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Procedia CIRP 104 (2021) 1783–1786

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Affective Production Systems: Foundations, Reference Model and Roadmap for Implementation and Validation

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Abstract

Affective Production Systems approaches the future socio-technical systems inspired by the new technology, Affective Computing. The Affective Production concept and the Reference Model innovates through two continuously integrated Core and Factory Affective Loops, which enable the human-driven system self-configuration based on required embodied intelligence at two levels: the first loop at workplace (human-machine) level and the second at all factory scales, from micro to production network. The paper presents the Affective Production foundations, a motivation scenario, envisioned demonstrator and the Roadmap for the development and validation of the innovative concept, bringing forward the production systems state-of-the-art.

Keywords: Socio-technical systems; Affective Computing; Intelligence Embodiment.

1. Motivation for next-generation human-centered production

The next generation of socio-technical systems is seen as a kind of "focal point" for the convergence of several current trends in computer science, information systems and information technology. These trends include the technology-driven instrumentation of infrastructure through ubiquitous computing and/or the "intelligence" embodied in machines and devices with the prefix "smart/cognitive". They also include advances in Artificial Intelligence, which are sparking growing interest in e.g. driverless cars, self-configuring production, deep learning and data analysis, i.e. intelligence interacting directly with the physical world. A third trend is the progress in deep learning and rule-based multi-agent systems and self-organizing systems.

Consequently, the next generation of socio-technical systems will be underpinned by the most advanced and potentially "most intelligent/cognitive" technology invented to this date; but the "socio" part - which includes human behavior, non-deterministic decision making and interactions, complex social structures such as production companies, culture, morals, ethics and, above all, values - will remain essentially unchanged, except to the extent that they are irrevocably altered by technology itself.

The result is that the next generation of socio-technical systems holds both opportunities for participatory self-organization and corresponding risks of disenfranchisement, exclusivity, and disempowerment. There is a danger of becoming "slaves of the algorithm", so that no opportunity for "social innovation" remains in the holistic optimization of production processes on all production scales.

With the further development of "affective computing" [1], which involves a synergy of the three core sciences of computing, cognition and psychology, there is an opportunity to equip the socio-technical systems of the future with the strategic role of the human being, who will drive the embodiment of the necessary intelligence as the core for self-organizing and optimizing systems in machines, plants and all devices and systems that control mission-critical and supporting activities in production. Only through the synergy of human competence, which is the key to future industrial

10.1016/j.procir.2021.11.300

work, with technical intelligence, can the competitiveness of socio-technical production in the future be ensured.

2. Foundation technologies State-of-the-Art

Affective Computing, first published by MIT Professor Rosalind Picard in 1997, deals with the creation of machines capable of recognizing and expressing emotions. This is done by capturing different verbal and non-verbal signals, which are then merged and combined. In today's landscape of approaches to affective computing, five different categories can be distinguished with which emotions can be modeled: dimensional, anatomical, rational, communicative, and evaluative models. All models use different frameworks and approaches to implement an application with affective computing [2]. Today, affective computing is used in various application areas, such as e-learning [3], CAD activities [4], or decision making [5].

The development of intelligent, socio-technical systems goes hand in hand with the permanent, ubiquitous and automatic data acquisition of individuals. Therefore, it is relevant to consider the ethical, legal and social implications (ELSI) when developing such systems. Requirements regarding data sovereignty, information transparency, informational self-determination and user sovereignty must be considered [6, 7]. Some issues are already covered by the Basic Data Protection Regulation (DSGVO) [8], and there are also recommendations for the ethical design of intelligent systems such as those of the EU High Level Expert Group [9].

Artificial Intelligence (AI) has become an indispensable part of our everyday life, even without noticing it ourselves. For apps, online shopping and especially social media, data storage and learning of AI algorithms on this data is a large part of the value creation. For industrial companies this is currently still somewhat different. A large part of the potential is not yet being exploited. Currently, 16% of global companies have implemented more than one AI application (15% in Germany). However, before AI can be introduced into companies and processes, it is necessary to involve and educate people, and especially workers. [10]. Regarding the interaction of man and machine by and with AI methods, digital assistance systems are specifically used in production. It is recommended to use these systems where the human sensory-motor and cognitive abilities are far superior to those of machines, but where human capabilities are limited due to fatigue or the ability to absorb and process information at high speed [11].

AI is playing a crucial role in today's central developments in **production**. At the center of AI use is the so-called smart factory. In Germany, the term Industry 4.0 is also used for this. The central component is a networked informatization of manufacturing technologies. Developments in the context of the smart factory include the removal of boundaries in product design, in production processes and within the supply chain or the tracking of production facilities, processes, resources and products. Industry 4.0 therefore stands not only for process optimization, but for the development of new products/services as well as innovative business models.

Such networked and intelligent factories enable highly individualized production. Due to intelligent networking of the manufacturing plants with a high degree of autonomy of the plants, production processes can be designed more individually and thus more flexibly. This makes it technically and economically feasible to produce small batches and to produce individual items. In this context, we speak of mass customization, i.e. mass production of individual items, which was unthinkable in the past. The intelligence of the production system offers the possibility of creating customized solutions with the advantages of process-optimized mass production. The customer can put together the product he wants from a modular system. Based on the customer's requirements, the production processes are independently improved so that the time and cost targets are reached [12].

Assistant systems support workers by providing the right information in the right place at the right time. Suitable technologies in this context are algorithms, for example, to identify the prevailing stress level of a worker. With the help of Natural Language Processing (NLP), the input and output of the human-machine interface can be sustained. Furthermore, assistance systems can use certain algorithms to determine, for example, the qualification level of a worker, for the adaptation of content. Accordingly, an untrained worker would first receive instructions via a video.

The stringent need for assistant systems in manufacturing factories evolved in industrial applications developed inside industry, e.g. TRUMPF GmbH + Co. KG implemented an assistant that supports the worker when sorting cut-out sheet metal parts from large sheets. The assistant system uses a camera to determine the last component removed, checks the order data and compares it with that. Based on this, the worker is shown the suitable storage location.

In the area of **process optimization**, AI makes it possible to include not only current process data but also historical data into the control processes, which in some cases can enable better process cases, better process results can be achieved. Historical data can be either information from previous machine runs or upstream processes. Another use of AI technologies in the area of process optimization is the analysis of large data sets from complex systems, such as interlinked production lines. Here, for example, causes for bottlenecks in production can be determined.

The industrial developments in the field of AI evolved exponentially. A technology that uses already existing data from systems in order to automatically create process models can be used to compare the current state with the target state. If problems occur in the process, the system also supports the search for causes by identifying deviations [13].

3. Research Gap towards Affective Production

Our research on affective socio-technical production systems for affective interaction differs from the goals of Affective Computing. As previously described, AI like affective computing, is a technology already used in many areas of life. However, many AI applications in industry are still only found in relation to machines or processes, as the focus on humans is still missing. Affective computing is also already used in some areas, such as e-learning or CAD design, but it is not yet used on the shop floor. The combination of AI, humans, and affective computing, in production, is therefore new and requires further research [14,15].

To maintain and enhance human resources in the socio-technical work system, sophisticated thinking activities are inevitable. This requires a human-centered design approach of work, which is a core concern of our research. This approach is not primarily concerned with the sensory recording of a process-related work progress (i.e. actual-target comparison), from which concrete action requirements for the human being are derived. Rather, primarily affective modes of action and states of the person are to be recorded in order to derive an individual, situational and possibly time-dependent performance profile (e.g. stress limits, recovery requirements). This information can be included in the parameterization of the (flexible) work process or can be presented to the person in the sense of a feedback that promotes learning.

The results of affective computing are a source of inspiration for our research. Many of the techniques for capturing human emotions and responding to or resembling human emotions found in affective computing are also used in our human-centered approach to socio-technical production system and affective interaction.

Therefore, the research group considers the holistic state of the socio-technical system to be achieved as a perfect synchronization (harmony) and human-driven optimal state of the machine (at all scales of a production environment from process, machine, shop floor to enterprise network) with the optimal state of the human.

4. Approach and Reference Model

Affective Production approach and Reference Model (Fig. 1) bring in a symbiosis three pillars: a) **multiscale factory planning and adaptive automation** at all dimensions of production (process, workplace, production system, area, line, site of production, network) driven by the b) "**affective state**" and **models** of **human-machine joint interaction** through c) a seamless **intelligence modelling and embodiment system** that aims not only at having a relevant impact on **planning** and **operational** factory hierarchy levels but also at increasing the workers' involvement and interaction in a total synergy with the machine and equipment.

The Affective Production Reference Model pillars are characterized by the following modules:

1) **Multiscale factory planning and adaptive automation**:

- Process plans at all factory levels
- Plan execution and monitoring
- Continuously plan adaptation based on real-time and context-aware **holistic model of the socio-technical system**

2) **Affective socio-technical production system and affective shopfloor:**

- Affective Worker models, based on Psycho-Physio and anthropomorphic (voice, posture, pulse, heart rate variability etc. recognition) captured real-time data
- Affective Machine models, based on process and holistic machine parameters captured real-time data (pressure, temperature, velocity in 3axis, etc.)
- Socio-technical context models
- Cognitive Assistant Systems front-end

3) **AI-Embodiment Platform: Cognitive Sensor-Edge Computing (Neuromorphic) Infrastructure (from micro to cloud scales):**

- AI Applications (Voice, Posture, Pattern, etc.) Back-end
- Neuromorphic hardware
- Cognitive Sensor Systems
- Holistic Factory information systems

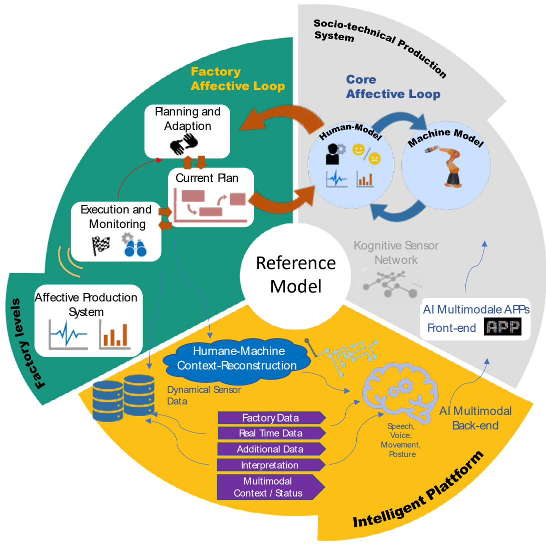

Fig. 1. Reference Model for Affective Production

5. Concept for Affective Production Loops

The Affective Production is implemented in so-called Affective Loops, acting on holistic factory and workplace levels. The first loop aims at dynamic plan adaptation in multi-scale factory and affective socio-technical systems, hereafter named **Factory Affective Loop**, which connects all pillars in a symbiosis, consisting of three steps/phases:

1) **Affective Recognition**, i.e. the recognition of a person's affect based on various body signals, e.g. speech, facial expressions, physiological signals, etc. (Fig. 2, point 1)

2) **Affect modelling** aiming at modeling the relationship between the human environment and the change in the human affect (Fig. 2, point 2) and

3) **Affect control**, where a controller outputs a suitable control signal to change the environment and thus bring the human affect into a desired safe and resilient state (Fig. 2, point 3)

The **Factory Affective Loop** shown in Fig. 2 is realized by the embodiment of AI technologies and systems for cognitive human-machine interaction in all three pillars and their components. The enablers of such an AI embodiment are neuromorphic computing, cognitive sensors, and cognitive interaction technologies.

In the second layer an internal **Core Affective Loop** between human and technical components is envisioned. It reproduces the same three phases:

1) Affective recognition,
2) modeling and
3) control,

which act intimately between the two components of the socio-technical system, human and machine/equipment.

By placing the essential production factors, which are fragmented today in terms of their structure and mode of action, on a similar basis, the **Reference Model** reveals three main advantages:

1) A fundamental simplification of all technical and organizational systems, combined with quickly adaptable production processes, leads to resource conservation, effort reduction and more flexibility
2) Humans can thus take over the control of the socio-technical system much more easily, since it is similarly structured to their cognitive and physical abilities and also provides similar intelligent functions to support them
3) With the help of the neuro-amorphous similar interface structure, the human being can use the channels and forms of communication with technical and non-technical partners in the most natural way, which seems most suitable for the person in the given situation

The creation of such a perfect fit between the social and the technical component is made possible by the harmonized embodiment of AI, IoT and digitization technologies across all production technologies, robotics, machine and equipment and IT technologies.

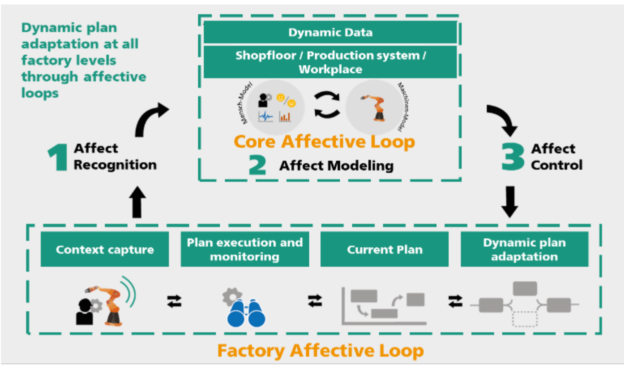

Fig. 2. Factory Affective Loop and Core Affective Loop

6. Conclusion and future work

The here shown approach is a human-centric approach: instead of automatically capturing abilities, emotions, and states of human in production process, the human should be allowed to express their state, needs, emotions both cognitively and physically actively, rather than having their emotions interpreted rigid and impersonal by the system, so that they can reflect and experience their emotions more strongly.

The Affective Production concept and the Reference Model innovates through the defined continuously integrated Core and Factory Affective Loops, which enable the human-driven self-configuration based on required embodied intelligence at two levels: the first loop at workplace (human-machine) level and the second at all factory scales, from micro to production network.

The development and validation of the concept main modules starting with their concept, methodology, employed technologies, prototyping, testing, and interfacing them with the cognitive interaction technologies represent the future work.

A critical aspect represents the consideration of ethic, legal and social aspects regarding the employment of Artificial Intelligence in production activities aiming at increasing flexibility, quality, and productivity. These aspects will be deeply analysed in evaluation of the planned demonstrators.

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