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Intelligent Process Control: A Case of Designing Predictive Service for Wastewater Treatment Plant

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ABSTRACT

The way we carry out our industrial operations needs to be radically transformed to foster sustainable development. In addition, the integration of advanced automation and emergence of AI-based solutions is poised to revolutionize the role of human operators as well as the industrial landscape in process control in general. In this paper, we present a case study on designing and implementing a predictive AI-based service to the wastewater treatment plant of a carboard factory. The new service is aimed at providing an improved overview of the process as well as giving suggestions about the chemical dosing. We have conducted user interviews accompanied with a user experience questionnaire to study how the operators experience the new AI-based service. The results show the potential of intelligent technologies in process control but also highlight the importance of carefully considering the human technology interaction and the need for better integration of expert users' experiences and knowledge into the AI system. It seems obvious that only human centric approach can lead to smooth and resilient human technology interaction and enhanced industrial operations.

Keywords: Process control, Artificial intelligence, Operator work

INTRODUCTION

Many societal and environmental challenges today drive us to find new solutions and develop and change the way we work and run our industrial operations. The change must be all-pervading requiring change in values, operative approaches, and industry policies (European Commission, 2021). The increased demands for sustainability and the deployment of higher levels of automation and the emergency of intelligent technologies such as Artificial Intelligence (AI) based solutions and services will, for example, all radically transform our industrial landscape.

One central principle, "the human turn", of the new Industry 5.0 paradigm emphasizes the human-centricity and foresees the work carried out in a balanced and synergistic cooperation between the human and the intelligent technologies. The new human-centric AI systems, which are flexible, adaptive, safe, sustainable, and trustworthy may integrate optimally the capabilities of both technology and human actors (Huang et al., 2022; Rožanec et al., 2023). Thus, from the human perspective, the Industry 5.0 aims to improve the wellbeing and empowerment of workers to reach their highest potential in creativity, talents, and skills and knowledge in carrying out different work tasks [1, 2, 3]. Consequently, from the point of view of designing intelligent work systems, the key question is how to enable the integration of human workers competence, knowledge, and skills into the system operation and make the human – machine interaction smooth and resilient (Kaasinen et al., 2022).

The research-oriented Intelligent Human Technology Co-agency in Process Control COACH project, supported by Business Finland, pursues a significant stride in the realm of human-technology synergy within industrial settings. The COACH focuses on the pivotal challenge of integrating intelligent technology into the everyday process control operations of companies. The COACH not only propels research in optimal/intelligent human-technology interaction but also serves as a practical response to the pressing need for technological adaptation in industry. The COACH project has two empirical use cases representing different process control sectors. The first case study examines the implementation of AI-based predictive services in wastewater treatment plant, focusing on the design and implementation process, as well as operator experiences. The second case study delves into a performance center concept, demonstrating how remote expert support can optimize process control with a focus on the demands and issues related to novel (e.g., remote and networked) type of technologically-assisted work. This paper focuses on the first mentioned case study.

As in the COACH case studies mentioned above, designing the human-technology interaction in general is a critical question for the successful deployment of intelligent technologies in work settings. This is because the promise of intelligent technologies to enhance the operations cannot be automatically realized, if not properly grounded in terms of advantages to human action, operational safety, and efficiency of the controlled system.

Many factors and phenomena have been proven to influence human and technology interaction especially when implementing AI-based tools and services. For example, trust has been studied to be a critical component when interacting with intelligent AI-based technologies and it may greatly affect the user acceptance of the technology (Joskowicz and Slomovitz, 2023; Karvonen et al., 2019). Especially in operational occasions in which decisions are involved, the trustworthiness of the AI based technology plays an important role. Rožanec et al. (2023) suggests that in these situations the human must in some way be able to evaluate the decisions, that is, the rationale behind the conclusions of the AI by making them explicit and explainable. For example, a user study by Panigutti et al. (2023) found that participants of the study were more likely to follow the advice of the AI system when explanations of some sort were provided alongside the suggestions. Thus, providing explanations may be one way to help increase trust in the AI system. Moreover, trust is not a static phenomenon, instead it is something that may change and develop over time in the human technology interaction (Siau and Wang, 2018).

Another issue discussed a lot in connection with human AI-based technology interaction is transparency. One simple way to describe what is meant with transparency concept is the degree to which the internal logic of the system is exposed to the users to help them to understand the functioning of the system (Seong and Bisantz, 2008). Thus, as with trust, transparency is related to explainability but also many other similar concepts such as understandability, openness of the system, accessibility, visibility, and interpretability to mention some (Adadi and Berrada, 2018; Felzmann et al., 2020; Larsson and Heintz, 2020). In a study on glass tempering process that includes a machine-vision-based quality control system and highly automated process control system Wahlström et al. (2024) discussed about the concept of balanced AI transparency that supports upskilling and resilience of the system. According to them, the complexity of automation system along with the complexity of the process physics that places critical emphasis on expert knowledge may result in so called "double black box effect" which may not be feasible to overcome by only improving the understandability of the system interaction with the line workers but instead they see that expert networks are needed to support the operations. Thus, transparency is a key issue that relates to the development of sustainable AI solutions for industrial operations, and it not only touches on the interaction between the individual and the AI system but can also be identified as essential when looking at the operations of the entire organization (Felzmann et al., 2020).

Finally, but not the least important, are mentioned the issues related to the ethics of AI based solutions development (European Commission, 2019; Jobin et al., 2019). For example, guidelines for trustworthy AI provided by the European Union (European Commission, 2019) raises seven main areas for requirements, that are, 1) human agency and oversight; 2) technical robustness and safety; 3) privacy and data governance; 4) transparency; 5) diversity, non-discrimination and fairness; 6) societal and environmental well-being; and 7) accountability. The listing is quite comprehensive and requires a lot of user and contextual understanding from the design and development process to be completely fulfilled. However, it is in line with Industry 5.0 "the human turn" and may help the industry to develop human centric AI solutions that truly follow the idea of what is meant with the concept of joint cognitive system and intelligent future operation (Woods and Hollnagel, 2006).

PREDICTIVE AI-BASED SERVICES FOR WASTEWATER TREATMENT PLANT

The research work presented in this paper draws from the COACH-project's empirical use case related to the AI supported wastewater treatment plant process control. Alongside participating in the COACH project, the two partnering project companies have had their own joint development project within which a new predictive AI-based service has been developed and implemented in one Finnish carboard factory's wastewater treatment plant. This development project has provided an interesting real-life example case to be followed about the design and development of AI-based process control tools that have also been implemented in real use.

Methods and Materials

The COACH project is fundamentally user-centric and thus takes the perspective of human activity and the promotion of human point of view in system design. Consequently, within both use cases we have aimed at creating a rich understanding about the contextual circumstances and direct involvement of the real users in question.

To collect relevant user data, we have conducted multiple empirical inquiries (Table 1). It is noteworthy that there are only two actual users, that is, two process control operators that operate and have the main responsibility of the wastewater treatment plant. In addition, there are few other user groups in the carboard factory that were relevant for the development of the new AI-based predictive service. One relevant user group was formed by the operators of the carboard machine and the other was the personnel that were responsible for reporting and following the fulfilment of the environmental permit of the wastewater treatment process.

Table 1. Overview of the empirical inquiries and data collection.

Empirical Inquiry	Number of Participants	Place
Designer interviews	Project manager (1), Development engineers (1)	Online/ Teams
User interviews	Operators (2), Production engineer (1)	Control room
User experience questionnaire	Operators (2), Production engineer (1)	Paper format

Designer interviews. As a part of the use case a series of designer interviews have been carried out. In the three interviews, the design process of the AI-based predictive service was followed and discussed with the development engineers. The first interview took place at the beginning of the development project, and it focused on the goal setting and user requirements of the development process. The second interview was conducted when the pilot version of the predictive service was implemented in the wastewater treatment plant and the last interview with the designers was when their service had been on use at the plant already about half a year and it was possible to discuss about the user feedback that they had received concerning the new service.

User interviews and observation. The users (i.e., the two wastewater treatment plant operators) were interviewed first prior to the implementation of the AI-based predictive service and second time after the implementation of the new service when they had been using the system already a few months. The interviews were all conducted in the actual workplace of the operators, that is, in the wastewater treatment plant's control room. The first interview concentrated on the work and process control tasks of the wastewater treatment plant operators whereas the second interview focused on the user experiences of the new service.

User experience and usability questionnaire. As a part of the second user interviews and the visit to the wastewater treatment plant, a user experience questionnaire was introduced. The questionnaire included 24 questions about the predictive wastewater treatment service. Most of the questions were in the form of a specific claim about the new predictive service; the claims were asked to be rated on a scale from 1 to 5 where "1" is strongly disagreeing and "5" strongly agreeing. Even though any conclusions from the questionnaire alone cannot be drawn due to the extremely small size of the sample, it can be used to compare with and emphasize the key issues found in the interviews.

RESULTS

The user interviews of the wastewater treatment plant operators brought to the fore several issues which operators found working well or adequately, or where there still were some challenges that should be addressed. These were issues related to trust, human-AI interaction and transparency such as usability, collaboration, information availability and understandability, reliability and validity.

Trust in the Predictive AI-Based Service

The wastewater treatment plant operators could not yet fully trust in the AI-based service, which was shown in the use of the service: it was not used as a guidance for actions, but rather as one source of information that can help in creating an overall understanding of the process. In the questionnaire, the specific questions on the trust in the measurements and in the recommendations of the predictive service were evaluated lower than most aspects of the service. The user interviews revealed several reasons for inaccurate information that hampers the users' trust in the service. These reasons included, for example, delays between adding chemicals and the system showing the response of the changes, dirt in the physical measurement devices and changes in weather temperature outside, where the wastewater pools are located. However, based on their extensive operative experience, the operators could still comprehend the overall situation and make conclusions of the data, and follow specific parameters that were relevant and perceived reliable and could not be accessed otherwise.

The operators expected their trust in the service to enhance in the future when the accuracy of the information and predictability of the parameters improves. In addition, the operators' attitude towards the service was positive and they were willing to contribute to the further development of it, for example by reporting the perceived errors in the information.

Human-AI Interaction

Currently, the AI-based predictive service shows a dashboard that provides the operators with process overview information on the current levels of chemicals and recommendations for chemical dosing adjustments. Besides viewing information, the operators could only accept a recommendation or reject it and add a short description for a reason for rejection of the recommendation. The wastewater treatment plant operators commented that they were not totally aware of whom the reason for the rejection is shown/informed and how it is processed, for example, how often these notes are checked and how this information is used within the service. However, the operators would be interested in adding more information to the service based on their own operating experience and observations and suggested that there could be a free field for that in the currently empty area of the main view of the service interface.

At its current stage, the service is used mainly by the two process control operators, but not by the other operators of the carboard factory, even though they would be responsible for some of the related processes at the plant. Integrating the service into the related operations could smoothen the workflow and solve possible communication challenges between the operators of the different parts of the factory. When more varied user and personnel groups are using the service, the human-AI interaction becomes more important, as it enables sharing relevant information between the parts of the process and thus, helps gaining a shared situation awareness and an overall understanding of the factory process.

Transparency

The current version of the service shows some visual cues, such as color coding, which helps interpret the values related to the levels of the chemicals and needs for actions. This helps especially unexperienced users of the service, but for experienced users, better transparency, that is, more information behind the values and recommendations would be useful, as there are several reasons for changes in values and several impacts of actions that need to be considered when making decisions. Integration of the users' knowledge into the system in reporting and explaining issues would add transparency of decisions and help develop the service. It could be a true win-win situation as the service developers would gain valuable hands-on understanding from the field and the operators' knowledge and experience would be acknowledged, giving them an opportunity to contribute to the design of their work tools. Furthermore, integration of the service to be used by the operators of the other parts of the factory would increase the transparency of the whole process by improving the awareness of the related parts of the process and their impacts on each other.

DISCUSSION AND CONCLUSION

Communication through language between humans is in many aspects different than communication between humans and machines, as only humans can have mental representations with semantically meaningful contents (Saariluoma and Karvonen; 2023). However, human representations can be manipulated into other forms of representations, where mental information processes are brought to certain levels of abstraction and organized on physical processes and systems corresponding to the information process of the source (i.e., the human cognitive processes) (Saariluoma and Karvonen; 2023).

Communication and smooth interaction are foundational in any human relationship; thus, it is also the most critical in human relationship with technology. Researchers and developers need to investigate, ontologize, and operationalize what is relevant information in each context and how that information is shared in different interaction situations between human and intelligent technological agents.

As noted by European Commission (2021, p. 15): “One of the most important paradigmatic transitions characterizing Industry 5.0 is the shift of focus from technology-driven progress to a thoroughly human-centric approach.” Human-centered design considers emotional, cognitive, social and even biological human characteristics. Designing joint cognitive systems which are by nature sociotechnical systems demand multidisciplinary and holistic approaches to be comprehensively considered by all their characteristics (Kaasinen et al., 2022).

In complex sociotechnical systems communication should be bidirectional. An efficiently communicative sociotechnical system should not only provide one-direction information outputs, but it should be dynamic and adaptive, allowing users to give feedback to their received information and have the possibility to put in the system new information that is acknowledged and shared between other agents who collaborate in the system (Rožanec et al., 2023; Kaasinen et al., 2022). This kind of interaction and communication in both directions, which is ”approximating a human conversation” (Rožanec et al., 2023, p. 6853), may improve interaction, mutual understanding, clarity, transparency, reliability, and trust. In could also enable users to improve functions, quality and validity of the operated system and its processes. It may also facilitate learning for both human users and the intelligent system, either by mutual learning which is based on bidirectional process and collaboration when solving joint tasks, or active learning, where AI-models learn from selected data, human expertise, and knowledge by asking questions (Rožanec et al., 2023).

Sociotechnical systems should entail settings for different scenarios that prepare them for operating correctly in alternative situations, such as, for instance, when anticipating and during a preplanned maintenance break. In our case study, the implemented system seemed to be able to proceed based on just one general process, and any deviations from it, even if they were normal and deliberate activities that occur on periodical basis, are not still properly considered in the service recommendations. Thus, whenever there are those deliberately executed process changes, the implemented service fails to provide precise enough information for the users during this time. In addition, this is something what the users have had to figure out through first observing and noticing an exception in the process, then finding the root cause through investigation and communicating with other people involved in other stages of the overall process. Presumably, if these situations are not made explicit and documented to be fixed later, there is a risk that the root causes become tacit information. Ideally, the system should be built so that it could take into consideration (at least the most common) possible variations in the process activities – also variations which may originate from machine or human behavior (Rožanec et al., 2023), so that it could accurately predict and make controlled adjustments on the information outputs for each specific event, thus increasing the intelligent system's and the underlying AI-model's reliability and trust.

Information should be reliable and valid. AI-supported system must use correct sources for information, synthetize information from different sources in an appropriate manner, update information in appropriate cycles, and maintain the reliability and validity of information (instead of, for instance, creating hallucinations). The user interviews confirmed the literature's findings on trust. Even though the operators used the system mainly as an advisor which recommendations are compared with their own knowledge, they agreed that their trust in the system has improved over time. This could be due to the enhancements made to the system or the time spent using it. As Siu and Wang (2018) state, trust is "a dynamic process, involving movement from initial trust to continuous trust development". Additionally, the operators have learned that incorrect IP addresses, for example due to a software update, affect the values the service proposes. This has increased the understanding of the system's functionality. The operators could benefit more from the visibility of this kind of information, as it clarifies the systems' actions and enhances transparency. It has been seen that explanations may help to increase trust in the AI system (Panigutti et al., 2023).

In this paper, we have presented a case study on development and implementation of predictive AI-based service on wastewater treatment plant process control and discussed how the first steps in using the new service have been experienced by the operators. It seems that we are still quite far from the most futuristic visions about the possibilities of the AI enhanced industrial operations, however, even these early experiments and solutions on the use of intelligent technologies may reveal many things that can be critical to bring about real change.

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REFERENCES

Adadi, A. and Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI), IEEE Access Volume 6, Article: 52138–52160.

European Commission (2019). Ethics Guidelines for Trustworthy AI. https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

European Commission, Directorate-General for Research and Innovation, Breque, M., De Nul, L., Petridis, A. (2021) Industry 5.0 – Towards a sustainable, human-centric and resilient European industry. Publications Office of the European Union. https://data.europa.eu/doi/10.2777/308407

Felzmann, H., Fosch-Villaronga, E., Lutz, C. and Tamò-Larrieux, A. (2020). Towards transparency by design for artificial intelligence, Science and engineering ethics Volume 26, Issue 6, pp. 3333–3361.

Huang, S., Wang, B., Li, X., Zheng, P., Mourtzis, D. and Wang, L. (2022). Industry 5.0 and Society 5.0—Comparison, Complementation and Co-Evolution, Journal of Manufacturing Systems Volume 64, pp. 424–428. doi: 10.1016/j.jmsy.2022.07.010.

Jobin, A., Ienca, M. and Vayena, E. (2019). The global landscape of AI ethics guidelines, Nature machine intelligence Volume 1, Issue 9, pp. 389–399.

Joskowicz, J. and Slomovitz, D. (2023). Engineers' Perspectives on the Use of Generative Artificial Intelligence Tools in the Workplace, IEEE Engineering Management Review Volume 52, Issue 1, pp. 258–267. doi: 10.1109/EMR.2023.3333794.

Kaasinen, E., Anttila, A.-H., Heikkilä, P., Laarni, J., Koskinen, H. and Väätänen, A. (2022). Smooth and Resilient Human–Machine Teamwork as an Industry 5.0 Design Challenge, Sustainability Volume 14, Article: 2773. doi: 10.3390/su14052773.

Karvonen, H., Heikkilä, E. and Wahlström, M. (2019) "Artificial intelligence awareness in work environments", Human Work Interaction Design, Designing Engaging Automation: 5th IFIP WG 13.6 Working Conference, HWID 2018, Espoo, Finland, August 20-21, 2018, Revised Selected Papers 5.

Larsson, S. and Heintz, F. (2020). Transparency in artificial intelligence, Internet Policy Review Volume 9, Issue 2.

Panigutti, C., Beretta, A., Fadda, D., Giannotti, F., Pedreschi, D., Perotti, A. and Rinzivillo, S. (2023). Co-design of human-centered, explainable AI for clinical decision support, ACM Transactions on Interactive Intelligent Systems Volume 13, Issue 4, pp. 1–35.

Rožanec, J. M., Novalija, I., Zajec, P., Kenda, K., Ghinani H. T., Suh, S., Veliou, E., Papamartzivanos, D., Giannetsos, T., Menesidou, S. A., Alonso, R., Cauli, N., Meloni, A., Recupero, D. R., Kyriazis, D., Sofianidis, G., Theodoropoulos, S., Fortuna, B., Mladeni'c, D. and Soldatos, J. (2023). Human-centric Artificial Intelligence Architecture for Industry 5.0 Applications, International Journal of Production Research Volume 61, Issue 20, pp. 6847–6872. doi: 10.1080/00207543.2022.2138611.

Saariluoma, P. and Karvonen, A. (2023). Theory languages in designing artificial intelligence, AI and Society, Advance online publication. doi: 1007/s00146-023-01716-y.

Seong, Y. and Bisantz, A. M. (2008). The impact of cognitive feedback on judgment performance and trust with decision aids, International Journal of Industrial Ergonomics, Volume 38, Issue 7–8, pp. 608–625.

Siau, K. and Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics, Cutter business technology journal Volume 31, Issue 2, pp. 47–53.

Wahlström, M., Tammentie, B., Salonen, T. and Karvonen, A. (2024). AI and the transformation of industrial work: Hybrid intelligence vs double-black box effect, Applied Ergonomics, Volume 118. doi: 10.1016/j.apergo.2024.104271.

Woods, D. D. and Hollnagel, E. (2006). Joint Cognitive Systems: Patterns in Cognitive Systems Engineering. Boca Raton, FL: CRC Press.