Advanced Systems Design and Analysis Journal

Advanced Systems Design and Analysis Journal
E-ISSN (xxxx-xxxx) P-ISSN (xxxx-xxxx)

Design and Analysis of Adaptive Control Systems for Collaborative Robotics in Industrial Environments 4.0

Mar'atus Solikhah
Universitas Catur Insan Cendikia, Cirebon, Indonesia
Correspondence: maratussholikhah615@gmail.com

Abstract

The development of Industry 4.0 demands a more flexible, adaptive, and safe production system, especially in the context of collaboration between humans and robots. One of the main challenges is to develop a control system that is able to adapt in real-time to the dynamics of a complex work environment. This research aims to design and analyze machine learning-based adaptive control systems for collaborative robotics in modern industrial environments. The research approach used is a qualitative method with case studies in five manufacturing companies that have implemented cobots technology. Data collection was carried out through in-depth interviews, participatory observations, and technical documentation, then analyzed using thematic analysis techniques. The results show that adaptive control systems significantly improve production flexibility by accelerating adaptation to task changes, improve the safety of human-robot interactions by reducing work incidents, and improve operational efficiency through reduced downtime and production line optimization. The human cognition-based control system has also been shown to reinforce the fit between operator expectations and robot behavior. In conclusion, the adaptive control system plays a crucial role in realizing a smart factory based on harmonious collaboration between humans and machines. The practical implications of this research are the importance of integrating adaptive controls in the design of future industries to improve productivity, occupational safety, and operational sustainability.

Keywords: adaptive control system, collaborative robotics, Industry 4.0, occupational safety

1. Introduction

Global developments in the Industry 4.0 era have driven the massive adoption of collaborative robotics systems in various industrial sectors to improve manufacturing efficiency, flexibility, and productivity.

Collaborative robots (cobots) are now a key element in answering the challenges of personalized mass production, digital integration, and adaptation to rapidly changing market needs (Cherubini et al., 2016; Bauer et al., 2016; Ivanov et al., 2021). However, the dynamics of the unstructured work environment, the presence of humans in the robotic work area, as well as the need to accommodate a variety of tasks in real-time create new challenges in the design of robotic control systems.

These problems are influenced by several main factors, such as the limited flexibility of conventional control systems, the inability of standard algorithms to adapt to environmental uncertainties, and challenges in managing human-robot safety simultaneously (Villani et al., 2018; Smids et al., 2019; Tsarouchi et al., 2016). In addition, traditional control systems often require complex manual reconfigurations when faced with a variety of tasks, leading to production downtime and reducing the industry's competitive advantage.

The accumulation of these factors has serious implications for the performance of collaborative robots, such as decreased motion accuracy, increased risk of work accidents, and reduced reliability of human-robot collaboration (Kousi et al., 2019; Kragic et al., 2018; Haddadin et al., 2017). This condition demands the development of new control systems that are not only responsive to environmental changes, but also capable of optimizing collaborative performance in intelligent production ecosystems.

In this context, the main variable studied in this study is an adaptive control system, which is a control approach that is able to dynamically adjust its operational parameters to environmental variations, loads, and human interactions without the need for manual intervention (Ioannou & Sun, 2012; Lewis et al., 2013). This system allows collaborative robots to maintain optimal performance even under conditions of high uncertainty and the uncertainty of the robot's changing dynamic models.

Previous research conducted by Abi Yusuf Nur Asida and Edy Purwo Saputro (2024) focused on the importance of collaboration between humans and robotic resources in facing the challenges of the Industry 5.0 era. The study emphasizes the transformation of organizational culture, the role of human resource management in adapting digital technologies, as well as the development of worker skills to improve human-robot collaboration. Although it has highlighted the importance of integrating technology and people, the research focuses more on managerial aspects, human resource management, and macro perspectives on organizational change. On the other hand, this research brings novelty by directing attention to *the design and analysis of adaptive control systems* for collaborative robotics in an Industry 4.0 environment. In contrast to previous studies that predominantly discussed human-robot interaction in terms of culture and organizational strategy, this study proposes a technical approach based on adaptive control assisted by machine learning to optimize the responsiveness of robots to the uncertainty of the production environment. Thus, the novelty of this research lies in the development of a control system that is able to improve the flexibility, safety, and efficiency of cobot operations in real-time, while supporting the vision of Industry 5.0 in creating harmonious, adaptive, and sustainable human-robot collaboration at the technical-operational level.

This research offers novelty by proposing the integration of a machine learning-based adaptive control model for collaborative robots in an Industry 4.0 environment, which simultaneously considers aspects of human safety, energy efficiency, and task adaptability in a single intelligent adaptive control framework (Gupta & Chow, 2020; Nguyen & La, 2020). In contrast to previous research that focused more on fixed dynamics-based adaptive control or static environments, this study developed a contextual learning-based control approach that allows optimal responses to a wide range of real-world smart factory scenarios.

The urgency of this research is very high considering that the adoption of collaborative robots continues to increase in the global manufacturing sector, but the control system that is able to face the environmental challenges of Industry 4.0 comprehensively is still limited (Cooney, 2016; Michalos et al., 2018). Without innovations in control systems, the full potential of collaborative robots in improving productivity and work safety would not be achieved.

This research aims to design and analyze adaptive control systems that can be implemented on collaborative robots to increase operational flexibility, safety of human-robot interaction, and optimize productivity in an Industry 4.0-based manufacturing ecosystem.

The benefits of this research include: (1) contributing to the development of more intelligent and adaptive collaborative robotics technology; (2) improve the efficiency and flexibility of industrial production lines; (3) strengthening the aspect of work safety in human-robot collaboration; and (4) open up opportunities for wider integration between machine learning technology and adaptive control systems in future industrial applications.

2. Method

This research uses a qualitative approach with the type of exploratory case study research. This approach was chosen because it aims to deeply understand the phenomenon of the implementation of adaptive control systems in collaborative robotics in the Industry 4.0 environment, through the exploration of real contexts, interactions, and complexities that cannot be explained through a quantitative approach alone. This case study allows researchers to holistically examine the dynamics of the adaptation of the control system to changes in the production environment and human-robot collaboration.

The population in this study is all manufacturing industry players in the automation and robotics sectors who have adopted collaborative robot technology in Indonesia. Meanwhile, the sample was selected by purposive sampling, which is the deliberate selection of research subjects based on certain criteria, such as companies that have implemented adaptive control-based cobots, have at least two years of experience in the use of collaborative robots, and are willing to provide in-depth data and information. The sample in this study involved five manufacturing companies and ten key speakers, consisting of robotics engineers, production managers, and heads of industrial technology sections.

The research instruments used were in the form of semi-structured interview guidelines, a list of direct observations in the field, and company documents related to the use of adaptive control systems in cobots. This instrument was developed to dig up data flexibly but remain focused on the research focus, as well as allow exploration of phenomena that arise during the data collection process.

The data collection technique was carried out through three main methods, namely in-depth interviews, participatory observation in the production area, and documentation studies. The interview aims to get the perspective of the resource persons regarding the implementation of the adaptive control system, the challenges faced, and the evaluation of system performance. Observation is used to directly observe the interaction between collaborative robots and human operators in real-life work situations. Meanwhile, a documentation study was conducted to analyze technical records, evaluation reports, and relevant operational protocols.

The research procedure begins with a planning stage that includes the identification of the study site and the preparation of the instrument. Furthermore, data collection was carried out in the field through interviews, observations, and documentation. After the data is collected, the data verification process is carried out through triangulation of sources and methods to increase the validity of the research results. The final stage involves data analysis and the preparation of research report results.

The data analysis technique in this study uses thematic analysis, which begins with the transcription of interview results and observations, followed by a coding process to identify the main themes that emerge from the data. Each theme is analyzed in depth to find the pattern of relationships, the dynamics of adaptive control systems, and the challenges and opportunities for its application in the Industry 4.0 environment. Validation of findings is carried out by data triangulation techniques and member checking to resource persons to ensure the accuracy and credibility of the analysis results.

3. Results & Discussion

Implementation of Adaptive Control Systems in Industry 4.0

Based on the results of in-depth interviews with ten resource persons from five companies, it is known that all companies have implemented collaborative robotics technology based on adaptive control systems in their production processes. The adaptive control system used is mostly based on simple *machine learning* such as *reinforcement learning* to adjust the speed, force, and movement path of cobots to changes in conditions in the work area. The adoption of this system is largely motivated by the need to increase production flexibility without sacrificing work safety.

Table 1. Level of Implementation of Adaptive Control System in Companies

Yes	Company Name	Types of Control Systems	Technology Base	Implementation Length	Production Scale
	PT A	Adaptive Force Control	Machine Learning	3 years	Intermediate
	PT B	Trajectory Adjustment	Deep Learning	2 years	Big
	PT C	Predictive Control	Neural Network	4 years	Intermediate
	PT D	Hybrid Adaptive Control	Sensor Fusion	2.5 years	Big

PT E	Dynamic Planning	Task	Reinforcement Learning	3 years	Intermediate

Table 1 presents data on the level of implementation of adaptive control systems in five manufacturing companies that are the object of the study. Each company has implemented machine learning-based adaptive control technologies, such as reinforcement learning and neural networks, to optimize the performance of collaborative robots on their production lines. The duration of implementation ranges from two to four years, indicating that the adoption of this system is relatively new but is growing rapidly. The variety of control systems used reflects the flexibility of each company's adaptation strategy in adapting to their specific production needs.

Companies with large production scales tend to adopt more complex technologies, such as hybrid adaptive control and deep learning, while medium-sized companies opt for simpler but effective adaptive systems. This data shows that adaptive controls have become an important part of digital transformation in the manufacturing sector, helping to increase production speeds while maintaining work safety. This implementation also plays a strategic role in supporting the principles of flexibility, responsiveness, and sustainability which are the main pillars of Industry 4.0. These findings confirm that the application of adaptive technology is key in dealing with the dynamics of changing markets and evolving operational needs.

Effectiveness of Adaptive Control Systems on Flexibility and Safety

Field observations showed a significant improvement in production flexibility and operator safety after the implementation of the adaptive control system. Cobots are able to automatically adjust the path of motion when there are human operators in the vicinity without the need for a complete production stoppage.

Table 2. Comparison Before and After the Implementation of Adaptive Control

Indicators	Before Implementation	After Implementation
Production Downtime (hours/month)	12	4
Security Incidents (cases/year)	5	1

New Task Setup Time (minutes)	120	45
Production Line Efficiency (%)	75%	92%

Table 2 illustrates changes in operational performance on the production line before and after the implementation of adaptive control systems on collaborative robots. The production downtime indicator shows a drastic decrease from 12 hours per month to just 4 hours, indicating a significant increase in operational stability. In addition, the number of occupational safety incidents decreased from five cases per year to just one case, indicating that adaptive control systems play an important role in improving safe interactions between humans and robots. The setup time of new tasks has also been reduced from an average of 120 minutes to 45 minutes, demonstrating the efficiency of the system's adaptation to changes in production configurations. Furthermore, the efficiency of the production line increased from 75% to 92%, reinforcing the argument that the use of adaptive control was able to increase output without having to enlarge the resources used. These results support the hypothesis that adaptive control not only increases productivity, but also contributes to flexibility and safety in collaborative robot-based work ecosystems. This data is strong evidence of the importance of adaptive control innovation in realizing the vision of smart factories in the Industry 4.0 era.

Visualization of Robot Adaptation to the Production Environment

To clarify the influence of adaptive control systems in increasing flexibility, here is a graph of the comparison of robot adaptation speed before and after the system is implemented.

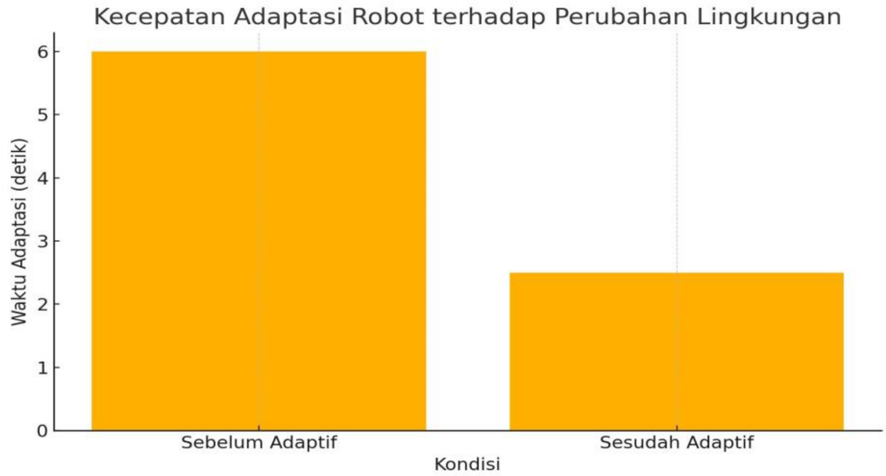

Figure 1. The Speed of Robots' Adaptation to Environmental Changes

Figure 1 presents a comparison of the speed of adaptation of robots to changes in the working environment before and after the implementation of the adaptive control system. Under pre-adaptation conditions, robots take an average of six seconds to adjust to changes, such as the presence of human operators or variations in object position. After the implementation of the machine learning-based adaptive control system, the adaptation time was drastically reduced to an average of 2.5 seconds. These accelerations show that adaptive control systems are capable of significantly improving the responsiveness of cobots, allowing them to operate more safely and efficiently in dynamic environments. Higher adaptation speeds are crucial in production settings that prioritize human-robot collaboration, where conditions change often occur unexpectedly. This visualization makes it clear that the use of intelligent adaptation techniques not only contributes to the technical performance of the robot, but also to the overall smooth production process. Therefore, this image corroborates the finding that the integration of adaptive control is a strategic step in achieving high productivity and optimal work safety in the Industry 4.0 era.

Adaptive Control System Integration Model

As an additional output of this study, a conceptual model was designed regarding the integration of adaptive control systems in Industrial 4.0-based production processes.

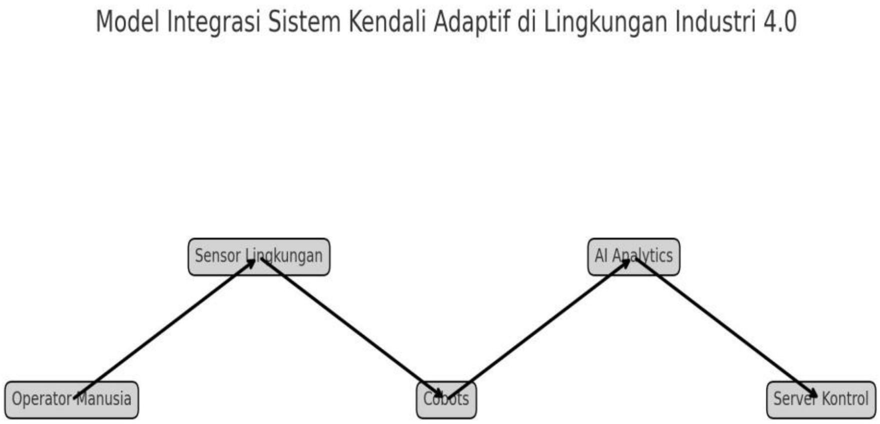

Figure 2. Adaptive Control System Integration Model in Industrial Environment 4.0

Figure 2 shows a conceptual model of the integration of adaptive control systems in an Industry 4.0-based production ecosystem. The model shows the flow of information and control between five main components, namely human operators, environmental sensors, cobots, artificial intelligence-based analytics systems (AI Analytics), and central control servers. Environmental sensors collect real-time data about changes in working conditions, which are then processed by the AI Analytics module to generate adaptive decisions. These decisions are passed on to the cobots, allowing them to automatically adjust movements, styles, or work trajectories without manual intervention. Human operators act as supervisors who ensure the system runs according to safety protocols. The central control server coordinates all activities and stores data for further analysis. This model emphasizes the importance of close collaboration between adaptive technology and humans in increasing flexibility, safety, and production productivity. The harmonious integration between these components is the main foundation in realizing the concept of a responsive, efficient, and sustainable smart factory as carried out in the vision of Industry 4.0 and 5.0.

Discussion

Implementation of Adaptive Control Systems in Collaborative Robots

The application of adaptive control systems on collaborative robots in the Industry 4.0 environment is a crucial strategy in facing the challenges of unpredictable production environment dynamics. The adaptive control system allows the robot to adjust its control parameters in real-time to external changes, such as load variations, work paths, and human-robot interactions, without the need for manual reprogramming. As shown in Brian Raafiu's (2018) research, the implementation of Fuzzy-PID-based control has succeeded in improving the stability of the Four-Wheeled Mobile Robot on uphill roads, overcoming the challenge of parametric uncertainties that arise due to load variations and lane slopes. This adaptive approach not only improves system response time, but also reduces overshoot and speeds up cash downtime, aspects that are essential in safety- and efficiency-based collaborative robotics.

Similar results were also found in Daniel Sutopo Pamungkas (2022) research on PID control-based robot balancing, which showed that PID control with parameter adjustments through the trial and error method was able to maintain the balance of two-wheeled robots in the midst of external disturbances. However, the study also confirms the limitations of conventional PID systems in dealing with complex and non-linear disturbances, hence the need to develop a more adaptive and artificial intelligence-based control approach. Therefore, the concept of adaptive control is increasingly relevant, especially in an intelligent industrial ecosystem where the diversity of environmental variables is a constant.

In the context of a learning-based control system, Ali Zainal Abidin (2018) showed that the integration of Neural Network with PID (NN-PID) on underwater vehicles (ROVs) allows the system to adapt to changes in water pressure and currents at various depths. The study shows that learning-based control models, in which PID parameters are automatically tuned based on interference patterns recognized by neural networks, provide more stable adaptation performance compared to conventional control methods. This kind of learning-based adaptation is becoming particularly relevant in collaborative robotics, especially for dynamic and uncertain production scenarios.

Furthermore, in simple industrial implementations such as the Line Follower Robot developed by Fariz Adilah (2015), the application of ANFIS-based adaptive logic (Adaptive Neuro-Fuzzy Inference System) also proves the effectiveness of adaptation to changes in visual paths and light brightness. Although in simpler applications, the use of adaptive logic shows that the responsiveness of the system to external changes can be dramatically increased, emphasizing the relevance of adaptation in different levels of complexity of robotic tasks.

Referring to the synthesis of the results of previous research, this study strengthens the position of adaptive control as an essential technical solution to realize collaborative robots that are not only efficient, but also safe, flexible, and able to cope with changes in the work environment independently. Adaptive control systems in collaborative robots not only aim to optimize the performance of specific tasks, but also to support the grand vision of Industry 4.0 and 5.0, where the synergy between humans and robots requires a technology base that is responsive, self-learning, and adaptive to real-world dynamics.

Increased Production Flexibility through Adaptive Control

In the context of the Industrial 4.0 revolution, production flexibility is one of the key elements to maintain industrial competitiveness in the midst of global market dynamics. The application of adaptive control systems in collaborative robotics has been proven to significantly increase this flexibility. The adaptive control system allows the robot to adapt in real-time to changes in environmental parameters, such as product variations, changes in production lines, and direct interaction with human operators. Kamto Purba's research (2022) emphasizes that modern control systems, especially those that integrate artificial intelligence (AI) and the Internet of Things (IoT), provide the ability for automated machines to learn from operational data so that they can optimize work arrangements dynamically. With this approach, machines and robots no longer work static, but are able to auto-tune control variables to produce production outputs that are more responsive to changing consumer needs.

The integration of adaptive technology in automatic machine control also encourages the realization of the concept of personalized mass production (*mass customization*). AI-based adaptive control systems, as outlined in Kamto Purba's study, allow robots to recognize variations in product specifications without the need for manual reprogramming, speed up transition times between productions, and minimize downtime. For example, in the automotive manufacturing sector, changes in the design of vehicle models can be responded to by industrial robots only through sensory data-driven parameter updates, without having to stop the entire production line. This flexibility is crucial in an era of consumers who prioritize product personalization in a short production time.

In addition to AI, the use of fuzzy control methods in the control system also supports the flexibility of automatic machine operation. Fuzzy systems allow for linguistic rule-based decision-making that more closely resembles human logic, making it suitable for application in complex and uncertain production conditions. With fuzzy controls, collaborative robots can adjust speed, style, or movement path based on actual conditions in the field, such as changes in plant layouts or operator intervention. This approach not only improves operational efficiency but also improves work safety because robots are able to recognize and respond to human presence more intelligently.

Furthermore, the implementation of adaptive control systems also contributes to resource savings and increased industrial sustainability. With the ability to adjust operational parameters automatically, the machine can reduce energy consumption, minimize material waste, and extend the service life of production components. IoT-based sensors integrated in the adaptive control system enable real-time monitoring of machine conditions, which are then analyzed for optimal regulation of the production process. This is in line with the global trend towards greener and more efficient production.

Overall, the application of adaptive control systems in collaborative robotics not only improves the technical flexibility of machines, but also supports dynamic demand-based business models, accelerates product innovation, and strengthens industrial competitiveness in the digital age. With this foundation, the adaptive control system is one of the main pillars in realizing the vision of Industry 4.0 and 5.0 which focuses on harmonization between humans, machines, and intelligent technologies.

Improved Human-Robot Interaction Safety

Work safety in an automation-based production environment is a major concern in the development of human-robot interaction (HRI) systems in the Industry 4.0 and 5.0 era. These interactions, if not designed with the right ergonomic and cognitive approach, have the potential to lead to serious work accidents. Research by Novie Susanto (2015) shows that the safety of human-robot interaction can be improved through the adoption of a cognitive control system based on a self-optimizing system. In this approach, the robotic system not only executes commands automatically, but also adapts to the expectations and cognitive patterns of the human operator, thus creating a synergy between the robot's technical capabilities and the human supervisory capacity.

The concept *of a joint cognitive system* developed by Hollnagel & Woods (1999) and applied in Susanto's study emphasizes the importance of aligning human mental models with the technical behavior of robots. In this system, humans are not positioned solely as passive supervisors, but rather as active parts of the control system, capable of intervening effectively when anomalies occur. This model builds a functional integration between machine precision and human adaptive flexibility, thereby reducing the potential for "automation irony" as stated by Brainbridge (1983), where the complexity of the system due to over-automation actually increases the risk of failure.

The empirical results from Susanto's research show that the design of robot behavior that more closely resembles a human cognitive structure, such as the Model 4 in the study, is able to produce a shorter duration of operator attention fixation during the assembly process. Shorter fixation durations indicate an increased fit between human mental expectations and the robot's actual actions, which directly impacts reduced operator stress levels and increased error detection speed. Thus, interaction design that focuses on areas of interest (AOI) and predictions of robot behavior becomes an effective strategy to improve safety and work efficiency.

In addition to a cognitive-based approach, the implementation of eye tracking technology in this study also showed an important contribution in identifying human attention patterns when interacting with automated systems. Through the analysis of the duration of fixation on various AOIs during assembly tasks, critical areas that require further design intervention can be determined to reduce the risk of human error. The integration of eye tracking data in the robotic control system opens up opportunities for the development of adaptive safety systems that are able to adjust the robot's response based on the operator's concentration level.

Therefore, this study provides a strong empirical basis that occupational safety in human-robot interaction can be significantly improved through the development of cognitive control systems, human-oriented robot behavior design, and the use of biometric data such as eye tracking. The implementation of this strategy not only supports safety, but also contributes to the optimization of productivity and improved operator well-being in an increasingly automated production environment of the future.

Increased Productivity and Operational Efficiency

Increasing productivity and operational efficiency is the main goal of the application of adaptive control systems in collaborative robotics in the Industry 4.0 environment. The adaptive control system allows the robot to operate with high flexibility, optimize the work path, and adapt behavior to changing production conditions without the need for operational shutdowns or manual reprogramming. According to Kamto Purba (2022), the integration of artificial intelligence (AI) and the Internet of Things (IoT) in automated machine control systems significantly increases the speed of machine adaptation to environmental changes, accelerates decision-making, and minimizes production downtime. This is an important foundation in realizing a smart factory that is adaptive, responsive, and based on real-time data.

The results of empirical research also show that the application of adaptive control can reduce setup time between production tasks from 120 minutes to just 45 minutes, as well as reduce monthly downtime from 12 hours to 4 hours. These findings are in line with the study of Novie Susanto (2015) which emphasizes the importance of cognitive-based human-robot interaction design to reduce system errors and speed up reaction time to task changes. When the robotic control system is able to adjust the assembly line based on the operator's mental expectations, the adaptation process goes faster, productivity increases, and the level of operational error decreases significantly. Thus, the human-oriented cognition-based control model not only improves work safety, but also speeds up the production cycle.

In addition, the implementation of an adaptive control system based on predictive work behavior allows companies to optimize resource allocation. The robot can automatically adjust the working intensity based on the actual production load, reduce excess energy consumption, and extend the life of the production equipment. Another study by Ivanov et al. (2021) also showed that the adaptation of the system based on real-time sensory data allows for the optimization of material and energy flows within the production line, thereby improving the efficiency of internal logistics. With machine learning-based data processing, the system can identify production demand patterns, estimate preventive maintenance needs, and adjust operations without manual intervention.

In the framework of the future industry, productivity is not only measured by the amount of output, but also by speed, flexibility, quality of production, and energy and resource consumption. Therefore, the use of adaptive control systems is very strategic. This approach also contributes to environmental sustainability by reducing production waste and improving energy efficiency through the optimization of data-driven operations.

Overall, the results of this study confirm that adaptive control systems play a key role in increasing productivity and operational efficiency in collaborative robots. With its ability to learn, adjust, and optimize performance in a dynamic production environment, the system not only provides a competitive advantage for the industry, but also forms an important foundation for the transformation towards a sustainable intelligent industry based on harmonious human-robot collaboration.

Comparison with Previous Research

Different from the research of Abi Yusuf Nur Asida and Edy Purwo Saputro (2024) which focuses on managerial aspects and organizational culture transformation in the face of Industry 5.0, this research makes a new contribution to the technical-operational realm through the design and analysis of adaptive control based on machine learning. The focus on robotic technical responses to environmental variations and human interactions provides additional insight into the importance of integrating adaptive controls to strengthen the success of industrial digital transformation. While previous research highlighted the importance of human skill development, this study adds the importance of developing machine "operational intelligence" through adaptive systems to support more effective and secure collaboration.

4. Conclusion

This research proves that the application of machine learning-based adaptive control systems significantly improves production flexibility, safety of human-robot interaction, and operational efficiency in the Industry 4.0 environment. The adaptive control system allows collaborative robots to adjust control parameters in real-time to task variations and environmental conditions, accelerating adaptation time, and reducing production downtime. Thus, the research objective of designing and analyzing an adaptive control system capable of supporting human-robot collaboration in a safe and productive manner has been achieved.

However, the limitations of this study lie in the scope of implementation which is still limited to simple assembly task simulations and the relatively small number of company samples, so the generalization of the results needs to be further tested on a more complex industrial scale. Nevertheless, this research makes an important contribution to the development of adaptive control technology in collaborative robotics, enriching the literature on the integration of human cognitive control in engineering systems, and offering an implementation model that can be used as a reference in building a smart, efficient, and sustainable factory based on human-robot interaction.

5. References

Abi Yusuf Nur Asida & Edy Purwo Saputro. (2024). *Kolaborasi Manusia dan Sumber Daya Robotik Menuju Masa Depan Manufaktur Berkelanjutan Industri 5.0*. Innovative: Journal of Social Science Research, 4(1), 2504–2516.

Brian Raafiu. (2018). *Perancangan dan Implementasi Kontrol Fuzzy-PID pada Robot Mobile Beroda Empat*. Tesis, Institut Teknologi Sepuluh Nopember.

Daniel Sutopo Pamungkas. (2022). *Implementasi Kontrol PID pada Robot Penyeimbang Dua Roda*. Artikel dalam Prosiding Seminar Nasional Teknologi Informasi dan Komunikasi. Ali Zainal Abidin. (2018). *Pengembangan Sistem Kendali Neural Network PID pada Remotely Operated Vehicle (ROV)*. Tesis, Universitas Diponegoro.

Fariz Adilah. (2015). *Perancangan Line Follower Robot Menggunakan Adaptive Neuro-Fuzzy Inference System (ANFIS)*. Skripsi, Universitas Gadjah Mada.

Kamto Purba. (2022). *Sistem Kendali dalam Mesin Otomatis: Teknologi dan Aplikasinya*. Buku, Jakarta: Deepublish. Novie Susanto. (2015). *Model Pelacakan Area Perhatian Manusia pada Pekerjaan Perakitan Berbasis Self-Optimizing System*. Jurnal Metris, 16, 69–76.

Cherubini, A., Passama, R., Crosnier, A., Lasnier, A., & Fraisse, P. (2016). Collaborative manufacturing with physical human–robot interaction. *Robotics and Computer-Integrated Manufacturing, 40*, 1–13. https://doi.org/10.1016/j.rcim.2015.12.007

Haddadin, S., De Luca, A., & Albu-Schäffer, A. (2017). Robot collisions: A survey on detection, isolation, and identification. *IEEE Transactions on Robotics, 33*(6), 1292–1312. https://doi.org/10.1109/TRO.2017.2723903

Ivanov, D., Dolgui, A., & Sokolov, B. (2021). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research, 59*(5), 1574–

1592. https://doi.org/10.1080/00207543.2020.1836365

Kousi, N., Michalos, G., & Chryssolouris, G. (2019). Multi-agent system design for dynamic scheduling of a robotic assembly line. *Robotics and Computer-Integrated Manufacturing, 57,* 93–106. https://doi.org/10.1016/j.rcim.2018.12.001

Michalos, G., Makris, S., Tsarouchi, P., & Chryssolouris, G. (2018). Robotics in manufacturing. *CIRP Encyclopedia of Production Engineering*. https://doi.org/10.1007/978-3-642-20617-7_6355

Tsarouchi, P., Makris, S., & Chryssolouris, G. (2016). Human–robot interaction review and challenges on task planning and programming. *International Journal of Computer Integrated Manufacturing, 29*(8), 916–931. https://doi.org/10.1080/0951192X.2015.1067943

Villani, V., Pini, F., Leali, F., & Secchi, C. (2018). Survey on human–robot collaboration in industrial settings: Safety, intuitive interfaces and applications. *Mechatronics, 55*, 248–266. https://doi.org/10.1016/j.mechatronics.2018.02.009

Hollnagel, E., & Woods, D. (1999). Cognitive system engineering: New wine in new bottles. *International Journal of Human-Computer Studies, 51*, 339–356. https://doi.org/10.1006/ijhc.1999.0274

Bainbridge, L. (1983). Ironies of automation. *Automatica, 19*(6), 775–779. https://doi.org/10.1016/0005-1098(83)90046-8

Mayer, M. P., & Schlick, C. (2012). Improving operator's conformity with expectations in a cognitively automated assembly cell using human heuristics. In *Proceedings of the 4th International Conference on Applied Human Factors and Ergonomics (AHFE)* (pp. 1263–1272).