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Cognitive Human Modeling in Collaborative Robotics

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Abstract

In today's INDUSTRY 4.0 context, the growing need to improve performances and sustainability of working environment is looking forward to developing interoperable and service-oriented systems with real time capabilities. This is boosting the installation of decentralized and reliable robotics cells with flexible cooperative capabilities. They enroll smart operators'flexibility and robot productivity in collaborative robotics (properly cobots) applications. This paper consists of a state-of-the-art review on cognitive load in manufacturing with characterization of human-robot collaboration. A simulated analysis of a collaborative working cell is performed. An Agent Based (AB) model is presented with application in the automotive sector. The cell consists of logistics AGVs equipped with a manipulator. They interact with working robots and human operator. Robots collaborate in cell and they cooperate with operator on assisted task using Human Machine Interfaces (HMI). The load of human in the collaborative work-cell– set on state of art - is measured according with Functional states over different Behavioral Structures (FBS). We quantified the load of cognitive factors while reporting interaction analysis. Some factors as age and interface complexity and recovery strategy are investigated while reporting their effect on a dynamic variable, i.e., physical stress properly fatigue. This acts on productivity and operational outcomes.

Keywords: Cognitive models, Cobots, Human Factor, Smart Operator

1. Design principles for INDUSTRY 4.0

INDUSTRY 4.0 points on seven *Design Principles* [1]. They can be defined as [2, 3]:

1. *Interoperability* refers to the capacity of communication, integration and collaboration among all objects, machines and people through the Internet of Things (IoT). Therefore, it indicates the degree of smartness of a factory.
2. *Virtualization* refers to the capacity of Cyber Physical Systems (CPSs) to simulate and virtual copy the real world. It monitors surroundings by sensors and data management which are integrated into decentralized virtual system and digital simulations.
3. *Decentralization* refers to the ability of devices to get their own decision. They are embedded in decision-making processes so as to reduce hierarchies and to facilitate central control.
4. *Real-Time Capability* refers to the factory's ability to collect, store and analyse, real time data and easily adapt, react while responding to failures, to malfunctions and contingences.
5. *Service-Orientation* refers to the factories' capacity to comply requirements through IoT dedicated services.
6. *Modularity* refers to the capacity of the factory to chase seasonal changes and market trends by automatically configuring product, tasks and production's capacity.
7. *Sustainability* refers to the ability to limit the environment impact while satisfying people and

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society needs and maintaining cost and quality aims.

All these principles report structural and competences implications. Thus, a behavioural (argues that competencies are related to the exogenous factor rather than pointing on endogenous states as personality or intelligence), functional (related with skills and know-how required for conducting tasks) and holistic/multi-dimensional structure (which acts as a collection of individual competencies required on the organization level to achieve the desired results) approach is required [4]. Inside the Industry 4.0 context, new flexible (smart) work-cell configuration are approaching. Here, the smart operator acts, in collaboration with process, while using high-quality interfaces on product and manufacturing resources On the counterpart, the process is timed by logistics entities. Those interact with robots. Robots communicate and adapt as well as interacting – using sensing data - with the external behavioural structure. They make heavy task, cooperating with humans, reacting to product requirements. These report cooperative scenarios based on IoT data management. They are generally tested, trained and optimized, in cyber physical systems.

In the collaborative scenarios, the **H**uman operator adapts workload to the physical and visual and mental fatigue. These change with the dynamics structure of workplace **E**nvironment. Robots and AGVs (generally acting as process entities) have to be sensing in **W**orkstation while adapting, eventually safety reacting, to human movements. With this proposal we are expected to test and evaluate different digital scenarios in order to measure and demonstrate how industry 4.0 is strictly linked with the Human Factor. We are going to point out the attention on the cognitive issue as a major factor for performance optimization. We would like to underline that even though Industry 4.0 is stressed the virtualization, modularity, decentralization, human is still maintaining a major role inside the system. Here, operation management initiative have still to be included.

1.1. The Human-Robot collaborative (cobots) interaction

In the industrial environment, four different kinds of cooperation can be identified [5]: Autarkic (AU), Cooperating (CO), CLosed (CL) and Synchronized (SY). AU and CL are the safest types for humans and robots' interaction, due to the presence of temporal and physical (like barriers or cages) separations. SYnchronized cooperation contemplates a temporal separation with no local barriers. The COoperating type is considered the most modern and advantageous solution. It states that the human operator and robot work without physical and temporal separation. In the CO system, operator and the robot (cobot) work side by side with sensors controls and continuous data exchange. Here, safety measures are placed in the form of redundancy in sensors on robots rather than reaction and avoiding. Cooperation is used as a solution in the INDUSTRY 4.0 framework, because it combines both the operator flexibility and robot productivity. It reduces the space required for plant operation. It acts on the robustness of process while boosting performances in jobs and task. The new working station/desk points on safe and dependable machines, operating in close vicinity to humans or directly interacting with them. In this environment "smart" operators work. They are capable to interact and act with complex robotics and logistics entities, over system requirements, job related product, used for manufacturing operations. Thus, traditional human reliability models need to be enlarged in order to integrate and analyze new data coming from the collaborative scenario. Operators' physical, cognitive and sensorial skills (causally ageing by time and acting on production's performances), operators' adaptability (this changes in complexity of task) to the new manufacturing context, effect of smart human competences (related to training and personal skills) and perceptive capabilities on system performances and safety have to be investigated in a pro-active approach.

The objective of this paper is to analyze contribution on the state of art for human cognitive modelling while reporting, using AB modelling, results of collaborative (experimental) scenarios for decisional outcomes. The proposal is organizing contributions to share knowledge on design, control, safety and ethical issues, concerning the introduction of robots into everyday life. It investigates: new worked capabilities required to conduct and collaborate with robots; new operators' capability in the fit for factory of future optimization. It reports about modelling and simulating of different cooperative scenarios based on factors, functional maps and expert judgments. It conclude about frame for previsoinal test.

2. The Cognitive state of art for Human Load

To evaluate how important the human factor is in the manufacturing plant dynamics, a model of a collaborative cell - in the experimental scenario - was created (physical schema in figure 1). The simulation model of the collaborative work cell consists of an operator working in close contact with two robots and the goal of the simulation is the evaluation of the influence of stressful conditions - over the mental, perceptual and psycho-social states - in system performances (simulation blocks in figure 3). Assignment rules are tested while deciding which operator [WHO] - modelled according to factors based on age and experience- have to be assigned to that particular task [WHAT] -related to complexity and timely variability. The assignment in-time changes [WHEN] based on rules. Entities in system are locally routed [WHERE] pointing on overall performances [HOW] optimization. Performances are evaluated using scenarios analysis. Those populate databases used for features extraction/correlation (figg. 5 and 6).

A cognitive load analysis for operator modelling, with causal loop interferences between states, is performed. A systematic literature review was made [6]. We extracted the mapping process from a database - constructed from research questions and keywords selection. The screening process was organized in three steps to make the selection more agile and accurate. The first step (step 1) aimed at including only the papers in which at least two of the selected keywords were matched in the title. The keywords used for the literature review were: "*cognitive load", "human factor"* and "*industry".* The resulted publications were filtered (step 2) based on a deeper understanding of the abstract and conclusion sections. Exclusion criteria were, then, again applied manually based on the content of analysis, significance in methodology and the coherence with the collaborative work-cell scenario. This was declined in Research Questions (RQ_i) aiming at: *(i)* how can a cognitive effect be MODELled ?; *(ii)* Are there any relevant attempt to DESIGN the human cognitive state inside industry? *(iii)* Is possible to experimentally MEASURE the cognitive load? *(iv)* Is cognitive a collective TEST? *(v)* How can cognitive load contribution on operations be ANALYZEd?.

Finally, (step 3) the screened papers were aggregated, categorized and mapped in order to identify clusters for operator modelling. The database was extracted from IEEE Xplore, ResearchGate, Science Direct, Google Scholar and Scopus.

The three main area of analysis - we identified - are:

i. Cognitive ergonomics
ii. Human factor (HF)
iii. Human-machine interaction

Cognitive ergonomics refers to the study, evaluation and design of the systems and tasks and their interaction with the cognitive ability of humans. In the review, cognitive ergonomics was related with the behavioural (**E** column of table 1) research in human engineering and cognitive systems and how accident prevention can be achieved. Human factor (HF) refers to the psychological and physiologic aspect of engineering and design (**H** column of table 1). Goal of HF is to increase productivity, to reduce the human error and to enhance safety and comfort in the interaction of human with the related job and tasks. In the review map, HF was linked with the workload of human groups in relation to age and sex, and personnel training. The human-machine block is discussed on the aspect of interaction between human and machine (be it robotics, artificial intelligence or virtual augmented reality) and how better problem-solving and accident-prevention procedures can be planned and deployed on workplace environments (**W** column of table 1). In table 1, the literature papers are categorized based on whether they are **W**orkstation_, **H**uman_, workplace **E**nvironment-related. Furthermore, we added an additional category (NODE column) showing which interaction as per modelled frame (numbers as per categories identification of figure 3) can be attributed to each paper of the review map. The column "node" reports about the causality loop interaction between blocks and categories in system [28]. For each proposal (ref. number as per bibliography), temporally classified from the earlier to the oldest in database, we critically identified main objective – in order to extract main factors and effects with its transferring function, as reported in FOCUS column. We tried to differentiate the scientific papers on human-centered or technology-centered approach for cognitive analysis in industrial context. We, furthermore, clustered field of application in: Industrial/Manufacturing Engineering [Eng], Psychology-Social Science [P-S], Computer Science [C-S].

Table 1. Linking the Interactions between the Agents of the simulation model as per fig. 3 with the literature review and their relation to Workstation (**W**), Human (**H**), or workplace Environment (**E**) concept.

Ref. #	AUTHORS	NODE	W	H	E	FOCUS
[7]	Pacaux-Lemoine et al.	4, 5, 6	x			**Design** assistance system for Artificial Self-Organizing systems (ASO) and human cooperation
[8]	Peruzzini et al.	3, 6		x		**Design** cyber-physical based system for aged human-centered adaptive manufacturing system
[9]	Naikar N.	2, 3, 6		x		**Test** cognitive work analysis (CWA) for human problem-solving in industry
[10]	Lim J. et al.	6			x	**Model** fatigue based on 71 participants with different time length rests to develop
[11]	Reader et al.	2, 6	x			**Design** an accident model in high-risk workplaces based on non-technical skills (NTS)
[12]	Zhou et al.	6, 7			x	**Design** the affective and cognitive effect of mass personalization of customer needs (CN)
[13]	Village et al.	2, 6	x			**Model** cognitive mapping (CM) tools in operation and management research
[14]	Avila S. F. et al.	3, 5, 4	x		x	**Test** Social Hazards operation assessment (SH) tool in level control at separation equipment
[15]	Stone R. T. et al.	3, 6		x		**Measure** cognitive and physical impact through virtual reality (VR) training vs. traditional training methods
[16]	Lodree Jr. E.J. et al.	6		x		**Design** task sequencing accounting on workers' risk and performance improvement
[17]	Carvalho et al.	3 ,6	x	x		**Measure** cognitive task analysis (CTA) approach for improving human/systems interfaces in risk control
[18]	Arezes et al.	6		x	x	**Test** Hearing Protection Devices (HPD) on 516 workers over noise levels
[19]	Erlicher et al.	6			x	**Analyze** the new patterns of cognitive cooperation in supply chain
[20]	Bagnara et al.	2, 3, 6		x		**Analyze** the human factor and cognitive ergonomics and their contribution in problem solving
[21]	Zhou et al.	6			x	**Design** a cognitive reliability and error analysis method (CREAM) with fuzzy logic
[22]	Loveday et al.	3, 6		x		**Measure** of four distinct cue-based tasks with 65 controllers of different expertise for in-service training
[23]	Lawler et al.	3, 6, 7	x		x	**Analyze** the impact of cognitive ergonomics within healthcare information technologies (HIT)
[24]	Zeng et al.	6	x			**Design** of creative design process on problem finding and formulating in ergonomic design
[25]	Langan-Fox et al.	4, 5, 6	x	x		**Model** the conceptual framework human-automation team adaptable control
[26]	Pezzulo et al	3, 6		x		**Test** PCP tools on mental models' analysis in hazmat logistics
[27]	Bertolini M.	3, 6, 7				**Test** fuzzy cognitive maps (FCM) for reliability factors that improve human reliability

Papers with conceptual and experimental application in manufacturing were under the Eng class; when applied machine learning solution for cognitive mapping, the proposal was included under S-C; finally, crowd based study were under the class of C-S. Multiple categorization are possible. Papers numbered 7-8-12-16-17-19-20-24-26-27 are recognized under Eng category. Papers 9-10-11-12-13-14-16-18-19-22-23-24-25 report P-S applications. Finally, papers 7-8-13-14-15-17-21-25-26-27 applied phyco-social analysis.

In the analyzed literature (as per table 1), the cognitive ergonomics is recognized as a safety issue which influences human error probability. It has relation with human and system performances. To understand how cognitive load (usually, across literature, measured by memory range) interacts with human reliability and comfort at work, the majority of state of art analysis introduce the Human Factory point. This acts in the design phase of process and task [29]. Human-machine interaction reports how to improve the current state and performance related to the cognitive capabilities of the human workforce. The betterment of human-machine systems and autonomous systems will provide a useful tool in problem-solving and accident prevention for industry. The state of art analysis concludes that cooperative behavior can be modelled as a network of agents that cooperate to perform job and tasks. Such agents (i.e., logistics and warehouses, machine, robots, products, equipment - in the form of software and artificial intelligence tools, humans) are interconnected by sensors and exchange "information data" to enhance human decisions. They move and work inside a modular manufacturing processes characterized by decentralized decision making (set on external parameters which influence internal factors) with real time capability. They can modify tasks based on a service oriented approach. They make use of virtualization to maintain control and decision (in terms of performances and safety and quality) in processes. Human decision starts from an equipment based actions and evolves over agents states. The cyber objects reflects the cyber physical conditions (sets) we can plan in order to optimize required performances.

3. The human in the loop cooperative agent based behavior

Despite the advancement of robotics and the enhanced role of *(i)* Internet of Things (IoT), *(ii)* cyber-physical systems (CPS), the human workforce fulfils a significant role in the Industry either as a workforce that collaborates with robots or in monitoring, strategy and planning. The human-machine coexistence can lead to an industry - extremely technological - focused on the achievement of high performance in terms of production volumes, quality, flexibility and time-reduction with lower costs (thanks to an integration between humans and machines).

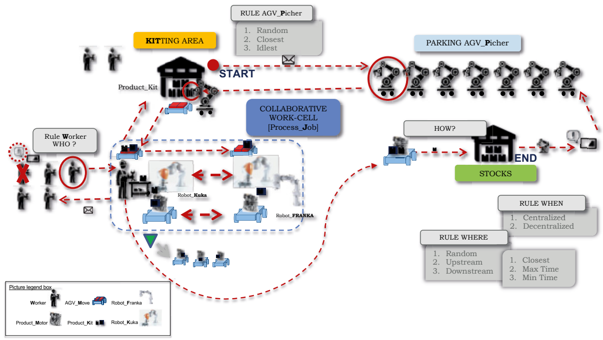

Fig. 1. The schematic PHYSICAL MODEL of collaborative system. Agents and paths are included as arrows. Decision rules are indicated in grey blocks. Main Job is reported in blue dotted box. Fixed and moving robots are under the class of Handlers and AGVs. Kit and Products are moved from internal and external warehouse. Picher is used for manipulation.

The cobots physical model, we analysed, is sketched in figure 1. Movements across entities are performed by logistic AGVs system moving, separately, assembly kits and products. The collaborative workcell represents the job entity under investigation. There, a worker collaborates with a lightweight robot for intelligent industrial work assistance (name Kuka). Operator acts on interfaces to start tasks. Kuka moves on rails and manipulate products. Process starts with an order requirements assigned across client demand forecasted on flow approach on daily schedule. Operator tests kit and performs assembly task whil using tools, kits and product's parts in collaboration - across HMI - with Kuka. The latter works in synchronized task with a gripped robot (named Franka). The simulation model of the collaborative work cell (figure 3) was designed using AB modelling approach. The process logic is designed according to timely transitions based on Discrete Event Simulation (DES). To model the causality loop across and between interactive states of humans, we used a System Dynamics approach (SD) [30]. Performances of systems are collecting, based on assignments, in statistics.
An agent of the class "main" decides assignment and manage performances.

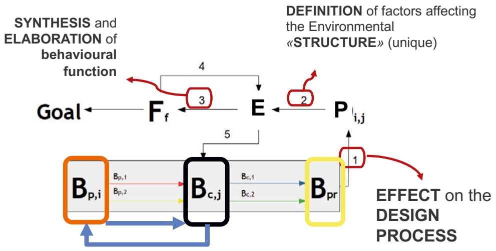

Fig. 2. The B=f(P,E) structure of design set. Basing on perception (B_p), we selected the behavior comprehension (B_c) for predicting (1) human state (B_p). This defines the design structure (2) of the environment for functional (3) measurement of design experiment. In the behavior set, cognitive and perceptual, psycho-social and motor system factors act (colored arrows) in causal loop inside the environmental structure (5). Rules settled on performances (F_f) can change the structure of design (4).

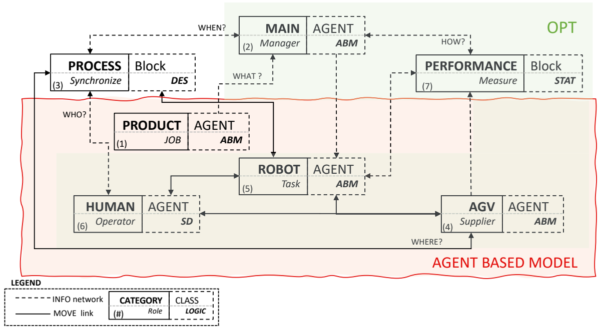

Fig. 3. The schematic SIMULATION MODEL of the Collaborative work-cell We identified physical and data flow in arrows. Main Agent Based transitions are reported. Main simulation logic is indicated. Each block is numbered in order to identified procedural relation between entities.

The simulated scenarios is designed in figure 4. It consists of six agents: Picker agent equipped on AGV (AGV_**P**icher); a logistic agent for moving paths (AGV_**M**ove); an operator agent (**W**orker); a fixed plate manipulator robot (Robot_**F**ranka); a manipulator robot with autonomous handling system (Robot_**K**uka); a process agent with main job paths (Process_**J**ob). Simulation model is completed with a Product_**K**it as resource and Product_**M**otor of the agent class as assembled output. Each agent is modelled across rules transition between states. The agent Product_**J**ob contains the main process logic. It works as manager of the simulated behaviour. It was modelled on Discrete Event (DE) approach. The agent of the class **W**orker moves across states using dynamic state transitions. A conceptual Causal Loop states' transition was build, reproducing the cause and effect links between physical and mental and psycho-social states. We adopted the System Dynamic modelling approach as per Sterman [30] created based on the scientific evidence as per consideration of table 1.

Human behaviour was set evolving as per the proposal of by Lewin [31]:

$$B = f(P, E) \tag{1}$$

where B is the behaviour, P represents the person and E is the environmental structure (fig. 2).

Perception is related with the way as worker assimilate the environment in which he is included (it is set on parameters level). Comprehension is related to the reaction of human inside the working space (defined according to dynamics variables). Prediction is related with the way as human is going to perform task (related with the simulated scenarios). These elements define the structure in which the collaboration system acts. Behavioural analysis is analysed and monitored across synthesis of cardinality f of performances manifestation (F_f). P term interferes inside behaviour (E) according with Performance blocks (F_f). P acts on the Environmental structure according to the design behaviour. Inside the behaviour, comprehension of state starts with a perception state (B_p). It needs comprehension (B_c) based on psycho-social and perceptual factors. The level of comprehension is translated to in the form of prediction (B_{pr}).

These define the structure of Environment that can timely report the behavioral structure. On fixed structure we performed performance analysis.

We identified four categories of factors affecting the person behaviour: Cognitive Factors, Perceptual Factors, Psychosocial Factors, Motor System Factors.

Cognitive Factors (CF) refer to all aspects of the worker's ability to learn about the task to be performed. **Perceptual Factors (PF)** refer to the way in which the operator interfaces with the robot. **Psycho-Social Factors (PhSF)** refer to the way in which the worker interacts with others and to his capacity to create empathy and harmony in job. **Motor system factors** refer to the way in which the task has to be executed. It contemplates layout arrangements and locations area. Those types and subtypes are used to compute the human effects which, along with the robot and process effects, define the performance of the production system. Simulating the human-robot cooperation

In our simulation model the behaviour is fixed according to Parameters, Factors and Dynamic Variables. **Parameters** are components those depend on the analysis context. They are fixed and can assume two or three values which correspond to the fuzzy membership as per literature [32]. Hence, it has been considered that they can be set by the analyst. **Factors** represent measurable functions that create linkage between parameters and **dynamic variables**. **Dynamic variables** represent, through the use of flows and levels, the effects of parameters and factors on the system, as it changes over time, which, in turn, will directly influence the Key Performance Indicators (F_f) chosen for investigating the production system.

The Parameters we used are: Cognitive Factors (Competence Level, Hard Skills and Age); Perceptual Factors (Interface Complexity, Stress and physical Fatigue); Psycho-social Factors (Motivation, Soft Skill in problem solving, Personal problem State); Motor system Factors (those report the collaborative grade, Task Complexity, Rhythm and rate of agents in system).

Dynamic Variables evolve across shaping factors based on model equations. The dynamic variables used were motivation, stress, fatigue and cycle time. The fatigue variable depends on the human factor, ergonomics, rest allowance, which is calculated considering engaged time, task requirement and rest rules.

By the literature the effect of factors is modelled according to Performance Shaping Factors (PSFs) affected by weights

$$PSF_{TOT} = w_1 * X_1{}^2 + w_2 * X_2{}^2 + \cdots + w_n * X_n{}^2$$

Where X_i is the parametric value (type and subtypes) and w_i is the relative weight we assigned based on expert opinion.

The values for the weights, have been chosen based on their importance regarding the factor and the influence on Physical Stress Factor [33]. Those values can be seen on table 2. The sum of weight for each level is 1. Once the Fuzzy Logic values were defined, parametric simulations were carried out considering all possible combinations (with ANOVA test).

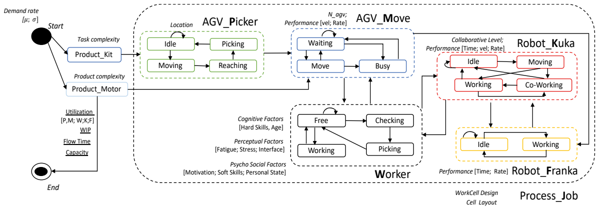

Fig. 4. The schematic DESING of EXPWRIMENT structure. We selected state inside agent and transitions based on rules. The Worker component is modelled using dynamics states evolving in causal loop. Inside the human component a stress contain on dynamic block is set. In italic form we set factors of OFAT experiments.

This to see which of the factors taken into considerations was most influential on the operator's fatigue. In the simulation model weights were distributed according to different levels. Those types and subtypes are used to compute the human effects which, along with the robot effects, define the performance of the production system. In our simulation model, these effects were represented as Parameters and Dynamic Variables.

The Parameters used are age, task type, personal problems, environment, interface complexity, hard skills, problem solving and recovery factor. Parameter can be extract from a cyber physical system created on the case test analysis. Parameters represent the behavioural set. We made use, in same cases, of Virtual reality interfaces and experimental tests to compute the relative weight. Cyber physical system evolves on Deming approach [34] and learn on rules based. Dynamic Variables depends on the Parameters through specific equations. The Dynamic Variables used were motivation, stress and Cycle Time (table 2). The weight of parameters is set as per III level in motivation, II level in Stress and I level in Time. These all act on main dynamic variable named real Task Time. The Dynamic Variables "Task Time" was then related to the Physical Stress Factor (properly Fatigue). The amount of physical stress the worker is storing up can be defined as L_T after time T.

$$L_T = \sum f_i t_i - a_i b_i \quad (2)$$

Where t_i is the length (of time) of task i, b_i is the break time following task i (in cycle j), *fi was set to 0,31 as* and a_i is the allowance rate defined in

$$a_i = \frac{L_{max}}{RA_i \times MET_i} \quad (3)$$

With RA_i (Rest Allowance) required for task i as fraction of MET_i (assumed as $3 \times MET^{-0,41479}$ – [35, 36]). t_i depends on the assignment, worker capacity and workload history. Time depends from the workload. It is un-directly connected with training and mental complexity. The longer the worker is performing task i (on k-time-repetitions), the lower the cycle time (as per Wright 1936).

The Recovery Factor, as per figure 5 and 6, of 0,8 is set in order to evaluate break when the 0,8 (level 1 as per fig 5 and 6) of Physical stress (properly fatigue modelled according to 2) is over-reached. In this case, a break is assigned to obtain recovery down to the 0,5 of maxim load limit.

The recovery rate of 1 (level 2 as per fig. 5 and 6) is set to contemplate full recovery over the 0,8 of physical load limit.

Table 2. Performance types and their subtypes used to compute the term P in the Kurt Lewin equation. Cognitive (CF) and Perceptual (PF) and Psycho-Social (PhSF) Factors are selected in OFAT tests

Dynamic Variable	Factor	Parameter	Range	Numerical Value	Qualitytative Value	I level	II level	III Level
Task Time	CF	Age	18-30	0,5	1			
			31-45	1	2			
			46-67	1,5	3	0,4		
	CF & PF & PhSF	Task Type	Non-Repetitive	0,5	1			
			Sometimes Repetitive	1	2			
			Repetitive	1,5	3	0,6	0,6	
	PhSF	Personal Problems	Not Relevant	0,5	1			
			Common and not too serious	1	2			
			Very Relevant	1,5	3		0,2	
	CF & PF & PhSF	Environment	Favourable conditions	0,5	1			
			Acceptable contitions	1	2			
			Unconfortable conditions	1,5	3		0,2	0,3
	PF	Interface complexity	Low [On/OFF control]	0,5	1			
			Medium [Haptic Screen]	1	2			
			High [VR/AR devices]	1,5	3			0,2
	CF	Hard Skills	Reaction	0,5	1			
			Action	1	2			
			Vision	1,5	3			0,3
	PhSF	Problem solving	Yes	0	0			
			No	1	1			0,2

For detailed system dynamic modelling the readers can be referred to Fruggiero et al., 2019 [36]. To simulate scenarios, we set a task standard time of 1 [min/unit]. This changes according to the dynamics of the system based on factors whose parameters report levels of scenarios weighted upon sensitiveness.

The model was run a One Factor at A Time (OFAT) sensitivity analysis. For each run we reported 5 tests over a 1-year simulation time. The mean, between simulations (apart warming period settled to reach steady state conditions in 2 weeks) and across hour capacity, rate [unit/hour] is reported for performance measurement (fig. 6). Percentage of mean utilisation across humans and task is used for agent availability. A 2 and 3 values sensitiveness is set in OFAT analysis. In the 2 values sensitiveness we set the upper and the lower categories of the membership class. In the 3 values scenarios, we included an intermediate - may be modal- amount (table 2).

We simulated 1548 scenarios. Table 2 shows factors by factors the level we simulated in the AB model. To check the interaction between different factors, we used Interactions Plot as per fig. 5 and 6. Interaction between factors in performance is evident when a response change in relation to the combination of factors.

3.1. Reporting about the interaction between human & robots

Parameters and PSFs act as internal "conditions" or variables on the transferring function for behavioral analysis. It is Task Time. In the collaborative work-cell scenario we recognized that the Worker utilization depends on the interaction - based on Interface complexity - with robot. Passing from on/off signal (botton) to virtual devices, we can report a rise of up to 10% in utilization, which is related with the risen up of work-cell capacity.

This is not worrying in low rate productivity systems but can report congestion in over assignments for dual resources constraints systems. The influence of Interface complexity changes over age level reporting - for older operators - the highest utilization in worker (may be based on slowdowns) and lowest capacity rate (less than 25% in comparison with best performance). If worker reports reaction capacity in skills, production rate is near standards.

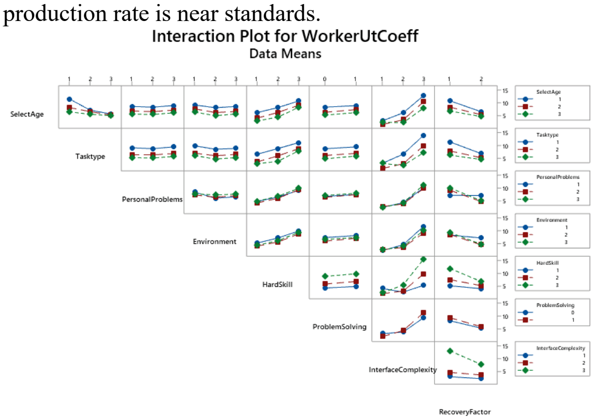

Fig. 5. Interaction plot analysis for WORKER utilization [%] in the collaborative workcell scenario over sensitivity OFAT test. Levels as per table 2

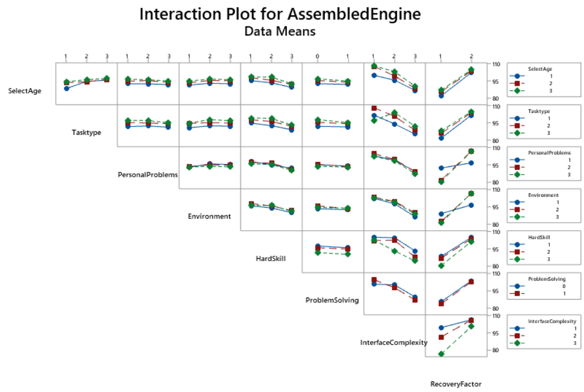

Fig. 6. Interaction plot analysis for assembly PRODUCT capacity [unit/hour] in the collaborative workcell scenario over sensitivity OFAT test. Levels as per table 2.

A correct recovery schema in fatigue can guarantee an optimal strategy for workforce management. Moreover, it can report improvement in capacity rate and neutralization of cognitive factors. A full recovery in physical stress (level 2 in fig. 5 and 6) - after 80% of load limit - reports, as intuitively manifested, a lower utilization rate. On the counterpart, we can significatively improve productivity avoiding continuous breaks. The influence of Interface complexity changes over age levels, the older the operator, the highest utilization (+10%) and the lowest is capacity rate (-15%). The more repetitive is task the higher is capacity and lower is worker utilization. Repetitiveness in task can act over capacity rate under different interfaces between operator and robot. The difference due to the age-gap can be reduced in the form of learning from more experienced operators. Favorable conditions in working environment can invert the action of recovery strategy over worker utilization and production capacity. Cognitive Factors (hard skills and Age) act over utilization of worker while reporting quite stable effect on capacity. Phyco-Social Factors (soft skills and personal state) slowly act on work utilization while manifesting correlation with recovery strategy in common to relevant personal psycho state. Fatigue, measured as a personal state, reveals an action on utilization, as well as on capacity rate (suggesting, on the whole, full recovery after fatigued task). The cooperation between human and robot over full factorial analysis (fig. 7) generally acts on productivity while suggesting to extensively use robots for major elements in tasks if capacity rate is going to be increased. Human operators can gain from cooperation (generally reducing stress), while raising utilization at the highest capacity. Higher worker utilization reports lower capacity of system.

4. Conclusions

Industry 4.0 concept is based in autonomous and self-organized machines and components, which is leading to more complex manufacturing scenarios. In this context, Human factor continued to get relevance in decision and performances. As a result, people should be integrated into the conceptual model of factory of future. Their skills and talents should be developed, and managed, to meet those complex systems. In this context the cognitive load concept should be investigated to determine the ability of human workforce to adapt to the increasing needs of automation. For this purpose, virtual augmented equipment should be used to monitor the physical and mental stress of the human workforce when interacting with automated machines and systems to determine the factors that contribute to (i) improvement of skills and working memory and (ii) to the stress and deterioration of mental health. The results of this research will provide information on how to improve conditions for the human workforce that will allow improvements on the cognitive ergonomics. In particular this paper reports about simulated scenarios in a collaborative workcell. The model is created based on agent modelling with discrete transition between blocks. Agents are modelled according to states and transitions between state is based on rules. The worker component inside the model is implemented with a dynamic perspective while causally modelling factors and dynamics variable. Dynamics variable like Fatigue and stress acts on task time. This reports, under fixed requirements, increasement in utilization for agents and improvements in system capacity performances. The proposal suggests that collaborative cell can all gain in small breakdown. Those act on worker utilization while increasing capacity.

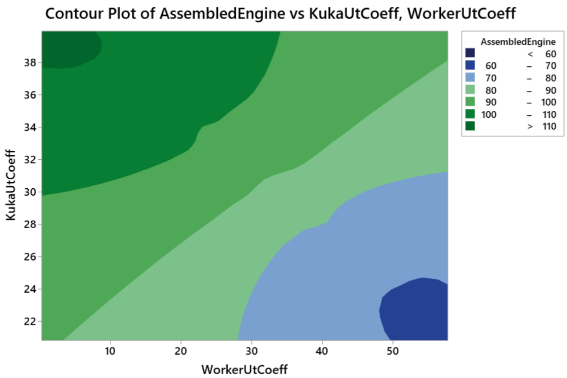

Fig. 7. Contour plot analysis reporting about inference between collaborative agents (Worker and Robot_Kuka) over the full factorial analysis.

The sensing cooperation can be supported by training in order to recovery mental and manual qualms over ages. The simpler the interface, the faster is response. This acts over system capacity. The cooperation between human and robot can gain in reducing the workers load while increasing capacity. In this case it is required a correct assignment of humans to task and It is possible to point on training to recovery gaps and mental hesitancy.

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