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Mutualistic and Adaptive Human-Machine Collaboration Based on Machine Learning in an Injection Moulding Manufacturing Line

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Abstract

This paper proposes an adaptive human-machine collaboration paradigm based on machine learning. Human-machine collaboration requires more than letting humans and machines interact according to fixed rules. A decision-maker is needed to assess production status and to activate adaptations that improve productivity and workers' well-being.
The proposed solution has been tested in an injection moulding manufacturing line. By introducing a physiological monitoring system and a smart decision-maker, relief from fatigue and mental stress is pursued by adjusting the level of support offered through a cobot. Results reported a reduction of operators' physical and mental workload as well as productivity increase.

Keywords: human-machine collaboration; adaptive automation; machine learning.

1. Introduction

The introduction of collaborative robots, also called cobots, in the shop floor is a challenge that more and more industries have been taking up in recent years [1]. Under this approach, human operators are supported by an intelligent agent, the cobot, that shares spaces and tasks with the operators while complementing their capabilities and adapting to their current conditions. The main reason behind this choice lies in the synergic effect of cobot's precision and repeatability combined with operator's flexibility and ability to manage unpredictable situations [2]. In such a way, human abilities are enhanced and complemented by those of the robot, and vice versa [3]. However, in many industrial settings, the use of cobots is relegated to specific repetitive tasks, instead of dealing with more challenging human-machine collaboration (HMC) scenarios, mainly due to the difficulties in modelling, interconnecting and managing the cooperation between humans and cobots active on same workstations [4]. As a result, in actual approaches, the cobot is not endowed with a flexible behaviour and thus the worker is forced to adapt to the introduction of the cobot and cope with its pace. Although the cobot is able to recognize where the operator is working and modify its trajectory accordingly, it is left to the human to ultimately manage the process and adapt her/his job to the tasks the cobot, according to the area that the cobot is occupying and the pace it is dictating in performing the task.

In order to overcome these limitations, in this paper a conceptual framework and implementation to enhance HMC in industrial environments through a cobot-enabled smart workstation is proposed. This is achieved by introducing a smart decision-maker, that is fed with information about worker's physical and mental workload and about process

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status, and that is capable to orchestrate the production line pursuing productivity and well-being targets at the same time.

In the designed framework this human-aware orchestration concretises into reconfigurations of the production line, either by acting on single parameters of the process control, or by dynamically reallocating tasks to the cobot or to the human. In such a way, cobot's flexibility is leveraged to fit the varying conditions of its human counterpart, making the two actors – human and cobot - work together fruitfully and supporting each other to a maximum level of performance and comfort.

In literature, several frameworks and models for Human-aware HMC have been proposed [5] [6] [7] [8] [9]. The works in [5] [6] consider assembly applications and propose dynamic task allocation between the robot and the human worker based on information coming from cameras and other similar devices. In [7] and [8], two different automation frameworks to improve workers' well-being have been introduced by exploring adaptive control systems that integrate human activities and machines operations in real time control loops. Finally, the research carried out in [9] presents a model to realize cooperative systems between humans and Artificial Self-Organizing agents. However, none of these researches lead to systems that are fully compliant with the criteria to realize human-centred automation solutions as suggested by Sheridan and Parasuraman [10], according to the points mapped in the list below:

- Assign to the human tasks best suited to the human, and to the automation tasks best suited to it.
- Maintain the human operator in the decision-and-control loop.
- Maintain the human operator as the final authority over the automation (missing in [5] [7] [8]).
- Make the human operator's job easier, more enjoyable, or more satisfying through friendly automation (missing in [9]).
- Empower or enhance the human operator through automation (missing in [9]).
- Support trust by the human.
- Make automation intelligible by operators providing advice and insights about its behaviour and about everything they should want to know.
- Automation has to reduce human error and minimize response variability.
- Make the operator a supervisor of subordinate automatic control systems (missing in [5] [7] [8]).
- Achieve the best combination of human and automatic control.

The envisioned human-aware approach to HMC presented in this paper exploits information about current worker's workload detected via machine learning applications out of data coming from commercial non-invasive wearable devices. Such devices allow to monitor different physiological parameters, such as heart rate (HR), electrodermal activity (EDA) and skin temperature (ST). The outcome of this monitoring and detection process is provided to a smart supervisory system with information about the process, such as production schedule, machine parameters and queues, that is in charge of reconfiguring the controlled workstation.

In order to validate the proposed framework, on-field tests were carried out within the production environment of a company manufacturing plastic products with different kinds of processes, such as injection moulding, bi-material moulding, etc. Moreover, a set of key performance indicators (KPIs) is proposed with the aim to evaluate the significance and impact in industrial applications and the effectiveness of the envisioned adaptive HMC approach.

The paper is organized as follows. In Sec. 2 the adopted framework and its core concepts are presented. Then, in Sec. 3 a focus is made on the developed hardware and software infrastructure and on how the physiological parameters can be gathered and elaborated to provide a flexible HMC environment. The system architecture and use case is presented in Sec. 4, while Sec. 5 discusses the achieved results. Finally, what has been achieved is briefly summarised in Sec. 6, together with an analysis of the future steps.

2. The proposed Mutualistic and Adaptive Human-Machine Collaboration

Traditional decision-making systems, such as those supporting labour scheduling and production planning, are not enough to support companies in the creation of the best conditions for the worker, to maximise performance, exploiting his/her full potential and guaranteeing workers well-being. This can happen only by assigning the right person in the right place, in the right moment, and creating the right workplace (environment and job) [11]. Moreover, it is necessary to integrate this approach in complex system.

Moreover, new technologies, such as wearable devices, cyber-physical systems, virtual and augmented reality and digitalization can support the achievement of this goal, significantly increasing the benefits for both organizations and workers. The integration of these technologies need to tackle and be fused with the automation and control elements that nowadays characterise any complex production system [12].

A disruption is needed that promotes worker-centric HMC by reversing the way design of complex production systems is carried out. The adoption of responsible approaches based on anthropocentric design methodologies [13] that reintroduce the users in the decision and feedback loops needs to achieve the goals mentioned by Sheridan and Parasuraman in today's data-driven industrial environments. To this end, new criteria have to be added to enforce Mutualistic and Adaptive HMC:

- Rely on flexible and reconfigurable production systems that allow to modulate the interaction between human and machines;
- Monitor the status of the human-machine system by continuously collecting human, context and process data;
- Fuse seamlessly human decisions with those taken by the smart decision-makers which adapt in a mutualistic way to the varying endogenous and exogenous factors;
- Make decisional processes and the underlying technologies explainable to humans;
- Set goals aiming at improved worker's well-being and process performance and share them between humans and all the agents operating in smart production systems;

- Assess periodically the effectiveness of the adopted solutions to identify and solve any misalignment or side effect towards incremental improvement of the mutualistic approach.

Fig. 1 introduces the architectural model that realizes Mutualistic and Adaptive HMC in a production system. Coupled with the process represented in Fig. 2, designed in BPMN, this embodies the conceptual framework proposed in this research. that realizes Mutualistic and Adaptive HMC in a production system. This relies on flexible workstations whose behaviour adapts in a mutualistic way to cope with workers' physical and mental conditions while aiming at optimal performance. Moreover, information about the system is collected and conveyed to the decision-making system to allow effective orchestration of the workstation in alignment with the defined objectives. On the one hand, **static data** from Factory IT systems, such as the operators' profiles (focusing on experience, knowledge, training, health status, competence and education) are gathered and periodically reassessed to form a knowledge base allowing personalised interventions. On the other hand, thanks to the presence of sensors, wearable devices and vision systems, **dynamic data** can be also retrieved and brokered in real time. First come **human data**, including operator's physical and mental workload, which strongly depends on assigned tasks and situational constraints (such as psychological pressure and presence of external pace determinants), creating a "worker digital shadow". If these data are coupled and harmonized with **process data** (e.g. buffer levels, machines productivity, etc.) and **context data** (e.g. ambient temperature, production planning data, etc.), a complete and human-aware digital representation of the **production system** is achieved.

Short term reconfigurations at the level of the single workstation, and to the production system at large, have to be orchestrated so as to exploit the flexibility of the **reconfigurable workstations** to support operators whenever their well-being and resulting behaviour deviates from optimal and safe ones. This is supported by a **smart human-aware**

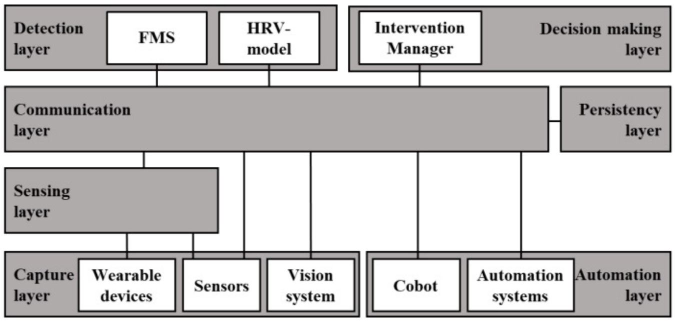

Fig. 1 Architectural model

decision maker that detects system features and status from the **production system digital representation** and reacts in order to optimize business and process performances along with workers' well-being. Short-term reconfigurations can be launched at different levels (single component, single workstation, whole production system). The operator is involved in the decision-making process, having the possibility to ask for reconfigurations, or to veto a decision thus avoiding out-of-the-loop situations. Such a solution changes in real time the behaviour of the human-machine couple based on evaluations by the smart decision maker.

In this way, automation system's capabilities become an extension of those held by the worker and are modulated in order to cope with the worker's specific characteristics, such as skills, physical and intellectual capacities, and with the conditions that she/he is currently experiencing including mental stress, loss of attention and fatigue.

If short-term reconfigurations are not enough to achieve desired performance levels, **long-term reconfigurations** have to be identified and planned to promote convergence of workstation design and related demand with workforce peculiar characteristics, processes requirements and business needs. Long-term reconfigurations focus on solving problems that, due to their systemic nature (i.e. they are intrinsic to the design of the job carried out at the workstation), are not associated to an immediate solution, but need instead further analyses, normally performed by an external "expert".

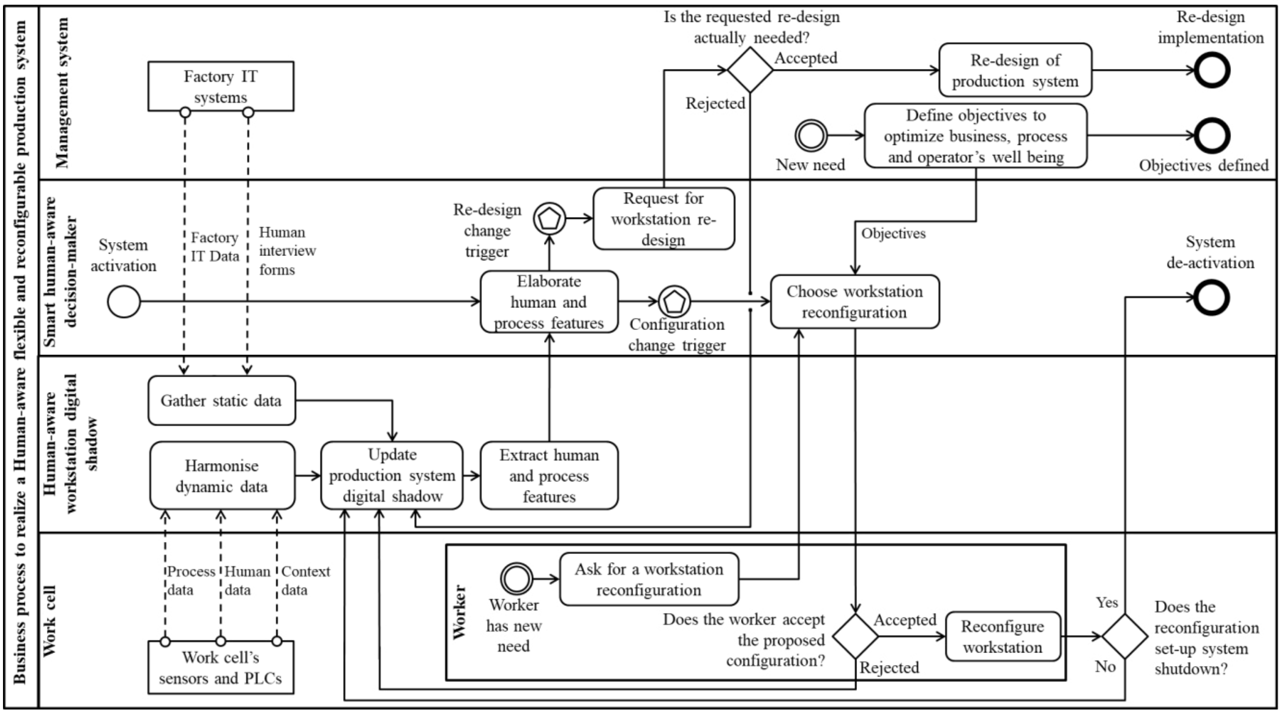

Fig. 2 BPMN process to realize a Human-aware flexible and reconfigurable production system.

3. A hardware-software solution to realize a Mutualistic and Adaptive Human-Machine Collaboration

In order to achieve the described human-aware flexible and reconfigurable production system, the modular architecture, represented in Fig. 2, has been developed and applied in an industrial application through a complete hardware-software solution composed by the following components divided in conceptual layers:

- **Automation layer**: a system composed by a cobot (UR5) equipped with a programmable LED ring and visual information device, an automatic tool for quality control and a semi-automatic tool for performing complex assembly operations.
- **Capture layer**: a wearable sensory apparatus composed of a set of wearable devices which collects worker physiological parameters and a vision system which monitors buffer levels and production priorities to implement a First-In, First-Out (FIFO) policy;
- **Sensing layer**: which gathers, pre-processes, stores and aggregates data extracted from the wearable devices and the environment, making them available to the monitoring and decision-making components;
- **Communication layer**: a middleware based on an event broker which offers interoperability and implements a mechanism of asynchronous communication among all software components;
- **Persistency layer**: a data persistency module which formalizes, stores and exposes, through APIs, the persistent information of the application domain and manages authentication;
- **Detection layer**: a worker monitoring system which detects in quasi real time any deviation of worker psychophysiological stress level from safe patterns relying on machine learning algorithms;
- **Decision-making layer**: an Intervention Manager (IM) capable to assess the stress conditions of the worker and suggest best system configurations by evaluating: (i) currently active worker in the workstation and his/her related data; (ii) previously activated system configurations and currently on going one; (iii) worker's physical stress level (FMS output) and mental stress (HRV-model output); (iv) status of the process and cobot operative status; (v) all the possible configurations of the system and their triggering conditions.

3.1. Worker Monitoring through Machine Learning

Monitoring of worker's condition is a key element in the proposed system and is achieved by merging worker's physiological parameters with static information (such as age, weight, etc.) by applying machine learning techniques to elaborate in real time his/her mental and physical condition. In particular, the adopted system relies on those parameters that can be measured with commercial unobtrusive wearable devices suitable to be used in an industrial environment, such as armbands, chest straps and smartwatches, since they do not limit the freedom of motion of the worker and their validity has been widely studied in literature [14] [15] [16].

To calculate worker mental and physical conditions, two models have been developed: the HRV-model for the detection of mental workload and, the Fatigue Monitoring System (FMS), which adopts Machine Learning for the detection of fatigue level.

HRV estimates worker's mental fatigue as a function of cardiac activity. It relies on the analysis of HR, measuring heart beats per minute (bpm), and RR series, calculating time intervals between consecutive heart beats. HRV-model computes HR and RR every 5 minutes and compares the most recent values with those measured in the previous time windows. The model was preliminarily validated in [17]. From this comparison, it defines if the worker is stressed (mental stress level=1) or not (mental stress level=0).

FMS detects physical (e.g. tiredness) discomfort or harmful situations for a worker. Different researches deal with cognitive load and mental stress of human during a specific activity [18] [19] [20]. However, very few treat exertion, fatigue or physical workload, mainly investigating human workload adaptation in rehabilitation robotics [21] [22].

In the adopted solution, a modified version of the Borg RPE scale [23], the Borg CR-10 Scale has been used to assess and predict workers' fatigue level. The AI algorithm chosen to classify the fatigue level of the workers is a Random Forest Classifier. FMS's AI-model has been trained elaborating data collected for 8 hours from 4 workers and tested using different feature sets, different scales of output classes and computation windows. The adopted feature sets, with reference to the proposed conceptual framework, include dynamic data, such as HR, HRV, GSR, etc., and static data, defined between the most relevant parameters included in the OREBRO musculoskeletal pain questionnaire [24]. The best performances were obtained with the combination of 75 trees and 29 features, obtaining a Mean Absolute Error (MAE) of 0.70 (on a 0-10 scale) and an accuracy of 68%. A benchmark comes from [25] in which a system to estimate physical and mental effort in HMC reaches a MAE of 12.7 (but on a 0-100 scale).

4. Validation use case

The proposed framework was tested at a manufacturing company on a workstation that is part of a plastic-injection assembly line. A video of the validation use case is available at [26].

The workstation is located in proximity of a moulding press, which produces the raw piece to be worked by the human. Once a moulded piece is ejected by the moulding press, manual tasks need to be carried out to obtain the finished piece. The entire process is dictated by the cycle time of the moulding press (approximately 55 seconds). As a result, workers are forced to operate under an external, and very fast, pace determinant with consequent effects on the cognitive workload and on the quality of the output. Another aspect that increases the complexity of the assembly line is that different operations on moulded components need to be carried out within specific time windows following the ejection times from the press, otherwise the piece could break due to hardening of cooling plastic. To address this problem, workers are instructed to follow a FIFO approach so to operate on a fixed delay from the moulding time and thus interact with each component at the correct temperature. However, being a repetitive task, workers often suffer from lack of attention and do not respect the correct FIFO order, leading to low quality levels. Therefore, with the aim of improving worker's job satisfaction and production quality, the assembly line has been revamped introducing the presented cobot-enabled system in the workstation that collaborates in a mutualistic way with the worker along the entire process.

The overall assembly process is divided in 13 tasks and 4 buffers and has been modelled using Business Process Model and Notation (BPMN). Tasks have been labelled as either commutable or non- commutable. A commutable task can be carried out by both human and robot while a non- commutable one belongs only to one of the two. Thanks to the possibility to dynamically allocate some tasks to both human and cobot, 10 system configurations have been designed. A configuration is defined as the sequence of tasks together with the agent (cobot or human) they are assigned to. The set of all the configurations represents all the possible combinations of task allocations between the human operator and the cobot. Each configuration has a specific purpose. Some configurations are dedicated to ramp-up the workstation, others are intended to be used at operating speed and others for specific purposes such as worker's pauses, and workstation shutdown.

The workstation configuration is dynamically changed through a policy based on information about the status of the human, the cobot and the process. While the workstation is operating, the most appropriate configuration is periodically selected by the IM that analyses the data coming from the workstation, namely measurements of worker's parameters, activity and status of the cobot and process workflow. The IM relies on the digital shadow of the worker and of the workstation and defines the behaviour of the cobot and of the other complementing elements of the automation (e.g. hydraulic actuators, communication lights, etc.). The IM is set up so as to suggest a new configuration not less frequently than each 5 minutes.

The operator is then notified when a new configuration is selected and is requested to approve (or reject) the change. To this end, it is important to communicate new configurations to the worker in an easy and effective way to avoid discomfort and job interruptions. In the presented demonstrator, the use of a smartwatch with haptic feedback, provided by means of vibration and visual notification, has been tested. The user can approve or reject the proposed change of configuration through the touch screen of the smartwatch. Moreover, light interfaces attached to the end effector of the cobot are used to reinforce notification of changes in the behaviour of the cobot. Other solutions such as the use of tablets or monitors has been considered but discarded as they would require the operator to interrupt her/his task every time a notification is received.

Worker's fatigue is monitored by 3 different wearable devices: the chest strap Polar H10 to measure HR, the wristband Empatica E4, which records HR, EDA, skin temperature and wrist acceleration, and the Huawei Watch 2 with the primary function of gateway to collect data via Bluetooth from Empatica E4 and Polar H10, forwarding them to the digital shadow. Huawei Watch 2 was also used to interact with the operator through a push-notification system activating haptic feedback and visual notifications. To enrich the worker digital shadow, two models, the HRV-model and the FMS, have been used to detect and measure physical and mental stress from physiological data. Finally, in order to contextualise the acquired human data, the process is monitored by using a vision system, mainly used to track buffer status, and sensorized tools, such as the quality check device and the bore drill, which are directly connected to the IM.

The proposed system has been validated in 2 sessions involving 4 workers (1 female, 3 males). In the first session, workers operated without the cobot and the IM. In the second session, the same workers, after being instructed, worked in collaboration with the cobot, under the IM's orchestration, realizing the Mutualistic and Adaptive HMC. In both sessions, workers wore wearable devices recording physiological data, allowing to compare mental and physical stress levels detected in the two different setups. Moreover, at the end of each session, a questionnaire, adapted from NASA Task Load Index [27] has been used to investigate on subject's perception of mental effort and physical effort related to the job and the workstation.

5. Results and discussion

The overall results showed a general reduction of the mental and physical workload in both subjective and objective indicators. The mutualistic and adaptive system overcomes the main issues that afflicted the workstation: need to rush to coordinate FIFO sequences and cooling of pieces; boredom and exhaustion due to repetitive and monotonous tasks.

Table 1 summarizes the achieved outcomes. In particular, the introduction of the cobot was seen as an improvement by the company, thanks to the increased safety and better management of the process, resulting also in an overall increase of the job engagement. Intrinsic job variability is achieved through the ten different configurations. Positive feedback was collected from the workers as well, who reported a decrease in the monotony of the job itself. Regarding the risk of accidents, a possible reduction has to be assessed on the long-term period. However, the adopted solution helps reducing near-miss and injuries since it achieves a reduction in mental and physical demand. The goals in terms of process productivity, measured in terms of number of assembled pieces in each shift (+16%), operating costs (-11.6%), quality checks (100%) and quality issues (-95%), have been fully satisfied.

Table 1 Validation results

KPI	Values
Risk of accidents	No near-miss, neither accident registered during experiments (to be further evaluated in the long-term)
Job engagement	Increased, evaluated by workers as 5 on a 6/grade scale
Physical stress	Subjective = -12%; Quantitative = -1.45%
Variability of job	Configuration shift on average every 5.45 minutes
Mental stress	Subjective = -16.7%; Quantitative = -6.9%
Quality checks	100% of pieces checked by design
Quality issues	-95% (From 4.1% to 0.2%)
Productivity	+16%
Operating costs	-11.6%

6. Concluding remarks

In this paper we proposed a novel framework for human-aware flexible and reconfigurable production systems. The proposed approach continuously monitors worker's physiological parameters, measured by wearable devices, and couples them with context information about the process, to dynamically assign tasks to either humans or cobots. The goal is to support the operator in case of high cognitive or physical demands, hence increasing well-being and safety within collaborative human-robot scenarios. Real time interventions are provided in terms of process reconfiguration based on worker's mental and physical fatigue and on the process status. Ultimately, the cobot is intended as a flexible agent that supports operators particularly when their behaviour deviates from an optimal and safe performance. The system was tested in a real size industrial plastic injection assembly line. Effectiveness was measured in terms of objective and subjective assessment of workers' satisfaction and of KPIs related to the company productivity. A reduction in the mental and physical workload was measured comparing the proposed collaborative approach to the manual workstation currently in use in the company. Additionally, KPIs indicated significant improvements in terms of productivity, operating costs and production scraps encouraging the adoption of this framework in the company. Given the flexibility and scalability of the proposed architecture, future research will consist in a more robust validation considering additional use cases. Moreover, it will be challenging to extend the framework in a multi-cobot multi-operator manufacturing process in order to have cobots that can serve more than one work cell and to extend the collaboration and the intrinsic job rotation between operators of an entire production line. Further effort in the research needs to be aimed at modularising the sensing, detection and decision tools so that ready-to-use packages can be put together for SMEs, the companies most needing, yet less exposed to this kind of innovative solutions.

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