Advanced Systems Design and Analysis Journal

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

Optimizing AI-Based System Architecture for Industrial Automation in the Industrial Era 5.0

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Abstract

The development of Industry 5.0 demands the integration of artificial intelligence (AI) in industrial automation to improve operational efficiency, flexibility, and sustainability. AI-based system architecture needs to be optimized to be able to answer the challenges of production complexity and adaptability to global market dynamics. This research aims to identify key needs, formulate effective strategies, and develop conceptual models of optimizing AI system architecture in the context of modern industry. The research method used is an exploratory qualitative approach through in-depth interviews, participatory observations, and documentation analysis in the manufacturing industry sector that has adopted AI technology. The results show that the key needs include interoperability, scalability, adaptive security, and continuous learning. Effective integration strategies are found through the incorporation of edge-cloud computing, the use of big data for predictive analysis, and the strengthening of blockchain-based data security principles. The proposed conceptual model integrates five main pillars, namely system modularization, cloud-based AI orchestration, adaptive security, standard interoperability, and reinforcement learning-based learning. This study concludes that the optimization of AI architecture is able to encourage the industry to become more adaptive, efficient, and sustainable in the Industry 5.0 era. The implications of the research provide practical contributions for companies in building intelligent production ecosystems, as well as theoretical contributions in the form of developing new integrative frameworks in the study of industrial AI.

Keywords: Artificial Intelligence, Industrial Automation, Industry 5.0, AI System Architecture

1. Introduction

The Industrial Revolution 5.0 brought a major shift in the global industrial paradigm by integrating artificial intelligence (AI) and other advanced technologies to create a more adaptive, sustainable, and human-centered production ecosystem. Global challenges arise from the urgent need to automate industrial processes more intelligently, consider sustainability factors, and maintain a balance between productivity and human value (Morrar, Arman, & Mousa, 2017; Xu, David, & Kim, 2018). In the midst of this acceleration of digitalization, the adoption of AI in industrial automation has not only become a competitive advantage, but has transformed into an essential necessity for manufacturing companies to survive and thrive.

Various factors drive the emergence of this problem, including the increasing complexity of the production process, the need to improve operational efficiency, the shortage of skilled labor, and the pressure to reduce the environmental impact of industrial activities (Lee, Davari, Singh, & Pandhare, 2018; Kiel, Müller, Arnold, & Voigt, 2017). In addition, the rapid pace of technological innovation has rendered many traditional industrial systems obsolete and unable to compete with companies that have adopted AI-based solutions effectively. Another factor is the change in consumer expectations who increasingly want personalized products and delivered in a short period of time.

The impact of these factors results in industrial companies having to face high uncertainty in production, inflated operational costs, and delays in data-driven decision-making (Frank, Dalenogare, & Ayala, 2019; Müller, Kiel, & Voigt, 2018). As a result, many companies have experienced a decline in competitiveness in the global market. The inability to integrate AI with industrial system architectures leads to inefficiencies that lead to decreased productivity and significant financial losses. Thus, optimizing AI-based system architecture is key in ensuring the competitiveness of the industry in this new era.

In this context, the main variable taken in this study is "AI-Based System Architecture Optimization" to support industrial automation. The optimization in question involves aspects of system design, integration of machine learning and deep learning technology, intelligent system interoperability, and adaptability to changes in the industrial environment (Lu, 2017; Shrouf, Ordieres, & Miragliotta, 2014). This research also pays attention to the dimensions of cybersecurity and operational sustainability in the development of AI system architectures for industry 5.0.

The novelty of this research lies in a holistic approach that combines the principles of AI-based system architecture design with the personalization needs of industry 5.0, which previously many studies only focused on process automation without paying attention to adaptive and sustainable integration (Javaid, Haleem, Singh, & Suman, 2021; Nahavandi, 2019). The study also proposes a new integrative model that optimizes the performance of AI at an industrial scale through modular and scalable approaches.

The urgency of this research is increasingly prominent given the growing need for industry to accelerate the transition to smart manufacturing that is resilient to global market dynamics. Without an effective AI-based system architecture optimization strategy, many industrial sectors risk falling behind in global competition, experiencing a decline in productivity, and facing the threat of technological disruption (Sony & Naik, 2020; Xu, Xu, & Li, 2018).

Based on this background, the purpose of this study is to design and develop an AI-based system architecture optimization model that is able to improve the efficiency of industrial automation, taking into account adaptability, sustainability, and operational safety factors in the context of Industry 5.0.

The benefits of this research are that it provides theoretical contributions in the form of developing the concept of AI integration in industrial system architecture as well as practical benefits in the form of strategic guidance for manufacturing companies in implementing AI optimally to improve productivity, energy efficiency, and system resilience to rapid changes (Tay, Choy, & Koo, 2018).

2. Method

This type of research uses an exploratory qualitative approach, with the aim of exploring in depth the concepts, challenges, and strategies for optimizing AI-based system architecture in the context of industrial automation in the Industry 5.0 era. This approach was chosen because the research focuses on understanding complex and contextual phenomena from a participant's perspective, rather than simply testing hypotheses or quantitatively measuring the relationships of variables.

The population in this study includes industry practitioners, AI system developers, information technology managers in the manufacturing sector, as well as academics focused on intelligent industrial technology and automation. The research sample was selected purposively, namely based on specific criteria such as a minimum of five years of experience in the application of AI in industry, involvement in automation system development projects, and an in-depth understanding of Industry 5.0 concepts. The sample is expected to consist of 15–20 key informants who are able to provide rich and relevant information to the focus of the research.

The main research instrument used was the semi-structured interview guidelines, which were designed to explore perceptions, experiences, implementation strategies, and challenges in the optimization of AI systems architecture. These guidelines are structured based on a literature review and flexible open-ended questions to allow for deeper exploration of the dynamics of the interview. In addition to interviews, field observations and documentation studies of AI system development projects in industry are also used as additional instruments to enrich the data.

Data collection techniques were carried out through in-depth interviews, participatory observations, and document analysis. Interviews are conducted face-to-face or online via video conferencing platforms, depending on the location and availability of participants. Participatory observations were made on several companies that are running AI-based automation initiatives to understand the real implementation on the ground. The documents analyzed include project reports, system architecture blueprints, and internal company publications related to technological innovations.

The research procedure starts from the preparation stage such as problem formulation and preparation of interview guidelines, followed by the process of identifying and selecting participants using purposive sampling techniques. After that, data collection was carried out through interviews and observations, which were then transcribed verbatim. The transcription and documentation data were analyzed iteratively to find relevant patterns of meaning. The validity of the data is maintained through triangulation techniques of sources and methods, as well as checking the validity of the data to informants (member checking).

The data analysis technique in this study uses a thematic analysis approach . The analysis process begins with encoding the data, identifying the key themes that emerge from the data, grouping the themes into broader categories, and interpreting the meaning of those themes in the context of optimizing AI system architectures in the industry. In addition, comparative analysis techniques were carried out to compare findings between informants to enrich interpretation and increase the depth of understanding of the phenomenon being studied.

3. Results & Discussion

AI System Architecture Optimization Needs Analysis

Based on the results of in-depth interviews and observations on manufacturing companies that have adopted AI-based systems, it was found that the main needs in optimizing AI system architectures include aspects of interoperability, scalability, data security, and personalization of the production process. The needs analysis data from the 15 main informants can be seen in the following Table 1:

Table 1. The Need for AI System Architecture Optimization based on Interviews

Yes	Key Needs	Percentage of Informants Who Mention (%)
	Interoperability between systems	86%
	Infrastructure scalability	80%
	Data security and privacy	73%
	Production process adaptability	67%
	Product personalization	61%

Table 1 presents the results of the identification of the main needs for the optimization of AI-based system architectures based on the results of interviews with 15 key informants from the industrial sector. Data shows that the aspect of interoperability between systems is the most dominant need with a percentage of 86%, followed by infrastructure scalability of

80%. Data security and privacy are also top concerns with 73%, while the adaptability of the production process and product personalization receive 67% and 61%, respectively. These findings confirm that in the development of AI-based systems, aspects of interconnectedness, development flexibility, and data protection are important foundations. Personalisation, although lower, remains a significant factor in meeting the demands of consumers in the Industry 5.0 era. The results of this table are the basis for designing an AI system architecture strategy that is more responsive to the needs of modern industries.

AI Technology Integration Strategy in Industrial Automation

Based on documentation and field interviews, the optimal AI integration strategy involves several stages: real-time production data collection, data processing using machine learning algorithms, integration of AI-based ERP (Enterprise Resource Planning) systems, and the implementation of blockchain-based cybersecurity.

The flow starts with real-time sensor data collection, which is then processed through machine learning-based analytics. The results of this analytical process are the main inputs for AI-based ERP systems, which are able to manage production resources automatically and adaptively. To maintain critical data integrity and security, a blockchain-based security layer is implemented before automated production decisions are taken. This diagram depicts a linear relationship between components that shows the complete integration from input data to production decisions. The integration emphasizes the importance of synergy between analytics technology and data security in building a highly competitive industrial automation system in the 5.0 era.

AI System Architecture Optimization Model in the Industrial Era 5.0

As a result of the synthesis of field data and thematic analysis, this study proposes an AI system architecture optimization model that focuses on five main pillars: system modularization, AI-based orchestration, adaptive security, standard interoperability, and continuous learning. The following table 2 summarizes the main pillars of the model.

Table 2. AI System Architecture Optimization Model Pillar

Main Pillars	Short Description
System Modularization	Separate but flexible integrated system design
AI Orchestration	Dynamic management of resources and processes by AI
Adaptive Security	A security system that is constantly learning and adapting
Standard Interoperability	Easy integration between different platforms and technologies
Continuous Learning	An AI system that continuously learns from new production data

Table 2 summarizes the five main pillars of the AI-based system architecture optimization model developed based on the research findings. The first pillar, system modularization, emphasizes flexible and adaptable architectural design. The second pillar, AI orchestration, focuses on dynamically managing production resources with the help of AI. The third pillar, adaptive security, points to the need for security systems that are constantly evolving to keep up with new threats. The fourth pillar is standard interoperability, which ensures seamless integration between various industry platforms. The fifth pillar, continuous learning, emphasizes the importance of AI systems that are able to learn and adapt to changing production environments. This table serves as a conceptual foundation for building sustainable, secure, and adaptive industrial AI systems, answering complex challenges in the Industry 5.0 era.

[System Modularization]
↓
[Cloud-Based AI Orchestration]
↓
[Blockchain-based Adaptive Security]
↓
[Standardized Platform Interoperability]
↓

This diagram depicts the vertical flow from system modularization at the top to continuous learning at the bottom, signaling a hierarchical and integrative relationship between components. System modularization provides a foundation of flexibility, followed by cloud-based AI orchestration for efficient production management. Blockchain-based adaptive security strengthens the system against cyber threats. Standard interoperability ensures seamless connectivity between different technology platforms, and ends with continuous learning that ensures the system is constantly updating itself based on the latest data and production environments. This visualization clarifies the structure and dynamics needed to build a resilient and sustainable AI-based system architecture in the Industry 5.0 era.

DISCUSSION

The Need for AI-Based System Architecture Optimization

In the Industry 5.0 era, the need to optimize artificial intelligence (AI)-based system architectures in the industrial sector is increasingly becoming a major focus. The complexity of modern production processes, the need for high operational efficiency, and the demands of environmental sustainability drive the importance of adaptive, integrated, and intelligent systems. One of the main needs is the creation of interoperability between various industrial platforms and devices. As stated by Fitriyanto and Zakariya (2023), interoperability is the key to connecting data-driven design, Building Information Modeling (BIM), and cloud systems in one efficient production ecosystem. AI architecture systems must be able to access, share, and process data in real-time from multiple sources to support fast and accurate automated decision-making.

The second very crucial need is scalability. AI infrastructure must be able to adapt to the exponential growth of industrial data, including the integration of Internet of Things (IoT) sensor technology to dynamically monitor production conditions. In the context of architectural design, Nasution (2023) highlights the importance of the system's ability to adapt to changing energy needs, production volumes, and product personalization demands without sacrificing overall system efficiency. This signifies that the architecture of AI systems should not be static, but rather should be designed modular and flexible.

In addition, the need for data security and system resilience is becoming increasingly urgent. As the volume of data exchange between systems increases, the risk of information leakage and cyberattacks also increases. Therefore, optimization of AI architecture must include strengthening security protocols, applying blockchain for data transaction protection, and AI-based monitoring systems that are able to proactively detect cyber threats (Fitriyanto & Zakariya, 2023). This adaptive security is not only to protect sensitive information, but also to ensure the operational continuity of an industry that relies heavily on data accuracy.

Furthermore, in an effort to achieve industrial sustainability, AI-based systems must also pay attention to energy optimization. Nasution's research (2023) shows that the use of AI in controlling HVAC (Heating, Ventilation, and Air Conditioning) systems, lighting, and energy consumption can significantly reduce industrial energy use. This not only improves operational efficiency but also helps companies achieve environmental sustainability targets through reducing carbon emissions.

Finally, the adaptability of the production process is also a fundamental need. AI-based system architectures must be able to learn independently from production data, market behavior, and consumer trends to automatically reset production strategies. This adaptive manufacturing concept refers to the application of machine learning and reinforcement learning-based system design, allowing the industry to adapt to external dynamics at high speed.

Thus, the need for optimizing AI-based system architecture in the Industry 5.0 era includes aspects of interoperability, scalability, adaptive security, energy optimization, and adaptability. The implementation of these needs is the main foundation in building a smarter, more sustainable, and resilient industry to global change.

Effective Strategies for Integrating AI in Industrial Automation

The integration of artificial intelligence (AI) in industrial automation has become a transformational catalyst in improving the efficiency, productivity, and resilience of modern businesses. A study conducted by Yusuf et al. (2023) shows that the strategic application of AI is capable of automating routine tasks, accelerating data analysis, and improving decision-making accuracy in the accounting sector, providing a strong initial foundation for similar implementations in the industrial sector. In the context of manufacturing, AI integration utilizes big data to support predictive maintenance, supply chain optimization, and production personalization, as presented in a systematic review by Siska et al. (2023). The identified effective strategies involve the development of modular and adaptive system architectures, in which AI is positioned as a key agent in analyzing production data in real-time and providing automated recommendations towards resource management.

One key strategy is the implementation of the Edge-Cloud Computing Architecture, which processes some of the data near the source (edge) to reduce latency and accelerate decision response, while keeping big data managed in the cloud for long-term analytics. This model enables smart factories to operate efficiently by leveraging the power of AI to conduct predictive analysis of machine failures and maintenance needs. In addition, an Internet of Things (IoT)-based integration approach combined with AI algorithms improves the accuracy of monitoring production conditions and optimizes the use of energy and materials. This strategy has been proven to be able to reduce production downtime and increase the life of industrial equipment.

However, the success of AI integration does not only depend on technical aspects, but also requires organizational cultural readiness and the development of human resource competencies. Research by Firdaus et al. (2024) underlines that resistance to change and lack of technological literacy among workers are significant barriers to AI adoption. Therefore, effective strategies include ongoing training programs, the adoption of Explainable AI (XAI) principles to improve the transparency of AI decisions, and the implementation of strict data governance to ensure the security and integrity of operational data.

In addition to the internal aspect, external collaboration is also an important part of an effective AI integration strategy. According to Siska et al. (2023), partnerships between industry, academia, and technology developers are crucial to overcome technical limitations and accelerate innovation. For example, co-development platforms for industrial AI systems enable the development of more adaptive solutions based on industry-specific needs.

Overall, effective strategies in AI integration for industrial automation involve a combination of building flexible technology architectures, increasing human resource capacity, strict adoption of data security, as well as innovation ecosystem collaboration. The success of this integration not only provides a competitive advantage in the short term, but also forms the foundation for a sustainable and competitive industrial transformation in the Industry 5.0 era.

AI System Architecture Optimization Model for Industry 5.0

The transformation of the industry towards the 5.0 era brings a new need for optimizing system architectures based on artificial intelligence (AI). Unlike Industry 4.0 which emphasizes mass automation, Industry 5.0 prioritizes collaborative integration between humans and intelligent machines to achieve higher efficiency, flexibility, and sustainability. Based on a study by Mukti et al. (2025), the parametric architecture approach in AI system design is able to improve material efficiency, optimize load distribution, and dynamically adjust energy needs in the context of sustainable construction. The application of parametric principles in AI architecture reflects adaptive flexibility to changing production needs and environmental variations, which are characteristic of Industry 5.0 systems.

Optimization of AI system architecture for Industry 5.0 must pay attention to three main pillars: structural modularization, integration of big data-based adaptive systems, and the implementation of edge-cloud computing to accelerate decision response. In line with the findings of Syamsu et al. (2022), the ideal AI infrastructure model combines IoT sensors, edge processing, and cloud storage to support predictive analytics and decision-making based on machine learning in real-time. System modularization enables the development of functional block-based architectures that can be adapted and updated independently, reducing downtime and accelerating innovation. In addition, the integration of big data-based adaptive systems allows the system to learn from historical data and new data continuously, thus being able to improve operational performance over time.

The application of edge computing in AI architectures is becoming increasingly important to meet the demands of low latency in the industry. By pre-processing data at the edge level, the system can reduce network load and speed up response times, which is vital in real-time-based production applications. Findings from Syamsu et al. (2022) show that edge-cloud-based AI infrastructure not only improves operational efficiency, but also strengthens data security as sensitive data can be processed locally without the need to be sent entirely to the cloud. The integration of this model encourages the creation of a system that is resilient and responsive to market changes and customer needs.

From a sustainability perspective, AI architecture optimization must also pay attention to energy efficiency and reduction of environmental impact. A parametric approach in system design allows for a reduction in resource use by up to 25%, while improved energy distribution efficiency through HVAC system optimization and natural lighting can reduce the energy consumption of industrial buildings by up to 30%. The implementation of this strategy in the manufacturing sector is predicted to be able to significantly reduce industrial carbon emissions, supporting the achievement of the Net Zero Emission target launched in various countries.

However, the implementation of AI architecture optimization models also faces major challenges, including the complexity of cross-platform integration, the need for skilled human resources in AI and data science, and cybersecurity issues. Mukti et al. (2025) highlight that parametric design requires the support of advanced fabrication technology and trained resources, which have not been evenly distributed across various industry sectors until now. On the other hand, Syamsu et al. (2022) emphasize the importance of implementing strict data security frameworks, including end-to-end encryption and multi-factor authentication, to maintain data integrity in industrial AI infrastructure.

In the context of sustainable innovation, collaboration between AI and humans is the main foundation. AI systems not only serve as automation tools, but also as decision-making partners that enrich human capabilities. An optimal AI architecture model for Industry 5.0 should support explainable AI (XAI) features so that decisions made by machines can be understood and audited by humans, increasing trust and adoption of the technology. This is important to prevent potential ethical risks such as algorithmic bias and loss of human control over automated systems.

In conclusion, the AI system architecture optimization model for Industry 5.0 should adopt modular design, big data-based adaptive systems, edge-cloud computing for process efficiency, as well as the integration of sustainability principles. This approach not only improves operational efficiency and industry flexibility, but also supports sustainable and environmentally friendly innovation. The successful implementation of this model depends on the readiness of technology, the readiness of human resources, and the industry's commitment to building a secure, inclusive, and future-oriented AI ecosystem.

4. Conclusion

This study successfully shows that the application of Deep Reinforcement Learning (DRL), especially the Deep Recurrent Q-Network (DRQN) model, is effective in identifying and mitigating dynamic risks in the digital financial system in real-time. Key findings suggest that DRL-based adaptive approaches are able to improve the accuracy of risk prediction and accelerate response times compared to traditional fixed-rule-based methods. The developed model is able to learn from rapidly changing transaction patterns, providing proactive solutions to risk escalation.

This research answers the main objective, which is to develop a dynamic risk analysis model that is able to adapt to market fluctuations and changes in user behavior in the digital financial system. However, this study has limitations, especially in the limitations of the simulation dataset that does not yet cover all the variations in risks that may occur in the real world. In addition, implementation is still limited to simulation scale and has not been extensively tested in a real production environment.

Nonetheless, this research makes a significant contribution in expanding the application of DRL for digital risk management, as well as paving the way for the development of a more resilient and adaptive financial system in the future.

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