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GOING ONE STEP FURTHER: TOWARDS COGNITIVELY ENHANCED PROBLEM-SOLVING TEAMING AGENTS

Leonardo Puricelli[1]; Stefan Brandenburg[2]; Andreas Wendemuth[3]; Stephan Husung[4]; Diana Armbruster[5]; Bertolt Meyer[6]; Marco Ragni[1]

[1]Prädiktive Verhaltensanalyse, Technische Universität Chemnitz
[2]Allgemeine Psychologie und Human Factors, Technische Universität Chemnitz
[3]Informations- und Kommunikationstechnik, Otto-von-Guericke-Universität Magdeburg
[4]Produkt- und Systementwicklung, Technische Universität Ilmenau
[5]Persönlichkeitspsychologie und Diagnostik, Technische Universität Chemnitz
[6]Arbeits-, Organisations- und Wirtschaftspsychologie, Technische Universität Chemnitz

ABSTRACT

Operating current advanced production systems, including Cyber-Physical Systems, often requires profound programming skills and configuration knowledge, creating a disconnect between human cognition and system operations. To address this, we suggest developing cognitive algorithms that can simulate and anticipate teaming partners' cognitive processes, enhancing and smoothing collaboration in problem-solving processes. Our proposed solution entails creating a cognitive system that minimizes human cognitive load and stress by developing models reflecting humans individual problem-solving capabilities and potential cognitive states. Further, we aim to devise algorithms that simulate individual decision processes and virtual bargaining procedures that anticipate actions, adjusting the system's behavior towards efficient goal-oriented outcomes. Future steps include the development of benchmark sets tailored for specific use cases and human-system interactions. We plan to refine and test algorithms for detecting and inferring cognitive states of human partners. This process requires incorporating theoretical approaches and adapting existing algorithms to simulate and predict human cognitive processes of problem-solving with regards to cognitive states. The objective is to develop cognitive and computational models that enable production systems to become equal team members alongside humans in diverse scenarios, paving the way for more efficient, effective goal-oriented solutions.

Index Terms - Human-machine teaming, cognitive modeling, problem-solving, goal-oriented-solutions, benchmark

1. INTRODUCTION

The fourth industrial revolution, known as "Industry 4.0", has catalyzed a significant transformation in manufacturing practices. This transformation is marked by the integration of technologies such as the Internet of Things (IoT), data analytics, and machine learning. These technologies have endowed automation components with intelligence and established a distributed data environment. This has fundamentally altered traditional manufacturing processes [33].

However, the use of these advanced production systems often requires a comprehensive understanding of the system. This includes knowledge of the heterogeneously distributed functions across the system components, and specialized knowledge of system configurations and programming. As a result, these systems are predominantly viewed as "smart tools". This perspective differentiates them from their users and creates a divide between "operator" and "smart tool", following the old but powerful idea of men-are-better-at, machines-are-better-at (MABA-MABA) lists of Fitts [19]. In this line of thought, operators are trained to develop more skills and to acquire more knowledge and machines are engineered that become more and more powerful over time [14]. On the other hand, this approach may foster a paradigm of task substitution without considering either variation of strengths and weaknesses in systems and people or additional cognitive demands through increasing complexity of supervisory control tasks [13].

Today, humans and machines takeover parts of tasks, but they do not work together as equal partners in a productive team. This partly originates in a discrepancy between the cognitive operations of human users and the intrinsic attributes of these systems, sometimes described as difficulties in "cognitive coupling" [6]. This disconnection can impact the experienced sense of agency in humans when working with the system, and thus impact trust and acceptance towards the system, leading to a diffusion of responsibility, increased stress consequently cognitive load [6] [30]. High cognitive load decreases human efficiency in various aspects [23], which can be relevant when working with technical systems. Long periods of training are additionally needed to gain the necessary expertise for engaging in working with complex systems.

One approach to avoid high cognitive load is to leave the MABA-MABA list line of thinking by trying to transform systems into true team members. Having two team partners instead of an operator and a (smart) technical system bears the potential to create collaborative working environments in which humans can interact with their technical team partners in the way they would do with other humans. We expect this to lower the length of initial training phases and increase the efficiency of human-system collaboration. To do so, technical systems should be augmented with aspects of human cognition. Cognitive algorithms have the ability to emulate and predict certain aspects of human cognition [20]. Examples include large language models (LLM) like GPT4 [35] for language processing, Convolutional Neural Networks (CNNs) [53] for image and pattern recognition, and Deep Neural Network models (DNNs) [17] for predicting human behavior. The aim is to establish a cognitive system that reduces the cognitive demands on human users by both taking over certain cognitively demanding aspects of a task or intertwining with human cognitions (mentioned "cognitive coupling"), thereby fostering a more integrated and effective workflow, and facilitating inherent problem-solving processes.

The necessity for such systems is emphasized by the complexities faced in real-world assembly systems, considering the variance and interference in assembly processes. These complexities include tracking the adaptability of assembly workers, optimizing assembly line planning and configuration, managing large amounts of data from multiple sensors, and maintaining effective communication and safety within the assembly environment [34].

Artificial Intelligence (AI) has demonstrated power to resolve such complexities, offering substantial cost reductions and efficiency improvements. For example, AI can be implemented to help workers with digital work instructions, guiding them through complex assembly processes, thereby relieving their working memory load. Real-time data analytics may lead to individual fitting of working tasks and procedures to maintain the workers high level of attention and medium levels of cognitive load [11]. In a small-scale pilot-study Shin and Prabhu [43] compared the effects of an AI-based support system and a Fault Tree (FT) based support system on peoples' ability to diagnose errors of a proximity sensor that mimicked a part of a real-world industrial machine. They found that the AI-based support system led to a decrease of 55% in time needed compared with the FT-group. In addition, participants reported lower levels of cognitive load with the AI-based support system compared with participants who used the FT-based support system. Additional work by Hudon et al. [24] revealed that cognitive load of operators decreases when these operators understand the decisions and actions of the AI systems.

The primary objective of this research is to design cognitive and computational models that empower intelligent production systems to operate as equal team members alongside their human counterparts in a variety of scenarios, leading to increased efficiency and effectiveness of goal-oriented solutions [46]. A proposal of elements to incorporate in such a production system is shown in Figure 1. The potential impact of this research direction on the evolution of production systems is significant, indicating a shift towards more human-oriented and cognitively advanced systems.

2. BACKGROUND AND RELATED WORK

As our focus lies on the development of cognitive algorithms for industrial production systems, it is essential to understand the technological milieu within which our research is situated. This milieu is heavily impacted by the convergence of several technological advancements, including IoT, data analytics, machine learning, and companion systems, which have collectively led to a shift from traditional to Cognitive Production Systems (CPS). CPS incorporate elements of cognition that help grasping the complexities of real-world problems. These complexities range from monitoring the adaptability of workers to managing vast amounts of data, including live data from various sensors [22]. Nevertheless, while CPS have brought significant enhancements to production systems, they still face challenges, especially regarding intertwining cognitive operations with those of humans.

A potential strategy to alleviate these challenges lies in the creation of modular and scalable Cognitive Architectures for Artificial Intelligence (CAAI) in CPS. These architectures could support a learning system capable of independently selecting suitable algorithms, thus minimizing the need for expert intervention [18] [45].

However, safety assurance in CPS, especially in critical applications such as automated systems, remains an area of concern. Researchers have proposed multi-faceted approaches that go beyond technical measures to include human factors, management and operations, and governance and regulation [4] [28] [32].

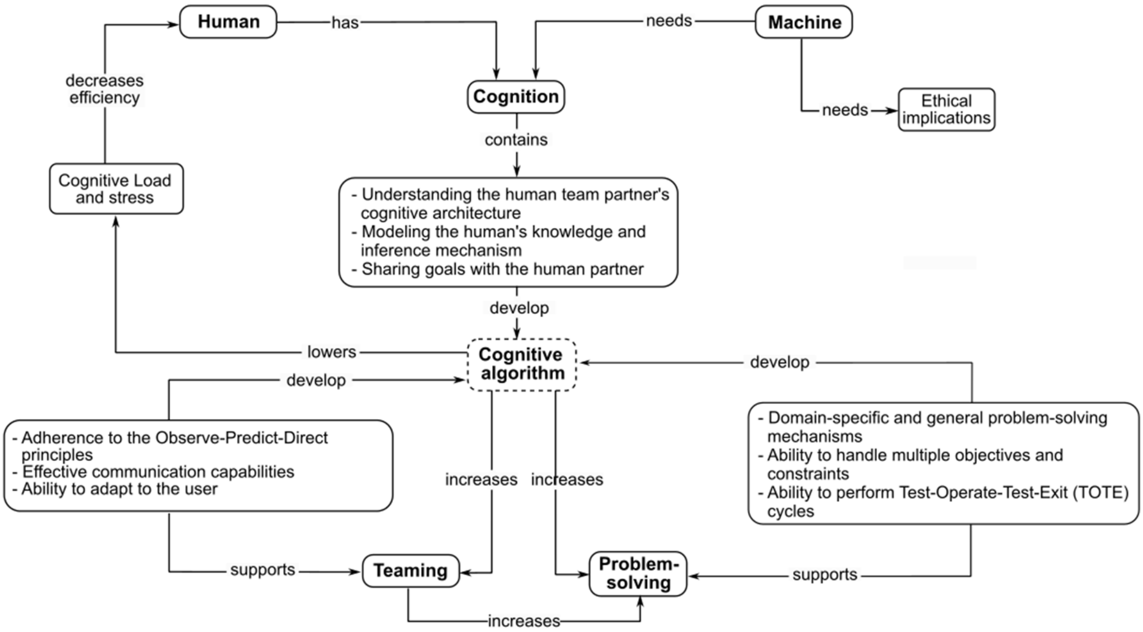

Figure 1 (own representation): Summary of key capabilities required for an effective cognitive system. These capabilities span across three main areas: Cognition, Teaming, and Problem-Solving. Cognition involves understanding the cognitive architecture of the human partner, modeling their knowledge and inference mechanisms, and the ability to share goals. Teaming requires adherence to the Observe-Predict-Direct principles, effective communication, and adaptability to the user. Problem-Solving encompasses domain-specific and general mechanisms to represent and solve problems, handling multiple objectives and constraints, and the ability to perform Test-Operate-Test-Exit (TOTE) cycles. Cognitive modeling, which occurs at the intersection of cognition and its algorithmic realization, serves as a bridge between humans and systems.

AI becomes highly relevant when it comes to potential disruptions in the process to support humans. A machine can support its human teaming partner by (i) providing respective information (the help-as-needed approach), (ii) providing users with help in problem solving, and (iii) supporting them in epistemic (re-)planning.

Support in problem-solving process requires that the human knows the initial state including its variance (e.g., the components to be assembled may be present with different desired and undesired properties, results of initialization of the production system, etc.) as well as the target state (e.g., assembly result, permissible energy consumption, etc.) [47]. Moreover, Meyer [37] investigated the effect of knowledge distribution in a Complex Problem-Solving Scenario (Tailorshop) between experimental participant dyads. It was shown that in the subsequent individual processing of the tailor store, groups that exhibited medium knowledge heterogeneity in advance showed the best performance measured by the profit made in the tailor store. In complex problem-solving tasks, the developer/programmer transfers the problem into a mental model suitable for him/her to systematically create the solution. This always involves Test-Operate-Test-Exit (TOTE) cycles [39] with definitions and detailings of the necessary functions and their implementation as well as their evaluation [25]. For humans, this iterative work is essential, as the problems always have a multiplicity of objectives, so in addition to basic functions of the production system, the numerous parameters must always be optimized in such a way that numerous other properties can be implemented (e.g., permissible vibrations, reproducibility, usability, etc.) [21] [48]. During the implementation of machine development and programming, the challenge arises that the analysis and evaluation can only be implemented in a target-oriented manner when a corresponding virtual verification or physical implementation has been performed [36]. In the case of a physical implementation on a real machine, machine-related constraints must be considered - for example, a source code should only be executed on a machine if it can be ensured that it will not cause any damage.

Action planning in AI has recently shifted towards epistemic planning, taking knowledge and beliefs of agents into account [5] [9]. In short: Epistemic planning is automated planning with theory of mind reasoning, i.e., considering the mental states of human agents in the computation process. This is relevant in multi-agent-scenarios where only decentralized information with restricted communication is possible. To model this formally Bolander et al. [10] have developed a Dynamic Epistemic Logic (DEL), a semantic (where states are represented by models), and *implicit* approach, i.e., the initial state and an action library are given. The computational complexity for finding a restricted subclass of DEL (with a propositional precondition in operators), an optimal plan, is PSPACE-complete [10]. In a recent test, the implicit coordinated planner [38] in a round-based testing was able to find all existing solutions, for two to three agents in seconds and almost no solution for 4 and 5 agents. While using a cognitively inspired algorithm [7] and heuristics the performance dropped to about 95% in two agent scenarios, and then with each additional agent for additional 5%, the solution times were orders of magnitudes smaller (about 5 ms per number of agents per scenario). Hence, cognitively inspired algorithms cannot only make a substantial contribution to solving such scenarios, they are closer to actual human processes and can offer a formal way to model the underlying processes in epistemic planning.

Johnson and Bradshaw [27] have identified three key factors as fundamental conditions for teamwork between humans and machines, which are like those for human-only teams: Observability, Predictability, and Directability (OPD). They are described as facilitating properties and efforts for effective teamwork and pose prerequisites for teaming as they lay the groundwork for understanding a situation, recognizing the contextual environment, and identifying each other's state and intentions. Observability involves mutual understanding and observation of each member's tasks, intentions, environment, and status within the team. Predictability allows team members to anticipate each other's behavior, states, and intentions, fostering trust and acceptance, and enabling the team to adapt to evolving needs and goals. Directability pertains to the ability to influence and be influenced by others in the team, including the delegation of roles and responsibilities or offering advice or resources, while considering the team's environment and each member's state. Converging these capabilities into machines' cognitive architectures for teaming situations allows them and their team members to align shared goals, strategize specific actions, and effectively collaborate on an operational level, forming a vital basis for mutual support, trust, and acceptance.

Action and *discourse coordination* depend on the personal state of human team members. Here, relevant dispositions [16] and timing factors [44] for action coordination have been identified. Multimodal observations of affective and attentional states, their change and team dynamics lead to a construction of a user-adaptive interfacing in the spirit of companion technology [8]. This type of interaction comes with models of team dynamics, specifically shared mental models (for the area of cognitions) about the expected success of the team as well as communication and cooperation strategies (behavior), which also allows for a joint approach in hybrid teams to adapt and define strategies of action and planning [51]. Structured discourse representations and flexible dialogue models implement policies for choosing the means/strategies for coordination and alignment of artificial and human team members which all appear as peers [50].

The development of cognitive algorithms for CPS is a suitable research direction to tackle the above-mentioned challenges. Such algorithms have the potential to harmonize cognitive operations of CPS with those of human users, thereby reducing cognitive demands and fostering effective problem-solving processes. In the forthcoming sections, we will expound upon these topics, detailing the current state of research, identifying gaps, and proposing future research directions in the field of cognitive algorithms for industrial production systems.

3. PROPERTIES OF A COGNITIVE ALGORITHM TO SIMULATIE AND ANTICIPATE A HUMAN TEAMING PARTNER IN UNCERTAIN SITUATIONS

One core aspect that enables smooth interactions between humans is the so-called cognitive theory of mind, i.e., the capability to reason about beliefs, knowledge, and intentions of another person). Through this reasoning process, less direct communication is necessary and subgoals and solution steps can be assumed. Hence, for collaborative problem-solving this capability to reason about what the other may or may not know, can significantly increase the efficiency in solving problems. Humans can infer the ToM of another human being because they are similar. It has even been reported that humans do ascribe a ToM to some animals [31] and even robots [3]. One can assume that human-machine teams may benefit from some form of machine theory of mind [42].

Machine-based ToM aims at embedding artificial systems with the capacity to perceive and attribute mental states like beliefs, intentions, and knowledge, integral for effective teamwork [42]. This includes discerning intentions for synchronizing goals [47], attributing beliefs to manage disparate knowledge landscapes, adopting perspectives to optimize task allotment, and recognizing deception and trust to bolster problem-solving precision [26] [12]. Learning cooperative behavior in multi-agent scenarios is a challenge at machine-based ToM because the complexity and dynamics of the state space while simultaneously adapting other agents result in non-stationarities (e.g., drift). Current work in this context only considers small teams (<5 agents) and is based on a variety of simulations in which approaches using hierarchical Reinforcement Learning or Deep-Reinforcement Learning [1] have achieved promising results [39]. Resource adaptive theory of mind capabilities [41] have been studied, as well as predictive algorithms for the interpretation and production of socio-intentional actions [29] [52]. As the integration of ToM in machines involves data-driven learning, there is high demand for suitable kinds of data. Shared focus and objectives align algorithmic operations with team aims. Ethical implications, predominantly privacy-related, are essential.

The benefits of ToM-integrated machines potentially lie in enhanced teamwork efficiency, problem-solving ability, and human-machine interfacing. However, challenges encompass the technical intricacy of implementing ToM and the ethical dilemmas revolving around privacy and potential data misuse. Regardless of these barriers, exploring ToM in machines opens promising avenues for understanding and applying AI. A system must be able to understand how its interaction partner processes information, reasons, and what respective beliefs might be. To develop a system that can take cognitive states into account to allow smooth interaction. We are not focusing here on the human part that may or may not understand the system. We will outline what a cognitive algorithm must be capable of - one that goes beyond a pure AI problem solver.

We humans have a naive understanding of another person's psychology. We know from introspection that we have a memory (that can make it easy or difficult to retrieve information), that we have reasoning and decision-making capabilities (including potentially different systems, and sometimes even deviating from optimal solutions due to a lack of concentration or biases), and that we can communicate to gather further information. There are specifically human ways to do this. A cognitive algorithm must take these into account. In the following, a selection of these will be briefly outlined.

If we want to equip systems with a theory of mind module, we need ways to formulate the theory of mind via an algorithm. Hence, we will consider some of the requirements of such cognitive models.

Causal cognition is of central importance for our conception of the world. It goes without saying that everyday life as well as technology and science heavily rely on causal inferences, such as explanations and predictions. Causal thinking comes as naturally as our three-dimensional vision or our sense of time. From a causal model, predictions as well as explanations can be deduced when information matches the rules. Here, the covariation between two events is crucial for a causal relation. However, research by Drewitz and Brandenburg [15] revealed that if peoples' causal models are devalued in a few specific instances, other causal models for which people did not perceive negative evidence were equally affected. Thereby, the authors argue that peoples' models of cause and effects do not exist separately in their minds but are instead interrelated. Cognitive models that are implemented in technical systems should consider this.

The central role of memory has been investigated in a widespread range of tasks. There is much evidence showing that especially declarative memory accounts for human performance usually seen as smart or intelligent behavior [2]. Research revealed that causal learning and causal reasoning is largely based on declarative memory as well [15]. Decision-making under uncertainty is an example where human performance relies on declarative memory. Human behavior in such situations can be explained by retrieving instances of memory. Drewitz and Brandenburg [15] found that changes in context of decisions lead to lower levels of peoples' confidence in their decisions and knowledge. This effect should also be considered by technical systems.

4. DISCUSSION AND CONCLUSION

The proposed enhancement of cognitive production systems (CPS) by incorporating elements of human cognition aligns with the current trend in the field but takes it a step further by suggesting a more cohesive problem-solving approach. We argue that integration of cognitive algorithms and artificial intelligence (AI) in industrial production systems can significantly improve collaboration between humans and machines. A central aspect of this improvement is the incorporation of a machine-based theory of mind into cognitive algorithms. This theory of mind, which involves the ability to perceive and attribute mental states like beliefs, intentions, and knowledge, could significantly enhance the ability of AI systems to work effectively with humans. However, implementing a machine-based theory of mind presents technical challenges and raises ethical dilemmas revolving around privacy and potential data misuse.

Another key aspect is the role of memory and causal cognition in human intelligence and decision-making. By incorporating these factors into cognitive algorithms, we could improve the ability of these algorithms to emulate and predict human cognition, potentially transforming how humans interact with production systems and reducing the need for expertise.

The shift towards epistemic planning in AI, which involves taking the knowledge and beliefs of agents into account, could also influence the development of cognitive algorithms. This shift presents both potential benefits, such as improved decision-making, and challenges, such as the increased complexity of the state space.

Effective teamwork between humans and machines is another crucial aspect. By incorporating key factors for effective teamwork, such as observability, predictability, and directability, into cognitive algorithms, we could improve human-machine interaction and foster a more integrated and effective workflow.

Finally, the real-world applications and challenges of cognitive algorithms should be considered. The complexities faced in real-world assembly systems, such as tracking the adaptability of assembly workers and managing large amounts of data, highlight the potential of AI and cognitive algorithms to resolve these complexities and enhance the efficiency and effectiveness of production systems.

This paper contributes to the existing knowledge base by providing a new insight into human-machine interaction and a novel approach to addressing the challenges faced by complex production systems. It also confirms previous research on the potential of AI and cognitive algorithms in enhancing the efficiency and effectiveness of production systems.

The proposed approach is theoretical and needs to be validated through empirical research. The complexity of human cognitive processes and the challenge of accurately simulating them in cognitive algorithms are significant limitations. The effectiveness of the proposed approach may also vary depending on the specific use cases and human-system interactions. Future research could focus on developing and testing cognitive algorithms that accurately simulate human cognitive processes. It could also explore the development of benchmark sets for various use cases and human-system interactions. Further research is also needed to validate the effectiveness of the proposed approach in real-world scenarios and to explore ways to overcome the identified limitations.

In conclusion, this research proposes a transformative approach to industrial production systems, aiming to foster a more seamless and efficient collaboration between humans and machines. The potential impact of this research direction on the evolution of production systems is significant, indicating a shift towards more human-oriented and cognitively advanced systems. It is hoped that this work will inspire further exploration and development in the field of cognitive algorithms for industrial production systems.

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CONTACTS

B.Sc. Leonardo Puricelli	email: leonardo.puricelli@metech.tu-chemnitz.de ORCID: https://orcid.org/0009-0000-0717-9822
Prof. Dr. Stefan Brandenburg	email: stefan.brandenburg@psychologie.tu-chemnitz.de ORCID: https://orcid.org/0000-0002-7628-5247
Prof. Dr. rer. nat. Andreas Wendemuth	email: andreas.wendemuth@ovgu.de ORCID: https://orcid.org/0000-0001-6917-8198
Prof. Dr.-Ing. Stephan Husung	email: stephan.husung@tu-ilmenau.de ORCID: https://orcid.org/0000-0003-0131-5664
Dr. Diana Armbruster	email: diana.armbruster@psychologie.tu-chemnitz.de ORCID: https://orcid.org/0000-0001-8649-6227
Prof. Dr. Bertolt Meyer	email: bertolt.meyer@psychologie.tu-chemnitz.de ORCID: https://orcid.org/0000-0003-4695-9252
Prof. Dr. Dr . Marco Ragni	email: marco.ragni@hsw.tu-chemnitz.de ORCID: https://orcid.org/0000-0003-2661-2470