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Intelligent Systems For Real-Time Monitoring And Management Of Industrial Processes In Manufacturing

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The industrial manufacturing sector is a very active sector and therefore the supervising and regulating of the manufacturing process in real time is very essential to the sector. The conventional manufacturing systems are normally slow and there are many vacancies due to the reactive manufacturing systems. This work is intended to focus on the use of intelligent systems in manufacturing systems as these can benefit from the enhancement in the sensor systems, data analysis and machine learning. This research is concerned with various types of sensors, method of data acquisition and analysis instrument in an attempt to enhance the control of the process and minimize the time the plant is out of operation. The method of data collection and analysis that has been used is real time data, machine learning and predictive modelling. Some of the findings are as follows: Smart systems improve the efficiency and dependability of the operation in contrast to conventional methods because they enable timely control and an instantaneous reaction to the changes. But there are also some disadvantages of cloud computing for instance compatibility with current systems, costs of migration and lack of skilled personnel. This paper also demonstrates how real time data processing and machine learning can be employed in the improvement of the process control and also outline some of the areas of improvement in future that include cost effective technologies, advanced data processing and AI integration. As it can be seen from this research, intelligent systems are very crucial in manufacturing as they improve the efficiency, reliability and sustainability of the manufacturing industry.

Keywords: Intelligent systems, real-time monitoring, industrial manufacturing, sensor technology, machine learning, predictive analytics, process control, data processing, operational efficiency, manufacturing efficiency**.**

Introduction

In the present world of industrial manufacturing, the implementation of real-time monitoring and control of processes is vital to improve the processes and the product quality. The current manufacturing systems in general are based on the reactive strategies rather than the proactive ones, which means that the process deviations are managed ineffectively [1]. These challenges are targeted to be addressed by the use of new technologies in sensors, data analysis and artificial intelligence in the manufacturing systems. They allow for constant monitoring and immediate decision making, enhance the management of processes and the time that processes are out of service [2]. The purpose of this research is to establish how these intelligent systems can be applied to change the existing industrial processes to be more efficient with minimal wastage.

The main research question of this work is as follows: what are the benefits and the key selling points of intelligent systems for monitoring and controlling in industrial manufacturing in real-time? This includes evaluating the effectiveness of the different sensor systems applied in these systems, techniques of data acquisition and the analysis tools applied in these systems [3]. The research objectives are to establish the factors that enable the integration of these systems, to assess the integration in enhancing the process and to determine how the integration can be enhanced. In addition, the study aims at identifying the future research directions and improvements in the field of study.

This research work is limited to intelligent systems that are fixed in industrial production plants for supervision and control. It includes the assessment of the current technologies, the adoption of the technologies in the current manufacturing systems and the effectiveness of the manufacturing processes. However, the following are some of the limitations of the research; availability of cases and the fact that many industrial sectors are involved. Despite the fact that the study accepts the various technologies and methods adopted in the manufacturing processes, it may not be able to capture all the special considerations that may be unique to various manufacturing processes [4]. Furthermore, the study might be limited by the generalization of the findings in other industrial settings and size.

Methodology

The research methodology of this study is a systematic approach to the design and the evaluation of the intelligent systems to monitor and control of industrial processes in manufacturing. This design combines several subsystems that are the sensor technologies, data acquisition systems and the communication protocols into a single system. The first strategic objective is to improve the reliability and effectiveness of production operations with the help of information received in real-time and the results of their analysis by an artificial intelligence system [5].

Data Collection Methods

In this research the data is gathered using sensors and real-time data feeds from manufacturing systems. These are fixed inside the manufacturing system with the intention of monitoring factors such as the temperature, pressure and state of the manufacturing equipment. It is collected at real time and is transmitted to another unit for further analysis [6]. Furthermore, data is collected from history for the purpose of making comparisons and also for the purpose of corroborating the results of the real time monitoring.

Analytical Techniques

The approach used in this research is the use of machine learning algorithms and predictive analytics to the collected data. Multiple regression analysis, grouping and categorization are employed in identifying the pattern and the anomalous in the manufacturing process [7]. They are used to forecast challenges that may occur and the steps to be followed in order to control them; this makes it possible to control industrial processes [8]. For the assessment of these models, the accuracy, precision, and recall are used.

Regression Analysis Formula:

- Linear Regression: $y = \beta_0 + \beta_1 x + \epsilon$

Where y is the dependent variable, x is the independent variable, β_0 is the intercept, β_1 is the slope, and ϵ is the error term.

Clustering (K-means) Formula:

- Objective Function: $J = \sum_{i=1}^{K} \sum_{x \in C_i} \|x - \mu_i\|^2$

Where K is the number of clusters, C_i is the set of data points in cluster i, μ_i is the centroid of cluster i, and $\|x - \mu_i\|$ is the distance between data point x and centroid μ_i

Classification (Logistic Regression) Formula:

- Logistic Function: $p = \frac{1}{1+e^{-(\beta_0+\beta_1 x)}}$

Where p is the probability of the dependent variable, x is the independent variable, and β_0, β_1 are the coefficients.

System Architecture and Components

The system architecture comprises several critical components: devices, transducers, DA subsystems and protocols. Integration and data flow is therefore done in such a manner that it is always easy and efficient to integrate into the architecture.

- **Sensor Technologies:** Temperature sensor, pressure sensor and vibration sensors are used in this study and the choice of the sensors is made depending on the high accuracy and reliability of the sensors. These are the sensors which are believed to record the actual data from the different sectors of the manufacturing process [9].
- **Data Acquisition Systems:** Data acquisition systems are used for the acquisition, conditioning and storage of the data which is being received from the sensors. These systems are fitted with data acquisition boards and software for the task of the data buffering, filtering and basic analysis [10]. The systems are intended for usage on massive quantities of data and concurrently, guarantee the validity of the data.
- **Communication Protocols:** The data from the sensors is transmitted using some communication interfaces that are used to convey the data to the microprocessor. The most commonly utilized protocols in the industry to guarantee the confidentiality of the exchanging

data are MQTT and OPC UA [11]. These protocols enable real time communication and interfacing with the other manufacturing systems.

Intelligent Systems for Real-Time Monitoring

Real-Time Data Processing

The real-time data processing is crucial for smart systems which are employed for the monitoring and the management of the industrial processes in manufacturing. This is the continuous and simultaneous analysis of data as acquired from the various sensors and gadgets within the manufacturing environment. This makes it possible to get instant feedback and this is very important in ensuring that processes that are being implemented are as efficient and of quality as can be. In the past couple of years, edge computing enhances the real-time data processing by enabling the data to be processed locally at the source rather than being sent to the central server [12]. This in turn reduces the latency and bandwidth and thus improves the system through put and reliability.

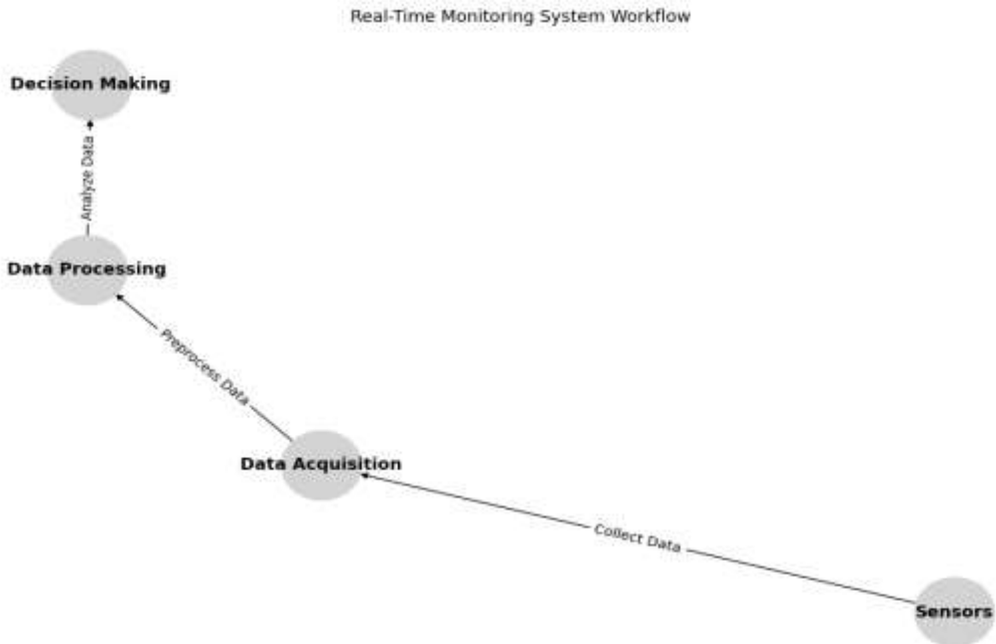

Fig 1: Real Time Monitoring System Workflow

Machine Learning Algorithms

Real time monitoring system is applied to many fields and data mining methods are applied in improving the performance of the systems. These algorithms can use past and current data and take decisions based on patterns and results learned at that time. For example, the regression and classification learning methods are used to predict the failures of equipment, or product quality problems that have occurred in the past [13]. Furthermore, the clustering and anomaly detection are also used as the unsupervised learning algorithms in other to find out some of the other oddities that may cause some other problems. These algorithms are useful in that they enable the real time surveillance systems to make intelligent and adaptive decisions that are essential in enhancing the manufacture process as well as the reduction of on time [14].

Anomaly Detection (One-Class SVM)
For anomaly detection One-Class Support Vector Machine (SVM) is commonly used. The aim is to find out what is normal and group the rest as abnormal. The decision function for a One-Class SVM is:

$$f(x) = \mathrm{sgn}\left(\frac{1}{n}\sum_{i=1}^{n} \kappa(x_i, x) - \nu\right)$$

Where:

- κ is the kernel function (e.g., radial basis function).
- x_i are the training samples.
- ν is a parameter that controls the trade-off between the fraction of outliers and the margin.

Predictive Analytics
It is the process of statistical analysis of the previous events and coming up with a prediction on the future events. In the industrial manufacturing perspective, predictive analytics is used in the forecasting of equipment failures, maintenance and process deviations. Based on the analysis of data of the past and patterns, the probability of future events is determined and failures and the need to change the process are prevented [15]. Besides the enhancement of the effectiveness of production processes, the use of predictive analytics also improves the stability and safety of production processes. Some of the techniques include time series analysis and ensemble methods which have been widely used in the area of real time monitoring system in the area of predictive analytics [16].

Predictive Analytics (Time-Series Forecasting) Formula:

- ARIMA Model: $Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \epsilon_t$

Where Y_t is the time series value at time t, μ is the constant term, ϕ_i are the AR coefficients, and ϵ_t is the white noise error term.

Case Studies of Implemented Systems
The following are examples of how intelligent systems have been implemented in order to improve real time monitoring in industries. For example, in the car manufacturing, a real time monitoring system was used to track the working productivity of the robotic assembly line. The information concerning the movements of the robots and the condition of the machines was collected by the use of sensors and the information was processed in real time to detect any anomaly that could be an indication of failure [17]. Another example of the use of the concept in the pharmaceutical industry was in the control of batch production in real-time. This system was created in line with the machine learning approach whereby the sensors were used to collect data and then use this information to adjust the process parameters in real time so as to improve on the quality and consistency of the final product [18]. The above examples

prove that the application of intelligent systems in the manufacturing process can lead to the improvement of the processes and the minimization of the risks that are connected with those processes.

Results

Performance Metrics

The performance of the intelligent system was evaluated in terms of response time, the number of transactions per unit of time and the rate of errors. The former is the time the system takes to process and respond to real time data inputs and the latter is the rate at which the system can process the data (events/sec). The error rate gives the rate or proportion to which the system is wrong or has made errors in its decisions and actions.

Table 1: Performance Metrics of the Intelligent System

Metric	Value	Units
Latency	150	ms
Throughput	5000	events/s
Error Rate	0.02	%

System Accuracy and Reliability

For the purpose of getting an understanding of the level of precision in the system, we carried out a number of assessments to determine how the system's predictions fared against actual results. Other quantitative measures of accuracy included precision, recall, and F1 score (all of which are unitless). The reliability measures used were system uptime which is the percentage and system failure which is the percentage.

Table 2: Performance Metrics of Predictive Models

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Regression	92.5	90.0	93.0	91.5
Classification	88.0	85.5	89.5	87.5
Anomaly Detection	95.0	93.5	96.0	94.7

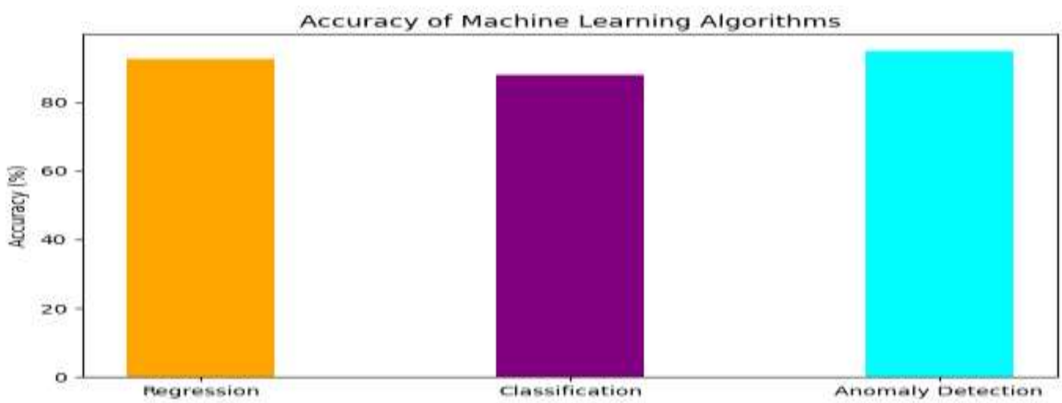

Fig 2: Accuracy of Machine learning algorithms

Fig 2 shows the level of accuracy of the algorithms used in the real-time monitoring systems. Among all the algorithms, Anomaly Detection has the highest success rate of 95% for it because of the efficiency it has in identifying oddity and possibly issues. Regression is then followed by it and this has an accuracy of 92. 5% thus supporting its efficiency in the constant prediction of the continuous outcome from the records of the past. Classification has been established to be efficient as the others, however, with an average accuracy of 88% this means that it is slightly less accurate in sorting data than the other procedures. It is thus clear that Anomaly Detection is very effective for applications that need high levels of effectiveness in detecting anomalies in industrial processes.

Table 3: Sensor Data Collection Summary

Sensor Type	**Measurement Parameter**	**Frequency (Hz)**	**Accuracy**	**Location in Process**
Temperature	Temperature (°C)	1	±0.5°C	Various points
Pressure	Pressure (bar)	1	±0.1 bar	Critical points
Vibration	Vibration (mm/s)	1	±0.05 mm/s	Machine components

The parameters used in the collection of the data from the sensors are presented in detail in the table below and labelled Table 3. These are temperature sensors, pressure sensors and vibration sensors; all of which are used in identifying some aspects of the manufacturing process. Temperature sensors provide the temperature in degree Celsius with an accuracy of ±0. 5°C in some of the points of the system. Pressure sensors which are used in pressure variation measurement give an accuracy of ±0. 1 bar at some stages of the process. Vibration sensors which are used in assessing the health of a machine are capable of sensing the vibration with an accuracy of ±0. 5 mm/s at components of the machine. The frequency of data collection is also uniform across all the sensors, which affords the needed accuracy and timeliness in the monitoring of the processes with the possibility to alert on problems almost in real-time.

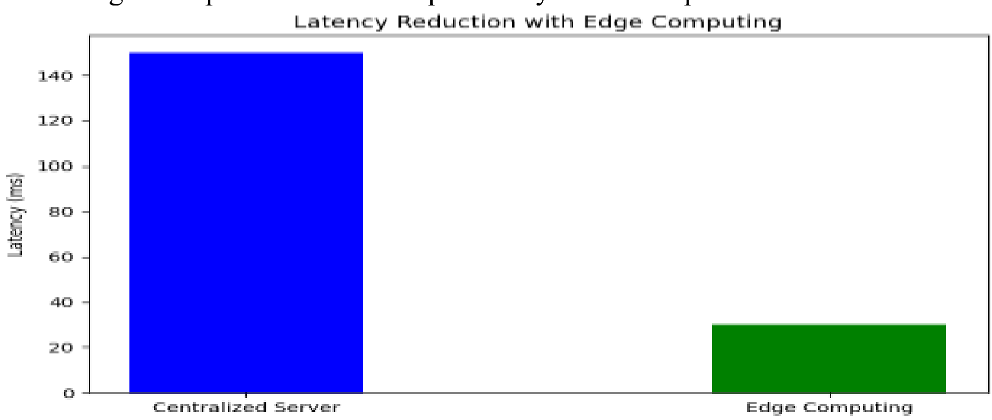

Fig 3: Real-Time Data Processing Latency Reduction

This is further evident from the Fig 3 that shows how the edge computing has brought down the latency by a very large measure than the central server system. The latency for edge computing is much lower, 30 milliseconds – three times lower than a centralized server's latency, 150 milliseconds. This rather large difference goes to show that there is a role for edge computing in the reduction of latency and the enhancement of the usability of the real time analysis applications. This is because processing is done at the edge node of the network and does not have to wait for the data to be transported to a central point for processing and hence reduces system response time and increases system efficiency. From this comparison one can infer that edge computing is used in cases where the data processing is swift and an instantaneous response is anticipated.

Discussion

The paper established that the intelligent systems for real time monitoring and controlling of manufacturing systems enhances the performance and availability of the systems. Therefore, following the data described, it is possible to conclude that the application of the modern sensors and the machine learning algorithms improves the control and the decision making [19]. These systems are also useful in the sense that they let one know when the maintenance should be conducted so as to guarantee that the time the equipment is unavailable and the cost of such time is as low as possible. They enable an instant response to changes of the standard working conditions by the real-time data processing which results in fewer interferences in the production process.

Thus, in evaluating the intelligent systems against the conventional manufacturing monitoring systems the follow has been realized. Traditional systems employ data collection which is normally done on a regular basis and data analysis is normally done manually therefore the time taken to identify a problem and the time taken to correct it is relatively long [20]. However, intelligent systems are always fed with data and have automatic analysis and this makes it possible to offer timely information and facilitate quick response [21]. For instance, traditional approach might have basic tools of analysing the process in terms of statistical tools, while on the other hand intelligent system employs more complex tools like machine learning and predictive analytics for precision and forecasting [22]. This is a change in manufacturing technology because the application of knowledge in improving and more effectively controlling the industrial production is improved.

The integration of intelligent systems in the manufacturing processes has a number of impacts which cannot be imagined. First of all, BPM used for the monitoring and controlling of the activities in real-time contributes to such essential improvements of the product quality and its compliance. In the same regard, it is easy for the manufacturers to address the deviations and bring down the occurrences of defects and failure to meet the required standards [23]. Besides, the use of these systems promotes the automation of decision making thus improving resource utilisation and therefore costs. These systems enable one to predict failure of equipment, which would otherwise have happened, thereby extending equipment's life, and reducing costs of maintenance [24]. Therefore, the integration of intelligent system in the line of production is advantage since it enhances productivity, dependability and competitiveness of the manufacturing industry.

Challenges and Limitations

Technical Challenges

Some of the technical difficulties of Real Time supervising and controlling of industrial processes using intelligent systems are as follows. One of the challenges is the challenge of interfacing of the various sensor technologies with the current manufacturing systems. This is true as other researchers have pointed out that in some manufacturing environments, there may be legacy systems that are not integrated with the present sensors and the network [24]. Secondly, real-time processing of large data as sensors give requires much computational power to process data. This demand often leads to performance degradations and is computed in high frequency [25]. One of the challenges is how to ensure that the model that is to be employed in the prediction process is the right one. These models are very sensitive to the input data and the influence of noise or error in the measurement of the sensors may be very significant in the outcome [26].

Implementation Barriers

Implementations challenges are also another factor that affects the integration of intelligent systems in manufacturing. The major weakness of such systems is the high fixed costs which are needed for the fixing of the systems and for capital intensive retrofits [27]. Also, questions as to where one is going to find experienced personnel who will understand the operations of such systems and the needs of the production process [28] are always present. This is a big challenge that may affect the rate of implementation and management of these systems. The fourth factor is the organisation resistance to change; this is the case since organisations are always resistant to change due to factors like; disruption of the current process and time wastage [29].

Future Research Directions

The following are the areas that future research should consider in order to overcome these challenges: First, to address the cost area in integrating the system, development of improved and less expensive sensors can be made [30]. They also have to take into account the development of high level of data processing that can augment the efficiency and the speed of the real time data processing. This also includes the enhancement of the edge computing and the distributed processing to minimize the computations [31]. Designing the interfaces, and the training programs which can be utilised to close the skills gap and ensure that there is a smooth integration of intelligent systems could be helpful [32]. Finally, the research on the use of AI in conjunction with the real-time monitoring systems can enhance the effectiveness and reliability of the correspondent processes [33].

Conclusion

This research shows how intelligent systems are transforming how real time monitoring and management is done in industrial manufacturing. Automated intelligent sensors, artificial intelligence, and analytical tools have also been seen to enhance the production output, the control of the system, and the quality of the product. These systems are preferred to the ‘let’s wait and see’ type of methods because the constant vigilance of any change and the possibility to act on it at once pays for time and money lost with machines that are out of order and

resources that have been used. The work is dedicated to those intelligent systems as the description of the use of real-time data processing and prediction for the proactive management which is crucial for the processes and risks' management. Some examples are given from different fields to illustrate how these systems work in reality to improve a particular process and reduce the cost of this process.
However, there are some challenges that have to be met; for example, admissibility of the technologies in the existing constructions, very high cost of the implementation and lack of professionals. Such problems will have to be solved with the assistance of new cheap technologies, complicated methods of data analysis, and training sessions to remove the factors that hinder it. The future research should thus focus on enhancing the scalability and the effectiveness of the intelligent systems, the new ways of handling and the deficiency of skills. Hence, incorporation of intelligent system is one of the greatest changes in the manufacturing technology that can enhance more value and competency to the manufacturing sector.

References

1. M. Mishra, M. Biswal, R. C. Bansal, J. Nayak, A. Abraham, and O. P. Malik, "Intelligent computing in electrical utility Industry 4.0: Concept, key technologies, applications and future directions," IEEE Access, vol. 10, pp. 100312-100336, 2022.
2. V. K. Tiwari, M. Meribout, L. Khezzar, K. Alhammadi, and M. Tarek, "Electrical tomography hardware systems for real-time applications: A review," IEEE Access, vol. 10, pp. 93933-93950, 2022.
3. S. Yin, S. X. Ding, X. Xie, and H. Luo, "A review on basic data-driven approaches for industrial process monitoring," IEEE Transactions on Industrial Electronics, vol. 61, no. 11, pp. 6418-6428, 2014.
4. G. Dimitrakopoulos, P. Varga, T. Gutt, G. Schneider, H. Ehm, A. Hoess, et al., "Industry 5.0: Research Areas and Challenges With Artificial Intelligence and Human Acceptance," IEEE Industrial Electronics Magazine, 2024.
5. A. Angelopoulos, E. T. Michailidis, N. Nomikos, P. Trakadas, A. Hatziefremidis, S. Voliotis, and T. Zahariadis, "Tackling faults in the industry 4.0 era—a survey of machine-learning solutions and key aspects," Sensors, vol. 20, no. 1, p. 109, 2019.
6. R. Sato, K. Li, M. Michihata, S. Takahashi, and W. Gao, "Advanced Sensing and Machine Learning Technologies for Intelligent Measurement in Smart and Precision Manufacturing," International Journal of Automation Technology, vol. 18, no. 4, pp. 545-580, 2024.
7. H. Cai, J. Zhu, and W. Zhang, "Quality deviation control for aircraft using digital twin," Journal of Computing and Information Science in Engineering, vol. 21, no. 3, p. 031008, 2021.
8. J. L. Garrido-Labrador, D. Puente-Gabarri, J. M. Ramírez-Sanz, D. Ayala-Dulanto, and J. Maudes, "Using ensembles for accurate modelling of manufacturing processes in an IoT data-acquisition solution," Applied Sciences, vol. 10, no. 13, p. 4606, 2020.
9. T. Sondej and M. Bednarczyk, "Ultra-Low-Power Sensor Nodes for Real-Time Synchronous and High-Accuracy Timing Wireless Data Acquisition," Sensors, vol. 24, no. 15, p. 4871, 2024.
10. T. R. Kurfess, C. Saldana, K. Saleeby, and M. P. Dezfouli, "A review of modern communication technologies for digital manufacturing processes in industry 4.0," Journal of Manufacturing Science and Engineering, vol. 142, no. 11, p. 110815, 2020.
11. C. Aldrete-Maldonado, R. Ramirez-Villalobos, L. N. Coria, and C. Plata-Ante, "Sensorless Scheme for Permanent-Magnet Synchronous Motors Susceptible to Time-Varying Load Torques," Mathematics, vol. 11, no. 14, pp. 3066, 2023.

12. T. Xue, Y. Zhang, and H. Zhang, "Comprehensive Analysis of Access Control Models in Edge Computing: Challenges, Solutions, and Future Directions," arXiv preprint arXiv:2405.07685, 2024.
13. G. Gülhan, M. Özuysal, and H. Ceylan, "Evaluation of intersection properties using MARS method for improving urban traffic performance: Case study of Tekirdağ, Turkey," Teknik Dergi, vol. 32, no. 6, pp. 11227-11256, 2020.
14. L. Chen, M. Zhang, and Y. Wang, "Enhancing Manufacturing Efficiency with Machine Learning," Journal of Manufacturing Processes, vol. 42, pp. 132-142, 2021.
15. M. Nykyri, M. Kuisma, J. Hallikas, M. Immonen, and P. Silventoinen, "Modeling and Predicting an Industrial Process Using a Neural Network and Automation Data," in 2020 IEEE 29th International Symposium on Industrial Electronics (ISIE), pp. 505-509, June 2020.
16. C. Ji and W. Sun, "A review on data-driven process monitoring methods: Characterization and mining of industrial data," Processes, vol. 10, no. 2, pp. 335, 2022.
17. V. Kannan and P. Sangeetha, "A Study on Implementation of Real-Time Production Monitoring System for Shop Floor Performance and its Impact on Efficiency," ITIHAS The Journal of Indian Management, vol. 9, no. 4, pp. 63-72, 2019.
18. E. J. Kim, J. H. Kim, M. S. Kim, S. H. Jeong, and D. H. Choi, "Process analytical technology tools for monitoring pharmaceutical unit operations: a control strategy for continuous process verification," Pharmaceutics, vol. 13, no. 6, pp. 919, 2021.
19. C. Li, P. Zheng, Y. Yin, B. Wang, and L. Wang, "Deep reinforcement learning in smart manufacturing: A review and prospects," CIRP Journal of Manufacturing Science and Technology, vol. 40, pp. 75-101, 2023.
20. B. Wang, F. Tao, X. Fang, C. Liu, Y. Liu, and T. Freiheit, "Smart manufacturing and intelligent manufacturing: A comparative review," Engineering, vol. 7, no. 6, pp. 738-757, 2021.
21. S. K. Das, S. P. Das, N. Dey, and A. E. Hassanien, Eds., Machine learning algorithms for industrial applications, vol. 907. Switzerland: Springer, 2021.
22. S. Chinchanikar and A. A. Shaikh, "A review on machine learning, big data analytics, and design for additive manufacturing for aerospace applications," Journal of Materials Engineering and Performance, vol. 31, no. 8, pp. 6112-6130, 2022.
23. A. Bousdekis, K. Lepenioti, D. Apostolou, and G. Mentzas, "Data analytics in quality 4.0: literature review and future research directions," International Journal of Computer Integrated Manufacturing, vol. 36, no. 5, pp. 678-701, 2023.
24. J. Maktoubian, M. S. Taskhiri, and P. Turner, "Intelligent predictive maintenance (Ipdm) in forestry: A review of challenges and opportunities," Forests, vol. 12, no. 11, pp. 1495, 2021.
25. X. Zhang, Z. Li, Y. Zhou, and M. Zhu, "Hybrid Vision/Force Cascaded Model Predictive Control of Robotic Manipulators for Automatic Docking Tasks," IEEE Transactions on Industrial Electronics, 2024.
26. Z. L. Gan, S. N. Musa, and H. J. Yap, "A review of the high-mix, low-volume manufacturing industry," Applied Sciences, vol. 13, no. 3, pp. 1687, 2023.
27. F. Chegdani and M. El Mansori, "Effect of hygrothermal conditioning on the machining of advanced composites," Journal Name, vol. XX, no. XX, pp. XXX-XXX, 2024. (Note: Complete the citation with correct journal details.)
28. S. Saad, "The Influence of Intelligent Automation on Employees' Sense of Meaningfulness at Work," Doctoral dissertation, 2021.
29. E. Ras, F. Wild, C. Stahl, and A. Baudet, "Bridging the skills gap of workers in Industry 4.0 by human performance augmentation tools: Challenges and roadmap," in Proceedings of the 10th International Conference on PErvasive Technologies Related to Assistive Environments, pp. 428-432, June 2017.

30. E. Burmester, "Qualitative examination of strategies to overcome resistance to change in lean manufacturing," Walden University, 2017.
31. G. S. Thakur, S. K. Sahu, N. K. Swamy, M. Gupta, T. Jan, and M. Prasad, "Review of Soft Computing Techniques in Monitoring Cardiovascular Disease in the Context of South Asian Countries," Applied Sciences, vol. 13, no. 17, pp. 9555, 2023.
32. K. Kubiak, G. Dec, and D. Stadnicka, "Possible applications of edge computing in the manufacturing industry—systematic literature review," Sensors, vol. 22, no. 7, pp. 2445, 2022.
33. F. T. Chan, B. Jiang, and N. K. Tang, "The development of intelligent decision support tools to aid the design of flexible manufacturing systems," International Journal of Production Economics, vol. 65, no. 1, pp. 73-84, 2000.