A mathematical model of human error probability for cognitive-oriented tasks

Digiesi S.*, Facchini F.*, Mossa G.*, Mummolo G.*

* *Department of Mechanics, Mathematics and Management, Polytechnic University of Bari, Viale Japigia 182, Bari, Italy (salvatore.digiesi@poliba.it, francesco.facchini@poliba.it, giorgio.mossa@poliba.it, giovanni.mummolo@poliba.it)*

Abstract: The reliability of a system can be defined as the capability of ensuring the functional properties of the system within a given variability of work conditions, considering the possible deviations due to unexpected events. In most cases, the reliability of a complex system is strongly related to the reliability of its weakest component. In a human-machine-work environment, the worker appears to be the weakest part, since he is considered the least known and more difficult to model component. Therefore, his capability to withstand the fatigue and psychological stress over time affects the safety of operator's performance and/or the possibility of his failure. Consistently, in the evaluation of man-machine-work complex system, the Human Error Probability (HEP) represents a key element to assess the reliability of the whole system. Traditional Human Reliability Assessment (HRA) approaches do not provide much attention to the cognitive content of tasks performed by workers, and model HRA by adopting approaches developed for machines, not considering factors affecting workers' behavior such as environmental, psychological, and physical factors as well as learning vs. forgetting, fatigue vs. recovery, and mental vs. physical fatigue phenomena. The aim of this paper is to develop a mathematical model, based on a multi-attribute utility analysis allowing to estimate dynamic variability of the HEP over time. In the model proposed effects of both learning and fatigue on HEP variability are considered. Learning effect is modeled based on Wright's theory. Fatigue and recovery effect is modeled according to a previous published model relating it with the rest schedule in the work shift. Results of numerical simulations show (i) the effect of task nature and of the learning rate on HEP variability over time, and (ii) the effectiveness of the model in evaluating the optimal rest schedule allowing minimizing HEP average values. They are consistent with values obtained in previous experimental works.

Keywords: Human Error Probability, Human Reliability Analysis, fatigue-recovery, Work-breaks schedule, Multi- attribute utility.

1.Introduction

The Human Error is a crucial factor leading to system accidents and disasters especially in high-risk work environments, such as nuclear plants, aerospace, and aviation (Pan et. al, 2016). In case of discrete tasks, the Human Error Probability (HEP) is defined in scientific literature as the number of errors divided by the number of opportunities for making errors. According to Health and Safety Executive agency (HSE) the errors can be classified in two different categories: first category includes the so-called "slips or lapses" errors, they are considered like "actions that were not as planned" or unintended actions. Generally, these kinds of errors occur during a familiar task and include slips (e.g. pressing the wrong button or reading the wrong gauge) and lapses (e.g. forgetting to carry out a step in a procedure). Therefore, they cannot be eliminated by training, but an improved workplace's design can reduce their likelihood and provide a more error tolerant system. The second category of errors includes the errors of judgement or decision-making, so-called "mistakes". They occur when the workers do the wrong action believing it to be right. In most cases, a mistake occurs in situations where the worker does not know the correct way of carrying out a task either because it is new task or because he has not properly trained, or both (Intranuovo et al., 2018). According to HSE, the training represents the key strategy to avoiding mistakes (HSE, 1999).

Recent studies showed that in automotive sectors more than 80% of defects due to assembly and visual inspection tasks depends on human behaviour. The equipment is to blame in less than 20% of the occurrences (Kujawińska and Vogt, 2015). In the case of Oil and Gas sector (O&G), the human error constitutes as the largest contributor of over 70% of all accidents (Alkhaldi et al., 2017). Different evaluations are discussed by experts about the high accidents rate due to human error in this field. According to Bhavsar et al. (2015), the cognitive tasks faced by operational workers during their interactions with the process and decision making are the main causes of human error in this kind of processes. Alkhaldi et al. (2017) argued that accidents in O&G industry are related to workers carelessness in the maintenance activities. Therefore, currently it is very difficult to identify the main causes behind this high error rate, and further empirical studies are required.

In the 2018 Safety Report of the International Air Transport Association (IATA, 2018), the 80% of total airplane accidents caused are addressed to a human error (i.e. pilots, air traffic controllers, mechanics, etc.) and only the 20% to components (i.e. equipment, device, etc.)

failures. A 2009 Harvard study on human error in medical field identified 19% of the adverse events due to human mistakes, while 14% were wound infections due to medical treatment and 13% for technical complications. The 58% of the adverse events identified in this study are labeled as "preventable" (Robbennolt, 2009).

Consistently with cases above described, Kujawińska and Vogt (2015) identified the 7 most important causes of Human Error in the automotive sector. According to the results of a survey published in 2016 (fig. 1), in most of the cases the human error is related to procedural problems (24%), fatigue (22%), equipment complexity (20%) as well as training deficiency (15%). If on one hand, it is possible to identify a strategy allowing to reduce the probability of occurrence of each aspect on the basis of the HEP, on the other hand, the strategy to be adopted is strictly related to the type of task performed, for instance a proper work-rest policy or a correct job rotation scheduling, two of most common methods adopted for manage the fatigue phenomenon, could be totally different for cognitive or physical-oriented tasks. Therefore, it is required a flexible approach that allows evaluating the best strategy to be adopted, according to specific characteristic of the task to be performed.

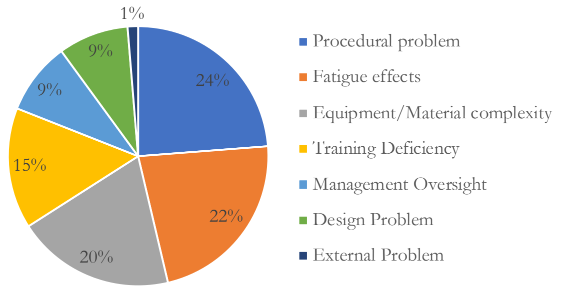

Figure 1: Data on the Causes of Failures in manufacturing process (adapted on figure published by Machinery Lubrification Magazine - www.machinerylubrication.com)

Although it is possible to claim that the scientific literature provides a good guide on how to evaluate the human reliability (see next Section), there are still aspects to be discussed in-depth. To fully investigate the research problem, the following subsidiary research questions are raised:

1. It is possible to evaluate the Human Reliability (HR) over time, and how the conventional strategies change the HR rate during the work-shift, what strategies can affect the worker's behavior in cognitive-oriented tasks?
2. There is a relation between HR and HEP, it is possible to evaluate the HEP in order to predict and avoid a generic system failure (e.g. assembly defect, accidents, complication, etc.)?
3. How the industrial strategies can support the Human Reliability Assessment (HRA), what are the limits of the current approach in which can be difficult to find common ground between needs of employees and business needs?

The purpose of the paper consists to develop a mathematical model, based on a multi-attribute utility analysis via learning-fatigue approach in accordance with Wright's theory, allowing to estimate the dynamic variability of the HEP over time. The model adopted is focused on cognitive, rather than physical, tasks. In all cases, the model allows considering the effect of fatigue and of recovery on HEP, due to breaks in work-shift.

The rest of the paper is structured as follows: a brief review on the HRA models already available in scientific literature is presented in section 2; in section 3 the model methodology's is introduced; results obtained by applying the model with three different work rest schedules are in section 4; finally, conclusions of this work are in section 5.

2. Literature Review

The HRA methods are applied in different industrial fields characterized by different kind of tasks, level of complexity, as well as work environments. According to a recent classification of evaluation methods already available in scientific literature, there are two different generations of HRA methods (Digiesi et. al, 2018):

- The first-generation, largely originated before the 1990s, includes evaluation methods mainly focused on applying structural models and calculation methods to solve mathematical problems. Generally, tools like Fault Tree Analysis (FTA) and Event Tree Analysis (ETA) are very common in this generation of methods. The best-known techniques included in first-generation are: The Technique of Human Error Rate Prediction (THERP), the Human Cognitive Reliability (HCR), and the Human Error Assessment and Reduction Technique (HEART);
- The second-generation HRA methods, originated after the 1990s, allow identifying a cognitive model of the human behavior, in order to explain the mechanisms of human error formation, and then to evaluate the corresponding HEPs. The second-generation methods are based on behavioral science, psychology, and other areas of scientific studies and in many cases tool based on artificial intelligence and other cognitive simulation techniques are adopted for the human error prediction. The best-known techniques in second-generation are: The Technique for Human Error Analysis (ATHEANA), the Cognitive Reliability and Error Analysis Method (CREAM), and Cognitive Simulation Model (COSIMO).

Comparing the first-generation of HRA methods with second-generation ones, it is clear that the latter are focused on process of human error development, considering the human interactions with the work environment and the system.

According to Trucco and Leva (2007) the first-generation HRA approaches have two main advantages: they are generalizable, i.e. can be applied to different context and circumstances, and allow providing a quantitative result, starting from a limited amount of effort in terms of processing time and experience. This is not true for the second-generation approaches that generally require more information and, in many cases, are not able to provide quantitative results. Therefore, the authors proposed a probabilistic cognitive simulator for HRA studies (PROCOS) allowing integrating the quantification capabilities of first-generation HRA methods with a cognitive evaluation of the operator, and the results show the capability of the simulator to provide coherent and accurate analysis (Trucco and Leva, 2007).

Givi et al. introduced a novel analytical model to measure the human error rate while performing an assembly job under the influence of learning–forgetting and fatigue–recovery phenomena. The results of the research highlighted that the error rate of an assembly task is reduced when workers move fast on their learning curves, in other words this means that methods to train workers about their jobs (e.g. overlaying 3D instructions, training specific path, etc.) as well as a suitable design of ergonomic workstations significantly reduce (around 80%) the HEP (Givi et al., 2015). A different approach is proposed by Elmaraghy et al. (2008) in order to develop a model for assessing the HEP in manufacturing systems based on tasks characteristics, work environment as well as workers capabilities according to a multi-attribute utility analysis. The application of the model to an industrial case study demonstrated its ability to assess the HEP, and the result obtained are validated by comparing them with results in similar studies.

The validation of new HRA models and the comparison of results obtained adopting different methods nowadays represent another challenge related to HEP evaluation (Boenzi et al., 2016). Consistently with the scope to provide a reliable methodological tool that allows reducing the uncertainties on the information to be collected for carrying on the HRA, some of human error empirical data for specific tasks have been introduced in the last years. Most common database are the Human Event Repository and Analysis (HERA) and the Human Factors Information System (HFIS). Their use allows to improve the validity and the reproducibility of HRA results (Di Pasquale et al, 2015a).

In 2017 an innovative methodology for HRA in emergency scenarios has been proposed by Falcone et al. The authors introduce a hybrid model that integrates the advantages of the methodologies HEART, Standardized Plant Analysis Risk-Human (SPAR-H) and Success Likelihood Index Method (SLIM), in order to evaluate the impact of all environmental and behavioral factors on the decisions and the actions of operators in case of accidents and disasters. Results obtained from the analysis of a real case study (petrochemical plant's control room during an emergency situations) provides an empirical and a theoretical contribution referring to the framework used to detect human error in risk and reliability analysis (Falcone et al., 2017).

A different approach is adopted by the Simulator for Human Error Probability Analysis (SHERPA) proposed in (Di Pasquale et al., 2015b). In this case the human reliability is estimated as function of the performed task, performance shaping factors and working-time. Consistently with this approach, the human reliability depends on the typology of tasks to be performed, on the working environment as well as on the time that the operators have spent at their work. Under this perspective, the tool allows identifying the optimal configuration of breaks jointly considering the economic nature assessment, due to productivity rate, and the human reliability due to psychophysical recovery of the worker. As far as concern the planning of different breaks from work in employee recovery and unwinding from work, Lim et al. investigated on a brain activation in a test of cognitive throughput interspersed with breaks of different lengths. The authors found that, in case of white-collar jobs, the regular short breaks result in more stable task performance and fewer errors (Lim et al., 2016)

According to Griffith and Sankaran, over 70 human reliability tools are available in scientific literature with the same target: to measure the human error. Even if methods have the same purpose, they are characterized by different methodological frameworks, priority, operator models and performance shaping factors (Griffith and Sankaran, 2011). Despite the efforts of HRA experts, many of the limitations and problems of these approaches have not yet solved. In particular, the existing models are characterized by following limitations:

- hard to be implemented for different users and different tasks;
- strongly related to 'context' both in error identification than in error probability estimation;
- are not capable of anticipating how and when an error will occur.

The model proposed try to overcome the limitations above listed in cases of cognitive-oriented tasks, by means of a method that combine the advantages of an approach learning-forgetting and fatigue–recovery based, with the advantages of a multi-attribute utility analysis. The application of the model allows evaluating the fatigue effects over time (considering the work-breaks schedule) on the HR in accordance with Wright's theory.

3. Materials and Method

The model to be adopted in case of cognitive-oriented tasks is based on a multi-attribute utility analysis (Elmaraghy et al., 2008) developed by a learning-forgetting and fatigue–recovery approach (Givi et al., 2015) where the time required to complete the x-th task in the cycle (t_x) is estimated in accordance with Wright's theory (see eq. 3).

According to Givi et al. 2015, the Human error utility function over time (U(t)), is given by eq. 1, where: T_1 is the time required to produce the first unit, ρ_l and ρ_f are scale parameters ranging in (0,1) for learning and fatigue effects, respectively. The parameters F(t) and F_{max} measure the accumulated fatigue over time t and the maximum fatigue identified in the same work-shift, respectively.

$$U(t) = \rho_l \frac{t_x}{T_1} w_l + \rho_f \frac{F(t)}{F_{max}} w_f \quad (1)$$

with: $w_l + w_f = 1$ (2)

The parameters w_l and w_f represent the relative weights of the learning and fatigue phenomena on the task to be investigated. The time to complete the x-th task (t_x) is given by following equation:

$$t_x = T_1 x^{\frac{log(LR)}{log(2)}} \quad (3)$$

where x is the number of units produced or tasks completed in case of cognitive-oriented tasks (e.g. visual inspection, signal recognition and interpretation, manipulate complex object, etc.), and LR identified the learning rate (0<LR<1). High LR-values correspond to reduced workers' learning ability; in case of LR≅1, tx≅T1 for all x values in the work-shift.

At the beginning of the work-shift (t=0,), the second term of equation 1 assumes null value, since the accumulated fatigue is negligible at the beginning of the working day, therefore given ρl, U(0) (eq. 4), and considering that tx = T1 for producing the first unit in the work-shift, it is possible to identify wl and wf values by means of equations 1 and 2, respectively.

According to Elmaraghy et al. (2008), U(0) depends on a set of attributes related to task error proneness (u_x), worker capabilities (u_y), and work environment (u_z). The evaluation of U(0) is described in the next Section.

3.1 Multi-attribute analysis for Human error utility identification

The overall utility function of human error utility (U(0)) is obtained as the weighted sum of utility functions of the task error proneness (u_x), the worker capabilities (u_y), and the work environment (u_z) (eq. 4), being w_x, w_y and w_z their relative weights (eq. 5). For more details on the evaluation of u_x, u_y, and u_z we refer the reader to (Elmaraghy et al., 2008).

$$U(0) = w_x u_x + w_y u_y + w_z u_z \quad (4)$$

$$w_x + w_y + w_z = 1 \quad (5)$$

Consistently with eq. 4, starting from the values of the utility function due to task error proneness (u_x), work capabilities (u_y), and to worker environment (u_z) it is possible to evaluate the human error utility function (U(0)). The value obtained neglects the effects of fatigue and of learning-forgetting phenomena, and therefore it corresponds, according to our assumptions, to the human error utility function at zero-time (i.e. at the beginning of the work-shift).

3.2 Learning–forgetting and fatigue–recovery approach

In the approach introduced by Givi et al. (2015) based on Learning-Forgetting-Fatigue-Recovery Model (LFFRM) of Jaber et al. (2015), fatigue is measured by means of an exponential model, expressed by eq. 6, where $F(t_i)$ is the accumulated fatigue over time t_i, $R(t_{i-1})$ represents the residual fatigue after break from cycle i-1 (see eq. 13), and λ quantifies the severity of the work performed (0<λ<1).

$$F(t_i) = R(t_{i-1}) + \left(1 - R(t_{i-1})\right)1 - e^{(\lambda t_i)} \quad (6)$$

$$R(t_i) = F(t_{i-1})e^{-(\mu \tau_i)} \quad (7)$$

Where μ represents the speed of recovery of the worker, after a break of length τ.

The accumulated fatigue $F(t_i)$, considering the work-breaks schedule in the work-shifts, allows thus to identify, by eq. 1, the Human error utility function over time (U(t)).

3.3. Human Error Probability Rate

The human error utility function in eq. 1 is required to identify the probability of human error. According to Elmaraghy et al. (2008), even if U(t) is different by HEP, there is a strong relation between the overall utility values and the HEP.

In particular, knowing that the human error rates, during the work-shift, may range from 1e-6 to 1 (Elmaraghy et al., 2008), it is possible to provide an analytically mapping between these two parameters over time (eq. 8):

$$log(HEP) = 6log\left(U(t)\right) \quad (8)$$

Consistently with the assumptions of the model proposed, it is clear that for t=0, HEP is provided by follows equation:

$$log(HEP)_0 = 6log\left(U(0)\right) \quad (9)$$

To sum up, the model developed consists of the following steps:

1. On the basis of the evaluation of task error proneness (u_x), worker capabilities (u_y), and worker environment (u_z) according to Elmaraghy model, the overall utility function of human error is identified at zero-time (U(0)), (eqs. 4-5);
2. Given U(0), it is possible to identify the corresponding HEP_0, by eq. 9. Moreover, assuming constant values for learning and fatigue scale parameters (ρ_l and ρ_f, respectively) by experimental cases or existing databases (for e.g.

HERA, HFIS, etc.) it is possible to identify the values of w_l and w_f, by eq. 1 and 2, respectively;

3. On the basis of characteristics related to task to be performed (T_1, λ), workers' ability (LR, μ) as well as work-breaks schedule (τ_i), the accumulated fatigue over time, considering the effect due to work-breaks, can be identified by eq. 6 and 7;
4. Finally, The Human error utility function (U(t)) and the corresponding HEP over time can be identified by eq. 1 and 8, respectively.

The steps above mentioned are implemented on excel VBA routine, in order to evaluate the HEP over time by changing the tasks conditions, workers' capabilities, work environment, as well as work-breaks schedule.

4. Numerical simulation

A numerical case study is identified in order to evaluate the effectiveness of the model; consistently with this target, three different work-breaks schedules (WB schedule) are planned (fig. 2).

The daily overall working-time and rest-time is assumed equal for all work rest schedules; only the number, frequency and length of breaks are changed. In the model it is assumed that the same kind of activities characterized all break times, therefore in case of the same worker, μ-parameter assumes the same value.

The case study considered is based on the following assumptions:

1. Task error proneness (u_x): the work is based on repetitive, cognitive-oriented activities with elementary tasks characterized by an average difficult and a high dependence between them, this means that if one elementary task is inappropriately performed it could result in an inappropriate execution of the other elementary tasks;
2. Operator's capabilities (u_y): a worker with average capabilities under mental, physical, and professional perspective, is considered;
3. Work environment and system operational characteristics (u_z): a well-built workplace under design, safety and ergonomic point of view is considered.

The evaluation of the human error utility function according to multi-attribute utility is conducted (tab. 1), and weights of different attributes are assigned; all values are evaluated in accordance with Elmaraghy et al. (2008).

Different numerical simulations, for each work-breaks schedule (so-called A, B and C-schedule, see fig. 2) are conducted, by changing the value of the following variables: parameters (ρ_l, ρ_f), assigned on the basis of empirical values corresponding to different cognitive-oriented activities ($w_l>w_f$, in all cases) as well as severity of the work performed (λ).

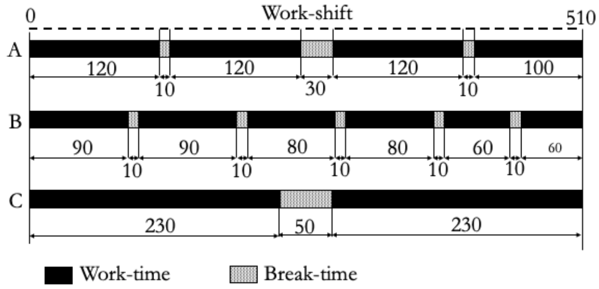

Figure 2: Plan of three different WB schedules

Table 1: Set of attributes related to task error proneness, worker capabilities, and worker environment identified for the case study

Attribute	Value	Weight
u_x	0.550	0.429
u_y	0.494	0.143
u_z	0.506	0.428

Consistently with operator's capabilities utility function (u_y), the same values are assumed, in all cases evaluated, in order to estimate the speed of recovery (μ=0.5) and the learning rate (LR=0.9) of the worker considered.

The results of the model for three different cases are shown in fig. 3. It is possible to observe that, in case of activities mostly characterised by cognitive task, in which the learning component prevails on the physical effort i.e. $w_l>>w_f$ (fig 3), the HEP is maximum at the beginning of the work-shift and decreases over time.

A change of slope of HEP trend (the slope of the curve significantly increases) is highlighted in correspondence of breaks period. The HEP trend shown in fig. 3 is obtained in case of WB schedule of type "A" (fig. 2); in this case the best HR is observed after many repetitions, i.e. the HEP reduces with the increase of the worker experience. This is possible since the specific task does not require a physical effort, therefore the effect of fatigue does not affect the HEP over time. Moreover, results obtained show that, in case of cognitive oriented activities, the HEP trend does not depend on severity of work to be performed: with the increase of the λ-parameter values, HEP average (on the work-shift) values slightly increase, but the HEP trend over time do not significantly change.

In case of activities characterised by both cognitive and physical tasks, in which there is a slight prevalence of learning aspects than physical effort, i.e. $w_l>w_f$ (fig 4a), the HEP increases over time, and hence the HR is reduced progressively over working time but it increases during the rest-time. It is very interesting note that:

- The slope of HEP evaluated after each break progressively increases. This is true since, considering the same work-shift, the effect due to recovery is reducing over time and increasing the effect due to fatigue.

- in accordance with LFFRM introduced by Givi et al. (2015), the HEP reduction is observed in break-time and in the first period of the work-shift. It is possible to observe that in case of high severity of the worke performed (fig 4b), the effect is more marked. According to our opinion, the HEP reduction in the first period depends on learning effects, in other words in this phase of the work-shift the fatigue effect is negligible and, consistently, the learning phenomenon leads the first part of the work-shift.

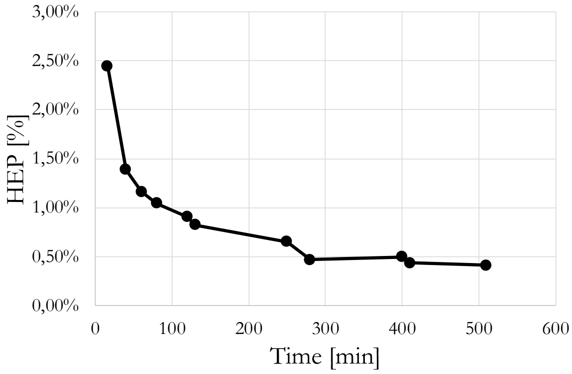

Figure 3: HEP over time for ρ_l=0.86, ρf=0.14, and λ=0.8

As far as concern the HEP, considering the different work-breaks schedule above mentioned (fig. 2), results obtained is shown that the average HEP increases when the work activities are characterized by both cognitive than physical task as well as by high severity of the work performed. On the contrary, for the activities with low value of λ-parameter and mostly characterised by cognitive task, lower values of average HEP are estimated by the model.

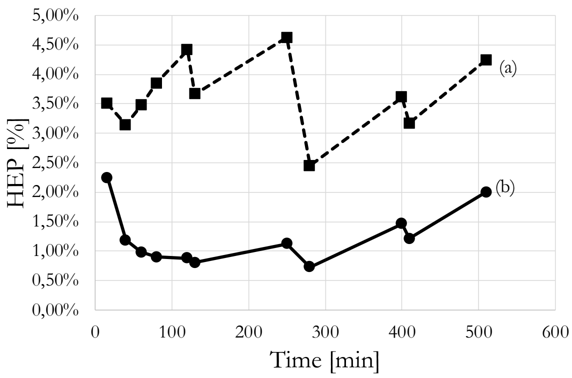

Figure 4: HEP over time for ρl=0.65, and ρf=0.35, and λ=0.8 (a) λ=0.2 (b)

Finally, with all the other parameters values been constant, the model identifies the "B" WB schedule, characterized by short breaks with high frequency, the one allowing obtaining the lowest HEP average (on the work-shift) values. This is in accordance with different experimental results (Lim et al., 2016, Zacher et al., 2014). On the contrary, the highest values of average HEP, in most cases, are obtained with WB schedule identified as "C", i.e. adopting only one long break in the work-shift.

The gap between the average HEP corresponding to different WB schedules decreases with the increase of the severity of the work performed. In these cases it is possible that the minimal HR is obtained by adopting WB schedule of type "B". In some cases, values of HEP higher than 1.00%÷1.50% are observed. Generally, they are not acceptable, and this strongly suggests the adoption other prevention measures in these cases.

λ	ρl	ρf
0,2	0,8	0,2
0,8	0,8	0,8
0,8	0,8	0,6
0,8	0,8	0,2
0,2	0,6	0,8
0,2	0,6	0,6
0,2	0,6	0,2
0,8	0,6	0,8
0,8	0,6	0,6
0,8	0,6	0,2

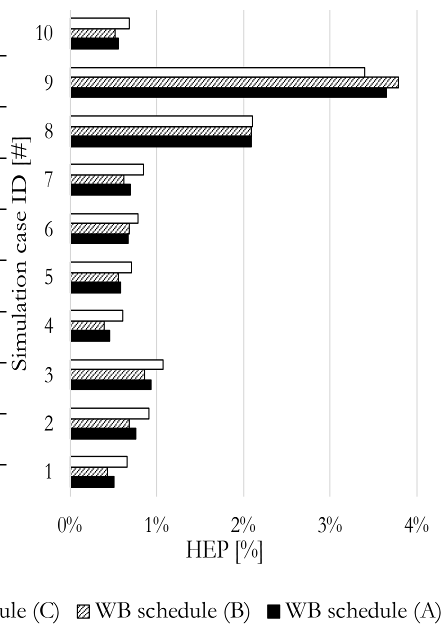

Figure 5: Average HEP changing λ, ρl and ρf for different WB schedule

5. Conclusion

In this study a mathematical model has been developed in order to estimate the dynamic variability of the HEP over time, mainly with regard to cognitive tasks. The approach adopted allowed considering the effect of fatigue and of recovery on HEP due to breaks in the work-shift. The results achieved are in accordance with existing evaluations and show the effect of different input parameters (i.e. severity of the work performed, physical effort required, as well as WB schedule) on the HEP variability over time. In this way, an answer is provided to the first research question (RQ1): for each WB schedule it is possible to predict the average HEP, and hence to identify the best WB schedule to be adopted. As far as concern the RQ2, results show that it is possible to identify an analytic relationship between HEP and HR. The limit of the existing approaches, about needs of employees and business needs (RQ3), are partially solved. Indeed, if on one hand a prediction of tasks completion times during the work-shift is provided (tx), that could be useful for evaluating productivity, on the other hand, in the model proposed this evaluation is based on Wright's theory that neglects other factors related to more complex phenomena able to provide, with higher reliability, the time required for the task completion at each repetition, over the same work shift. Further research will be focus on the adoption, in the model, of more reliable human performance parameters and on the evaluation of different task typologies and workloads, in order to developing scheduling algorithm, already adopted in other research field (Carli and Dotoli, 2019), for minimizing the HEP.

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