zero otherwise.

The weighted CLAM value for the i-th operator ($CLAM_i$) during the work shift is provided by equation 1, considering a time-weighted average of the values of

$CLAM_j$ at the respective j-th workstation, by means of the values $WT_{i,j}$, given in equation 2.

$$CLAM_i = \sum_{j=1}^{m} CLAM_j \cdot \frac{WT_{i,j}}{T} \tag{1}$$

$$WT_{i,j} = \sum_{k=1}^{K} T_k \cdot x_{i,j,k} \tag{2}$$

$$T = \sum_{k=1}^{K} T_k \tag{3}$$

The value $CLAM_j$, estimated in a net operating time (T) (eq. 3), is evaluated by adopting the CLAM method described in the previous section according to [26]. The eventual working time ($WT_{i,j}$) of the i-th operator at the j-th workstation, during the k-th time slot, is given in equation 2 and, in equation 3, T_k identifies the duration of the k-th time slot.

The model minimizes the collective cognitive ergonomic risk (eq. 4), assumed represented by the coefficient of variation (CV_c), given in equation 5, of the average CLAM index ($\bar{C}$):

$$OF = \min_{\{x_{i,j,k}\}} CV_c \text{ with } x_{i,j,k} \in \{0,1\}, \forall\, i,j,k \tag{4}$$

$$CV_c = \frac{\sigma_C}{\bar{C}} \tag{5}$$

where CV_c is defined as the ratio of the standard deviation (σ_C) and the average CLAM index ($\bar{C}$) of the n operators during the work shift, as reported in equations 6 and 7, respectively.

$$\sigma_C = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(CLAM_i - \bar{C})^2} \tag{6}$$

$$\bar{C} = \sum_{i=1}^{n} \frac{CLAM_i}{n} \tag{7}$$

For the calculations, it was assumed an initial condition identified with

$$k = 0,\; x_{i,j,0} = 0 \;\forall\, i = 1, \dots, n \text{ and } \forall\, j = 1, \dots, m.$$

Assuming a given number of units to be assembled in a work shift (P_{LT}), the total production of the line in a work shift (P_L) will be evaluated according to equation 8.

$$P_L = \min_{\{j\}} P_j \tag{8}$$

with $P_L \geq P_{LT}$

where the total production of the j-th workstation (P_j) in a work shift depends on the total number of parts assembled (Q_{ij}) by the i-th operator at the j-th workstation in a work shift, as shown in equations 9 and 10.

$$P_j = \sum_{i=1}^{n} Q_{ij} \tag{9}$$

$$Q_{ij} = \sum_{k=1}^{K} q_{i,j,k} \tag{10}$$

Assuming a standard operation time of the j-th workstation (t_j), a time loss due to job rotation (t_r), and a productivity factor of the i-th operator at the j-th workstation (k_{ij}), the number of parts assembled by the i-th operator at the j-th workstation, during the k-th time slot ($q_{i,j,k}$) is estimated in equation 11.

$$q_{i,j,k} = \frac{[T_k - t_r(x_{i,j,k} - x_{i,j,k-1})]}{t_j \cdot (k_{ij})} x_{i,j,k} \tag{11}$$

The k_{ij}-parameter depends on the operator's skills and age. Its value is included in the ranges $]0;1]$ where zero corresponds to a not skilled ageing worker, and 1 identifies a skilled young worker according to a subjective evaluation.

Three constraints (C_i) are identified:

- each WS can be used by only one operator during each time slot (C_1)

$$C_1: \sum_{i=1}^{n} x_{i,j,k} = 1 \;\forall\, j = 1, \dots, m \text{ and } \forall\, k = 1, \dots, K$$

- each operator can be assigned only to one WS during each time slot (C_2)

$$C_2: \sum_{j=1}^{m} x_{i,j,k} = 1 \;\forall\, i = 1, \dots, n \text{ and } \forall\, k = 1, \dots, K$$

- The weighted ergonomic risk of each i-th operator cannot exceed the maximum CLAM allowed ($CLAM_i^{max}$) (C_3)

$$C_3: CLAM_i \leq CLAM_i^{max}$$

V. NUMERICAL CASE STUDY AND DISCUSSION

The model is tested on a numerical case study. Four assembly workstations ($m = 4$) and four operators ($n = 4$) with different ages and skills are considered. The work shift duration is set to 480 $[min]$ and is divided into five-time slots ($k = 5$). The time and rests duration are summarized in figure 2.

	Work shift: 6:00 – 14:00								
k	$k=1$	r_1	$k=2$	r_2	$k=3$	r_3	$k=4$	r_4	$k=5$
$T_k[min]$	80	15	80	15	95	30	80	15	70

Fig.2 Time slot (T_k) and rests duration (r_i), for each slot (k), expressed in minutes

The standard operation time assumed for each of the four workstations (t_j) is provided below (table 1). The production time loss (t_r) due to job rotation, is equal to 2 minutes.

TABLE I
STANDARD OPERATION TIME FOR EACH WS $[s]$

	WS			
j	1	2	3	4
$t_j[s]$	30	30	35	30

In table 2, for each workstation, the cognitive workload ($CLAM_j$) has been evaluated according to [26].

TABLE II
CLAM INDEX OF THE J-TH WORKSTATION

WS				
j	1	2	3	4
$CLAM_j$	1	3	5	7

The assembly task performed in WS_4 requires a higher cognitive workload. On the contrary, the assembly tasks in WS_1 are more accessible since the tasks are not very flexible (the operator takes no decisions), and a guided procedure was applied.

Different scenarios have been investigated by varying the parameters k_{ij}-. In the first scenario (S1R), four skilled and young workers (i.e., Op_1, Op_2, Op_3, and Op_4) were considered, assuming the same k_{ij}-parameter $(k_{ij} = 1)$ for all. In the second scenario (S2R), four operators of different ages and skills have been considered (table 3). In the third scenario (S3R), four operators with different skills for each WS_j have been considered (table 4). In other words, in this case, the same operator can be skilled in using one WS, and less expert on another WS.

TABLE III
OPERATORS' PROFILE ASSUMED FOR SCENARIOS S2 AND S2R

ID operator	k_{ij}	Description
Op_1	0.1	Aged and not skilled operator
Op_2	0.6	Aged and skilled operator
Op_3	0.4	Young and not skilled operator
Op_4	1.0	Young and skilled operator

The results of scenarios S1 and S1R were to be expected. In S1, operators were assigned to WSs without any preference. In this case, all operators have the same profile; therefore, the model provides more job schedule alternatives. In the case of job rotation (S1R), the operators are assigned in each time slot to one WS, and the job rotation is considered. Here, the operators in each time slot are assigned to a WS different from the previous one. Therefore, the cognitive load is balanced since each operator accomplishes tasks on WSs with both low and high cognitive workloads. In this case, four WS and four operators were assumed. The mental effort required by different operators is slightly different since all operators were assigned to the same WS for two slots.

TABLE IV
OPERATORS' PROFILE ASSUMED FOR SCENARIO S3

WS_j	k_{1j}	k_{2j}	k_{3j}	k_{4j}
WS_1	0.7	0.8	0.8	1.0
WS_2	0.2	1.0	0.7	1.0
WS_3	0.4	0.6	0.6	0.6
WS_4	0.2	0.5	0.3	1.0

The results of scenario S2 showed a schedule depending on the cognitive workload of WS_j, and the profile of each operator. In this case, the minimum value of the $\boldsymbol{CV_c}$ is achieved by assigning the WSs with low workload (e.g., WS_1) to operators with low performance (e.g., Op_1). Similarly, WSs with a high workload (e.g., WS_4) were assigned to young and skilled operators (e.g., Op_4). In the case of job rotation (S2R), the WSs with higher workloads are assigned more frequently to more skilled and younger operators.

The operators' scheduling in the last scenario (S3R) is more complex to predict. In this case, the operators' performance is very close to real industrial cases, where operators are more skilled in accomplishing tasks on a specific workstation. The results showed that the assignment of more skilled workers to specific WSs occurs more frequently. For instance, the assignment of Op_4 to WS_4 is rather frequent since he/she is the operator with the best performance on this WS. On the contrary, the assignment of less skilled operators on specific WSs is not recurring (e.g., Op_1 to WS_2 and WS_4).

TABLE V
ASSIGNMENTS OF OPERATORS ($i = 1, \dots, 4$) TO WSs DURING THE WORK SHIFT ($k = 1, \dots, 5$) IN THE SCENARIO S3

Workstation	Time Slot (k)				
	1	2	3	4	5
WS1	Op_1	Op_1	Op_1	Op_3	Op_1
WS2	Op_2	Op_3	Op_4	Op_2	Op_3
WS3	Op_3	Op_4	Op_3	Op_1	Op_2
WS4	Op_4	Op_2	Op_2	Op_4	Op_4

The coefficient of variation of the average CLAM index, (CV_c), the total production of the line in a work shift (P_L), and the average workstation production (AvP_j), evaluated for each scenario, are summarized below.

TABLE VI
COEFFICIENT OF VARIATION OF THE AVERAGE CLAM INDEX (CV_C), TOTAL PRODUCTION (P_L), AND AVERAGE WS PRODUCTION (AV P_J) IDENTIFIED FOR EACH SCENARIO

Scenario	CV_c	P_L	Av P_j
S1	0.65	115.71	130.18

S1R	0.10	112.86	126.95
S2	0.65	15.00	20.76
S2R	0.10	17.95	20.28
S3R	0.14	26.5	58.74

According to the results in table 6, the model minimizes the objective function (eq. 4), providing the minimum value of the cognitive ergonomics risk in S1R, S2R and S3R. In these scenarios, the assembly tasks have been assigned adopting the job rotation schedule identified by the model application. Comparing the results with and without job rotations, although the cognitive ergonomic risk was reduced in the second case, the total production of the line in a work shift and the average workstation production are very close values. In fact, if, on the one hand, the performance of a single worker improves, the assembly line performance doesn't change since it is affected by time losses due to job rotation (t_r).

The comparison between scenarios with young and skilled workers (S1 and S1R) compared to cases where workers with different skills are employed (S2, S2R, and S3R) shows the benefits of smart operators in an assembly line. In these cases, it is possible to observe that skilled workers allow increasing 3-4 times the assembly line performance.

VI. CONCLUSION AND FURTHER RESEARCH

The increasing adoption of innovative devices in the manufacturing context leads to changes in the tasks performed by the operators. Recent studies proved that the Industry 4.0 revolution is favouring the increase of cognitive tasks and the reduction of physical tasks, increasingly being entrusted to innovative devices.

In the current research work, a model allowing to minimize the cognitive ergonomic risk of operators involved in an assembly line is proposed. Risk and its acceptability in this paper are evaluated using the CLAM method. The developed model allowed to identify an operator-workstation schedule, adopting job rotation, ensuring the minimization of the workers' cognitive ergonomic risk, in other words preserving them from the risk of cognitive overload e. Although the production line's performance is slightly decreased, the well-being of the workers is preserved.

However, the research work requires more investigations to assess the model reliability in more complex industrial cases. The proposed model is the first step in assessing the cognitive workload. It provides the decision-maker with a "preliminary" job schedule adopting a sustainable organisational strategy from an economic perspective. In this regard, an important assumption of the model consists of the workers' adaptability to perform all the assembly tasks on all the workstations. Since, in many cases, the training of workers requires cost and time and this assumption is not always true, further constraints should be considered in the model. It is possible that, under these conditions, job rotation could further reduce the line performance.

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