Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 120 (2023) 87–92

www.elsevier.com/locate/procedia

56th CIRP Conference on Manufacturing Systems, CIRP CMS '23, South Africa

AI-based Reconfigurable Inspection System (RIS): Comprehensive Model and Implementation in Industry

Sarat Kumar, A.[a], Milisavljevic-Syed, J[b,*]

[a]School of Engineering, The University of Liverpool, Liverpool, L69 3GH, UK
[b]Sustainable Manufacturing Systems Centre, School of Aerospace, Transportation, and Manufacturing, Cranfield University, Cranfield, Bedfordshire MK43 0AL, UK*

* Corresponding author. *E-mail address:* j.milisavljevicsyed@cranfield.ac.uk

Abstract

Due to global competition and continuously changing customer demand, manufacturers nowadays face frequent and unpredictable market shifts. Introducing reconfigurability into contemporary manufacturing systems can enhance cost-effective and rapid responsiveness to these variations. A Reconfigurable Manufacturing System (RMS) can provide a tailored production process in response to changes in operating procedures or machine statuses. Just like any other manufacturing system, RMS requires effective and timely diagnosis as well as prognosis to function smoothly. A Reconfigurable Inspection System (RIS) is designed within an RMS for data-oriented detection of product quality with a minimum number of inspection units. Existing studies about reconfiguration, however, focus on production while disregarding inspection. Artificial Intelligence (AI) has the potential to significantly assist manufacturers over the next decade due to their heavy dependency on data. AI applications such as Machine learning (ML) and Deep Learning (DL) can aid in addressing issues such as tracking manufacturing failures back to specific phases in the manufacturing process by learning relevant data patterns. Thus, this paper aims to provide an overview of the current literature on RMS as well as ML/DL technologies that can be integrated into RIS to enhance performance. Subsequently, a comprehensive model of an AI-based RIS is proposed based on the experimental results derived from existing publications, and the retrofitting procedure of a case study is presented. However, the proposed model and the retrofitting procedure are not validated by experimental results or physical implementation.

Keywords: Artificial Intelligence; Reconfigurable Manufacturing System; Reconfigurable Inspection System; Machine Learning; Deep Learning.

1. Introduction

Modern-day manufacturing systems are required to be economical, rapid, and responsive to market conditions. Although reconfigurable manufacturing systems (RMS) have been prevalent in the industry since the 1990s, it is still a promising solution suitable for changing the industrial environment defined by global competitiveness. They are easily upgradable into new technologies that can be readily incorporated. Responsiveness of the manufacturing system has become extremely essential due to unforeseen circumstances such as pandemics, natural disasters, etc., initiating massive fluctuations in the market demand for products and thus negatively affecting businesses [25]. This resulted in the evolution of engineering design in several strategic areas such as smart and connected products, end-to-end digital integration, customization and personalization, data-driven design, digital twins and intelligent design automation, extended supply chains, and agile collaboration networks, open innovation, co-creation, and crowdsourcing for the sharing economy [1]. A well-designed RMS with an efficient inspection system can reduce costs and improve the quality of the product because of

10.1016/j.procir.2023.08.016

its adaptability, convertibility, and scalability. However, at present, certain gaps and challenges concerning the research and implementation of RMS exist. These gaps can adversely influence the industrywide commercialization of RMS. One of these gaps includes the lack of an efficient reconfigurable inspection system (RIS) for the rapid detection of defects [4,13,14]. Existing studies on the subject primarily focus on production while ignoring the inspection aspect of RMS. Nevertheless, with the rapid growth in Artificial Intelligence (AI) technologies, there is an indication that AI can be utilized to address most of these gaps, specifically inspection-related challenges [26]. Machine Learning (ML) can assist in inductively understanding relevant data patterns and relating them to processing states and performance, whereas Deep Learning (DL) aids in enabling advanced computational setup, improving the proficiency of fault diagnosis and restoration [2]. Industry 4.0 (I4) digitalization technologies provide more connection, shared data, and better analytics across the whole supply chain, resulting in higher efficiency, optimization, and innovation across the manufacturing industry in the long term [3]. Consequently, this paper aims to research and provide an overview of the current literature on RMS as well as ML/ DL technologies that can be integrated into RIS for the enhancement of performance. A comprehensive model of an Industry 4.0 (I4) and AI–based Reconfigurable Inspection System (RIS) is proposed and the retrofitting procedure of a case study is presented. However, the model and the retrofitting procedure are not validated by experimental results or physical implementation.

2. Literature Review

This section looks at the gaps hindering the commercialization of RMS following a review of existing literature on the subject. Consequently, the focus is shifted to understanding the utility of AI technologies in addressing the critical gap of defect detection. Finally, it concludes with an outlook into the proposed solution to address this gap by introducing an AI-based RIS.

2.1. Reconfigurable Manufacturing Systems (RMS)

RMS is a manufacturing system that focuses on reconfigurability, performance measures, optimal configuration selection, demand scenario, and optimization technique [4]. Malhotra et al. [5] state that an RMS must possess two major components:

- **Reconfigurable Machine Tool (RMT).** The primary goal of an RMT is to accommodate changes in the products or parts being manufactured. In contrast to traditional CNC machines, RMT are tailored to a specific customized range of operational requirements and can be cost-effectively transformed when those needs arise.
- **Reconfigurable Controller (RC).** The RC is dynamically reconfigured for a specific mechanism after the configuration system sets up appropriate operational parameters such as machine joint limits.

The adaptability, convertibility, post-implementation cost savings, improved waste management, optimum scalability, rapid responsiveness, and enhanced product quality enabled by in-line inspection equipment integrated into the production system are the advantages of such a system. The difficulties accompanying RMS include high start-up costs, the need for highly skilled operators, incompatibility with existing systems and software, the need for seamless transition systems, the need for complexity reduction, and the need for reconfigurable logical support systems [5,6,7]. Research on supporting technologies is moving at an exceptional rate and therefore the development of more advanced RMT and Reconfigurable Inspection Machines (RIM) can be observed in the future [8]. However, the following challenges facing RMS were identified during the gap analysis (shown in Table 1). With the rapid advancement of information technology, advanced manufacturing systems must be capable of autonomously detecting the present status of a production process. Process detection can guarantee that process faults are recognized in a timely way, enabling the RMS to manufacture top-quality goods [8]. This is one of the main gaps that hinder the commercialization of RMS (see Table 1). The RIS, comprised of numerous reconfigurable inspection machines, is used in an RMS to recognize product quality. As a result, effective detection is mostly dependent on sufficient RIS status data [8]. At present, there are no systematic techniques for data collection, feature selection, and sensor placement within RIS (see Aspect (4) in Table 1). Digitization and AI technologies can considerably aid manufacturing industries over the next decade due to their reliance on data. Hence. an overview of digitization and how AI technologies can be used to address the challenges associated with error detection will be provided next.

2.2. Digitization of Modern Manufacturing Systems

Digitization has emerged as one of the most popular industrial themes. Digitization offers lower manufacturing costs as well as higher flexibility—two competitive characteristics that have historically been viewed as trade-offs [19]. The Fourth Industrial Revolution is characterized by a new industrial paradigm known as Industry 4.0. This advanced manufacturing model is characterized by intelligent, virtual, and digital performance in large-scale enterprises [19]. Industry 4.0 heavily incorporates AI technologies such as ML and DL. ML may be defined as the study of computer algorithms that enable systems to automatically learn and improve based on their experiences [20]. DL, which is a sub-technology of ML uses multi-layer neural networks to interpret the input data and develop data representations with multiple levels of abstraction [20]. Subsequently, a review of a few of the existing literature will demonstrate how AI principles and technologies can be used to address the lack of efficient fault diagnosis and prognosis.

2.3. Self-Diagnosis and Self-Repair Strategies

Epureanu et al. [21] used a deep convolutional reinforcement learning network to enable an AI decision-maker to

Table 1. Gap analysis of RMS from existing publications.

Journal/ Article	Aspects	Challenges	Potential Solutions
[10]	(1) Connectivity with the market	Considering demand stochastically only gives an insight into the real market uncertainties.	Deterministic demand definition. Consideration of all characteristics for determination of RI. Neural Networks can analyse hidden patterns in raw data and categorize them to improve over time. However, there are no existing works of literature addressing this challenge.
[10]		Reconfiguration Index (RI) aids in determining a production system's readiness to transition from one configuration to the next. As of now, all six of the characteristics of an RMS are not taken into consideration while measuring RI. Therefore, more research is to be conducted to come up with performance measures that include all the characteristics as well as practical aspects of the market conditions.	
[10]	(2) Manufacturing part families	Multi-part flow configuration brings the problem closer to the practical scenario enabling simultaneous manufacturing of the whole part family, however, it becomes more complex and difficult to manage/handle.	To bridge the gap between RMS and CMS, a unique hybrid manufacturing system called Reconfigurable Cellular Manufacturing System (RCMS) was devised by [9]. Reconfigurable Manufacturing Cell (RMC) is a logical entity, as opposed to a standard manufacturing cell, which is a physical entity. Devices in an RMC are conceptually grouped rather than physically moved.
[11]		Reconfigurable manufacturing systems with group technology (GT) and RMS cellular manufacturing systems (CM) are yet to be explored.	
[12]		Approaches and methods for grouping products and assigning the optimal family to each reconfiguration step are required.	
[10]	(3) Complexity due to discrete variables.	Traditional mathematical programming approaches cannot be conveniently applied to RMS design problems.	Intelligent manufacturing approaches such as multi-agent systems, cloud manufacturing, digital manufacturing, and cyber-physical systems can improve real-time decision-making.
[13]		Traditional analytical and decision-support tools are incapable of dealing with the complexities involved, resulting in ineffective real-time decision-making.	
[4]	(4) Lack of defect detection and inspection systems.	An efficient RMS-based manufacturing process necessitates dynamic reconfiguration management for the RMS to recognize process faults and explore relevant reconfiguration solutions in a timely fashion. A reconfigurable inspection system (RIS) configuration design allows for customizable detection that is sensitive to process problems and can gather enough data to facilitate the identification of the root cause of an issue. Currently, there is a lack of effective Reconfigurable Material Handling (RMH) equipment and reconfigurable inspection machines (RIM) in the market.	A key feature-based method for designing the RIS's configuration to achieve a satisfactory RIS design, which detects different processes and satisfies the inspection requirement for each phase of the RMS's lifecycle was proposed by [8]. However, there is a dearth of current literature and industrial applications for potential solutions.
[13]		Future research is needed to construct flexible or reconfigurable condition monitoring systems capable of integrating a variety of decision-support tools such as data collection, feature selection, and sensor placement.	
[14]		The most fundamental barrier to ramp-up is a lack of systematic techniques for diagnosing component failure.	
[15]	(5) Tooling difficulties.	The creation of a mathematical framework for the synthesis and validation of reconfigurable machine tools (RMTs) is a significant task.	The construction of a formal and unified representation scheme for module mechanical functionalities followed by the compilation of a machine module library and an approach for the systematic synthesis of reconfigurable machine tools that employ screw theory for kinematics and graph theory for structural synthesis.
[16]		In certain cases, reusing manufacturing equipment for new generations of products was thought to be more difficult than developing a new and improved version of the system.	
[17]		Tooling is expensive and variety handling is difficult.	
[18]	(6) Control system.	Most control systems on the market today have a fixed structure and are only partially programmable. This renders them unsuitable for RMSs.	Multi-sensor fusion modeling employing the CAN Bus standard, as well as the use of neuro-fizzy sensors and software agents' technology in intelligent control.
[17]		Difficulty controlling a reconfigurable machine tool (RMT) with multiple tools and difficulty locating axes.	

dynamically select a strategy to deal with defective components based on configuration information and to update the repair policy based on historical system performance. When a deficient characteristic is recognized, the system interrogation operation begins by altering the operations and products to acquire data and determine the deficient stage(s). Based on the current sensor signal, Wang et al. [22] examined Naive Bayes, KNN, and Support Vector Machines (SVM) for induction motor failure diagnosis. It was demonstrated that each technique had a distinct amount of sensitivity to certain features. The authors confirmed that SVM achieved the best results in the given scenario [22]. Images have a higher information density than standard time-series data, and their utilization is beneficial in getting insight into the items being watched. Caggiano et al. [23] developed a vision system based on Deep Convolutional Neural Network (DCNN) for process fault detection in selective laser machining (SLM). Surface textures induced by different process failures may share similar local properties, and higher-level abstractions are required to differentiate different fault-related patterns effectively. Traditional ML strategies become ineffective when the relationship between deterioration time steps becomes too complex to be described by a single regression model. Zhang et al. [24] constructed a bi-directional Long Short-Term (LSTM) neural network for estimating the remaining useful life (RUL) of aircraft engines. The Health Index (HI) is made up of a single-layer neural network that fuses onboard sensing information to reflect engine performance. The bi-directional LSTM allows information to travel forward for prediction and backward for disturbance smoothing. The new strategy has been shown to improve RUL prediction accuracy when

compared to uni-directional LSTM and traditional ML algorithms such as SVM.
The content in this section indicates the requirement for a complete model that unifies the aforementioned AI features to improve diagnosis, prognosis, and responsiveness.

3. Model

Based on the AI technologies that were examined in section 2.3, a comprehensive AI-based RIS model is proposed in this section.

3.1. Proposed Model

As mentioned in the previous section, results showed that when a Gaussian RBF kernel function is combined with the SVM technique for feature extraction from a motor current envelope, accurate results can be achieved in the domain of induction motor failure diagnosis [22]. Therefore, this technique is suitable for the RIS system to identify patterns and defects during the functioning of RMS. Bi-stream DCNN is an effective method to process higher information density from image data accurately without human supervision [23]. Since DCNN significantly outperformed HoG and Visual Words in the presented circumstances, RIS can use this online fault identification technique for image-based inspection and maintenance. Additionally, for prognosis and predictive maintenance, LSTM can be used when the relationship between deterioration time steps becomes too difficult to be described by a single regression model [24]. Industry 4.0 (I4) technology aids in the management and optimization of all areas of production and supply chain operations. It provides real-time data and insights to improve productivity within the organization. Cloud storage and database charges are only given to one machine as an upfront cost, the cumulative cost decreases after one machine, as these resources are distributed between the other machines.

Consequently, we are proposing a model that incorporates SVM, DCNN, and LSTM into RIS. The majority of the model comprises SVM, DCNN, and LSTM algorithms that are built around I4-based hardware and software. Performance estimation of this AI-based RIS model is conducted based on the past performance of these AI technologies in similar manufacturing conditions from existing research work [22,23,24]. By maximizing the separation distances between the classes, SVM converts the original feature space into a higher dimensional space to identify the optimal hyperplane. Given a training data set $\vec{x} = X$ as an input, the hyperplane function can be determined by the kernel function $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ by computing the inner products without specifying the explicit form of the transformation function ϕ. If y is a kernel parameter, α and b represent an n-dimensional vector and a scalar quantity respectively (used to define the position of the separating hyperplane), then the associated decision function can be written as [22]:

$$f(\vec{x}) = \operatorname{sgn}\left(\sum_{i,j=1}^{N} y_i \alpha_i K(x_i, x_j) + b \right) \tag{1}$$

Due to its popularity and documented success in machinery condition monitoring, the Gaussian RBF kernel is implemented in this model. The kernel parameter is denoted by the symbol y. The Gaussian RBF kernel expression is written as [22]:

$$\exp\left[-\frac{\| \vec{x} - x_j \|^2}{2y^2} \right] \tag{2}$$

The bi-stream DCNN has two streams, each of which is made up of several convolutional layers. Using non-linear activation and kernel-based convolution, the features of the input image are retrieved. The mathematical equation for feature extraction is [23]:

$$z_j^1 = \phi\left(b_j^l + \sum_{i=1}^{M} z_i^{l-1} . w_{ij}^{l-1} \right) \tag{3}$$

z_j^1 is the jth feature in the lth convolutional layer, b_j^l is the corresponding bias term, M is the kernel size, w_{ij}^{l-1} is the kernel weight linking the ith point in the (l-1)th layer and the jth feature in the lth layer, $\phi(.)$ is the non-linear activation function. By traversing the image, the kernel can generate a feature map comparable to the whole image [23].

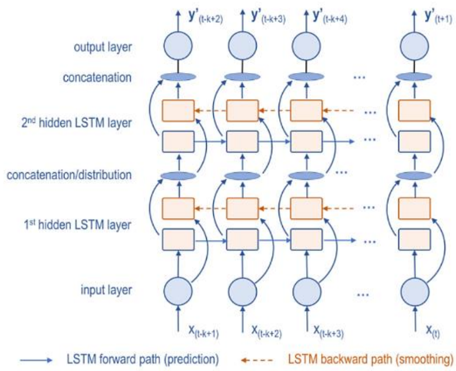

Fig. 1. Diagram of a two-layer bi-directional LSTM network [24].

Given sensing data collected from n time steps $X = [x_{(1)}, x_{(2)}, \ldots, x_{(n)}]$ and the corresponding underlying system states $Y = [y_{(1)}, y_{(2)}, \ldots, y_{(n)}]$, the functioning of a two-layer bi-directional LSTM network is depicted in Fig. 1. The time step for the recurrent neuron is indicated by the subscript in the parenthesis [24]. Access to real-time data is crucial for the efficient functioning of the model. However, purchasing and integrating new I4-ready machines is expensive and could have significant financial and logistical repercussions (see Fig. 3). As a result, the newly proposed model focuses on effectively retrofitting AI–based RIS into legacy machines (machines that have been on a production line for many years) thus forming a cost-effective RMS for financially restricted enterprises.

3.2. Six-Stage Implementation of the Model

To assess the viability and implement the model successfully based on indicators such as cost, time to reconfigure, quality, etc., a generalized six-stage implementation process is to be followed.

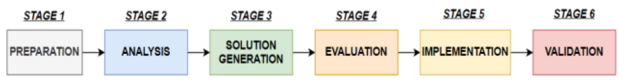

Fig. 2. Generalized six-stage implementation process of the proposed model.

Stage 1 is intended to provide the client with an opportunity to learn the basics of the I4 and AI-based RIS concepts. This stage will help the customer understand whether I4 AI-based RIS is the proper quality assurance technique to be employed. The analysis phase seeks to fully comprehend the client's current position in terms of reconfigurability, quality assurance, I4, and other competencies of the company. The information obtained in Stage 2 serves as the basis for Stage 3 when solutions to the client's problems are developed. Attention should be paid to the client criteria listed in Stage 1 to make sure the solution is suitably tailored. In Stage 4, the solutions developed in Stage 3 are weighed against each other, and additional criteria to select the optimal solution for the client. When an ideal solution inclusive of all the machines within the factory is not feasible, a combination of solutions may be utilized. The implementation stage is significantly influenced by the variations in different production contexts. The validation stage of the consulting process ensures that the I4 and AI-based RIS meets the client's initial criteria. The completed fit will be validated by comparing it to criteria encompassing technical specifications defined by the client.

4. Case Study

The chosen optimized design configuration is based on a case study from an existing research paper by Shang et al. [8]. As per the RIS configuration constraint models, which are based on detection capability and functionality, a total of 13 possible design possibilities were formulated. The solution (as shown in Fig. 3) was chosen because it had the lowest overall deviation and also because its economic cost and diagnosability were relatively balanced [8].

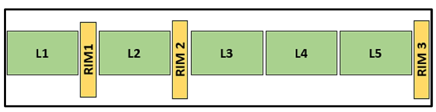

Fig. 3. Derived configuration of the five lathe machines and three RIMs involved in the case study.

The cost for upgrading and retrofitting the 5 legacy machines with AI-based RIS was found to be roughly £22016.80 (based on technical requirements for the integration of SVM, DCNN, and LSTM neural networks as well as I4 technologies), which is approximately £47720.75 cheaper than purchasing I4-ready inspection machines (see Fig. 4).

5. Results and Discussion

The foundation of the proposed model revolves around performance estimations derived from the results of previously conducted physical experiments by researchers. Thus, it can be understood that the model is structured around the key assumption that the performance and effectiveness would remain the same as proven in the existing literature. The costs that can be saved by retrofitting this model have also been presented (see Fig. 4).

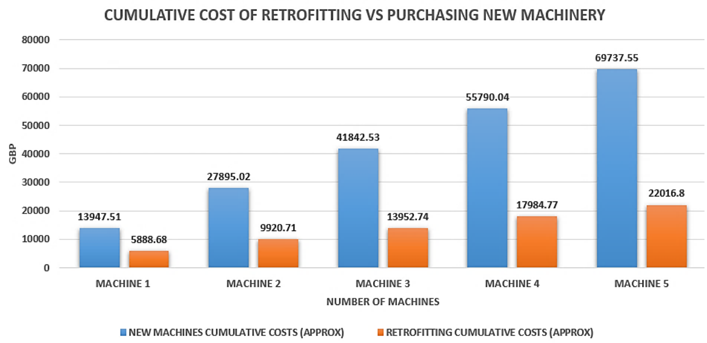

Fig. 4. – Comparison of the cumulative costs of retrofitting legacy lathe machines with I4 and AI-based RIS versus purchasing brand new I4-ready lathe machines followed by installation of RIS.

The overall cost of the proposed model is calculated by investigating the current market prices of hardware and software components required for the effective functioning of the abovementioned I4 and AI technologies from existing publications. Despite the paper's limitations, the most prominent one being the availability of limited literature on RIS and retrofitting as well as the lack of information from actual case studies rather than hypothetical ones, an effective model was proposed; however, the paper's weaknesses originate from the fact that the work described is theoretical and has not been validated by the actual implementation. Therefore, the accuracy of the consequent results post-implementation of this model in an actual setting is unknown and conceptual. The risks and barriers associated during execution and post-implementation include biases creeping into data modeling, management of costs, computing time, incompatibility, insufficient storage, inadequate processing power, adversarial attacks as well as compliance with strict data protection laws. These challenges can be addressed if the industries consistently:

- Possess high-quality and synthetic data in apt volumes to avoid imbalances that can result in discriminatory results.
- Have legacy machinery with sufficient and adaptable storage as well as processors.
- Be willing to make investments in applications and instruments with the necessary processing power.
- Break down algorithms and train personnel in the decision-making process.
- Remain within the constraints of the data protection laws of that particular region.

Consequently, the generalizability aspect of the retrofitting process is highly dependent on whether the manufacturing context possesses the aforementioned competencies.

6. Conclusions and Future Work

While performing gap analysis, the capability of autonomously detecting the present status of a production process to guarantee the timely detection of faults was recognized as a major gap that needed to be addressed. This emphasized the requirement of an AI-based RIS since AI neural networks can learn relevant data patterns and relate them to processing conditions. Consequently, an AI-based RIS model was developed regardless of the lack of existing literature on RIS and actual case studies. The model integrates SVM, DCNN, and LSTM neural networks as well as I4 features. Results were derived based on the fundamental assumption that the efficiency would remain the same as proven in the existing literature. Therefore, due to the lack of physical validation, the accuracy of results in a physical site of varied conditions is assumed and purely conceptual. Integrating I4 features makes communication between suppliers, manufacturers, and customers smoother. The results also portrayed the costs that can be saved by retrofitting the AI-based RIS with legacy machinery in comparison to purchasing brand-new I4-ready inspection machines. The key benefit associated with the implementation of this model is the enablement of real-time decision-making. I4 and AI-based RIS systems can facilitate organizations to make operational decisions based on the latest information. This makes the system more adaptable to product changes. Additionally, it can aid in triggering follow-up operations on the manufacturing line automatically without human intervention when an error is detected. Ultimately, it ensures the preservation of the reputation of companies by preventing poor products from being delivered to customers. By addressing the absence of structured techniques for sensor positioning, feature selection, and information extraction in RIS and by demonstrating how an AI-based RIS could improve fault detection, this model and the overall paper were effective in filling a gap within the existing literature. However, the paper's shortcomings stem from the fact that the theoretical work has been applied to an already existing case study (by Shang et al. [8]) and has not been verified by physical implementation i.e., model-based research work in an actual production environment. Consequently, future work would require a practical basis, utilizing the theoretical data offered in this paper to provide a physical case study. The physical case study must reflect quantifiable performance statistics that this paper lacks, such as percentage performance increment owing to AI-based RIS in an actual assembly line.

References

[1] Jiao, R., Commuri, S., Panchal, J., Milisavljevic-Syed, J., Allen, J. K., Mistree, F., & Schaefer, D. (2021). Design Engineering in the Age of Industry 4.0. *Journal of Mechanical Design*, 143(7). https://doi.org/10.1115/1.4051041

[2] Arinez, J. F., Chang, Q., Gao, R. X., Xu, C., & Zhang, J. (2020). Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook. *Journal of Manufacturing Science and Engineering*, 142(11). https://doi.org/10.1115/1.4047855

[3] Suleiman, Z., Shaikholla, S., Dikhanbayeva, D., Shehab, E., & Turkyilmaz, A. (2022). Industry 4.0: Clustering of concepts and characteristics. Cogent Engineering, 9(1). https://doi.org/10.1080/23311916.2022.2034264

[4] Khanna, K., & Kumar, R. (2019). Reconfigurable manufacturing system: a state-of-the-art review. *Benchmarking: An International Journal,* 26(8), 2608–2635. https://doi.org/10.1108/bij-05-2018-0140

[5] Malhotra, V., Raj, T., & Arora, A. (2009). Reconfigurable Manufacturing System: An Overview. *International Journal of Machine Intelligence*, 1(2), 38–46. https://doi.org/10.9735/0975-2927.1.2.38-46

[6] Reconfigurable Manufacturing Systems: From Design to Implementation. (2020). In L. Benyoucef (Ed.), Springer Series in Advanced Manufacturing. Springer International Publishing. https://doi.org/10.1007/978-3-030-28782-5

[7] Dashchenko, A. I. (Ed.). (2006). *Reconfigurable Manufacturing Systems and Transformable Factories*. Springer Berlin Heidelberg. https://doi.org/10.1007/3-540-29397-3

[8] Shang, X., Milisavljevic-Syed, J., Huang, S., Wang, G., Allen, J. K., & Mistree, F. (2020). A key feature-based method for the configuration design of a reconfigurable inspection system. *International Journal of Production Research*, *59*(9), 2611–2623. https://doi.org/10.1080/00207543.2020.1735664

[9] Barve, S., Khodke, P. and Sathe, P. (2011). Research issues in cellular manufacturing systems. *International Journal of Applied Engineering Research.* 6. 291-302.

[10] Milisavljevic-Syed, J., Allen, J. K., Commuri, S., & Mistree, F. (2019). Design of networked manufacturing systems for Industry 4.0. *Procedia CIRP*, *81*, 1016–1021. https://doi.org/10.1016/j.procir.2019.03.244

[11] Mahendrakar, S. (2018). Research Issues and Development in Advance Manufacturing Systems. *DAAAM International Scientific Book*, 141–150. https://doi.org/10.2507/daaam.scibook.2018.13

[12] Bortolini, M., Galizia, F. G., & Mora, C. (2018). Reconfigurable manufacturing systems: Literature review and research trend. *Journal of Manufacturing Systems*, *49*, 93–106. https://doi.org/10.1016/j.jmsy.2018.09.005

[13] Koren, Y., Gu, X., & Guo, W. (2017). Reconfigurable manufacturing systems: Principles, design, and future trends. *Frontiers of Mechanical Engineering*, *13*(2), 121–136. https://doi.org/10.1007/s11465-018-0483-0

[14] Mehrabi, M. G., Ulsoy, A. G., & Koren, Y. (2000). *Journal of Intelligent Manufacturing*, *11*(4), 403–419. https://doi.org/10.1023/a:1008930403506

[15] Koren, Y., Heisel, U., Jovane, F., Moriwaki, T., Pritschow, G., Ulsoy, G., & Van Brussel, H. (1999). Reconfigurable Manufacturing Systems. *CIRP Annals*, *48*(2), 527–540. https://doi.org/10.1016/s0007-8506(07)63232-6

[16] Andersen, A.-L., Nielsen, K., & Brunoe, T. D. (2016). Prerequisites and Barriers for the Development of Reconfigurable Manufacturing Systems for High-Speed Ramp-up. *Procedia CIRP*, *51*, 7–12. https://doi.org/10.1016/j.procir.2016.05.043

[17] Prasad, D., & Jayswal, S. (2019). Reconfigurable Manufacturing System - a New Class of Manufacturing System. *Semantic Scholar*. https://doi.org/10.24425/MPER.2019.131443

[18] Setchi, R. M., & Lagos, N. (2004). Reconfigurability and reconfigurable manufacturing systems state-of-the-art review. *2nd IEEE International Conference on Industrial Informatics, 2004. INDIN '04. 2004*. https://doi.org/10.1109/indin.2004.1417401

[19] Lorenz, R., Benninghaus, C., Friedli, T., & Netland, T. H. (2020). Digitization of manufacturing: the role of external search. *International Journal of Operations & Production Management*, *40*(7/8), 1129–1152. https://doi.org/10.1108/ijopm-06-2019-0498

[20] Sah, S. (2020). *Machine Learning: A Review of Learning Types*. https://doi.org/10.20944/preprints202007.0230.v1

[21] Epureanu, B. I., Li, X., Nassehi, A., & Koren, Y. (2020). Self-repair of smart manufacturing systems by deep reinforcement learning. *CIRP Annals*. https://doi.org/10.1016/j.cirp.2020.04.008

[22] Wang, J., Liu, S., Gao, R. X., & Yan, R. (2012). Current envelope analysis for defect identification and diagnosis in induction motors. *Journal of Manufacturing Systems*, *31*(4), 380–387. https://doi.org/10.1016/j.jmsy.2012.06.005

[23] Caggiano, A., Zhang, J., Alfieri, V., Caiazzo, F., Gao, R., & Teti, R. (2019). Machine learning-based image processing for on-line defect-recognition in additive manufacturing. *CIRP Annals*, *68*(1), 451–454. https://doi.org/10.1016/j.cirp.2019.03.021

[24] Zhang, J., Wang, P., Yan, R., & Gao, R. X. (2018). Long short-term memory for machine remaining life prediction. *Journal of Manufacturing Systems*, *48*, 78–86. https://doi.org/10.1016/j.jmsy.2018.05.011

[25] ElMaraghy, H. A. (2007). Reconfigurable Process Plans For Responsive Manufacturing Systems. *Digital Enterprise Technology*, 35–44. https://doi.org/10.1007/978-0-387-49864-5_4

[26] Schmitt, J., Bönig, J., Borggräfe, T., Beitinger, G., & Deuse, J. (2020). Predictive model-based quality inspection using Machine Learning and Edge Cloud Computing. *Advanced Engineering Informatics*, *45*, 101101. https://doi.org/10.1016/j.aei.2020.101101

AI-based reconfigurable inspection system (RIS): comprehensive model and implementation in industry

Kumar, A. Sarat

2024-01-12

Kumar AS, Milisavljevic-Syed J. (2023) AI-based reconfigurable inspection system (RIS): comprehensive model and implementation in industry. Procedia CIRP, Volume 120, 2023, pp.87-92
https://doi.org/10.1016/j.procir.2023.08.016