10.48047/jocaaa.2022.30.02.26

Machine Learning Algorithms for IoT-Enabled Smart Factories in Industry 4.0

Sharanagouda N Patil[1*]
Department of Electronics & Communication Engineering
Govt. Womens Polytechnic
Kalaburagi, -585102
snpgwpt@gmail.com

Rajshekhar S Heera[2]
Department of Science
Govt. Polytechnic Kalaburagi
Kalaburagi, -585102
rajshekharsheera@gmail.com

Raju Hajare[3]
Department of Telecommunication Engineering
BMSIT&M, Bengaluru
rajuhajare@bmsit.in

Abstract

The combination of the Internet of Things (IoT) and Machine Learning (ML) has become one of the enabling factors of smart factories within the Industry 4.0 paradigm. IoT infrastructures facilitate real-time collection of big sensor data of machines, production lines and industrial settings and machine learning algorithms convert the data into predictive, adaptive and autonomous decision-making. The paper provides an overview of the applications of machine learning in IoT-enabled smart factories, in which every mathematical formulation is described in detail to increase the readability and reproducibility. The key areas of application are predictive maintenance, intelligent quality control, optimization of the production processes, energy efficiency, safety monitoring, and optimization of the supply chain. Problems and future research opportunities of completely autonomous manufacturing systems are also addressed.

Index Terms **:**Industry 4.0, Smart Factory, Internet of Things, Machine Learning, Predictive Maintenance, Intelligent Manufacturing.

1. Introduction

Industry 4.0 represents a paradigm shift from conventional automation to intelligent, data-driven manufacturing systems [1], [2]. In IoT-enabled smart factories, machines and industrial assets are equipped with multiple sensors that continuously generate operational data. The sensor data collected at a given time instant *t* can be represented as

$$x(t) = [x_1(t), x_2(t), \ldots, x_n(t)] \qquad \text{-- (1)}$$

where x(t) denotes the complete sensor data vector, $x_i(t)$ represents the reading of the *i*-th sensor (such as vibration, temperature, pressure, or current), *n* is the number of sensors, and *t* denotes time. This representation allows simultaneous monitoring of multiple physical phenomena within a manufacturing environment.

Machine learning establishes a functional relationship between the input sensor data and manufacturing outcomes [3]

$$f_\theta : x(t) \rightarrow \hat{y}(t) \qquad \text{-- (2)}$$

Here, f_θ denotes the machine learning model, θ represents the trainable parameters (weights and biases), x(t) is the input feature vector, and ŷ(t) is the predicted output such as machine health state, defect category, or energy demand. This formulation highlights how ML converts raw IoT data into actionable intelligence.

10.48047/jocaaa.2022.30.02.26

2. IoT–Machine Learning Framework for Smart Factories

Fig.1 illustrates an end-to-end IoT-enabled smart factory architecture integrated with machine learning. Industrial sensors and edge devices continuously collect operational data, which are transmitted through an IoT gateway and network infrastructure to edge and cloud processing layers. Machine learning models perform data analytics, real-time inference, and anomaly detection, generating predictions and recommendations for smart factory applications such as alerts, dashboards, and production optimization. These decisions are translated into control signals that drive actuators, enabling adaptive and autonomous manufacturing operations. Secure communication, processing, and data management are enforced across all layers to ensure reliability, safety, and trust in Industry 4.0 environments

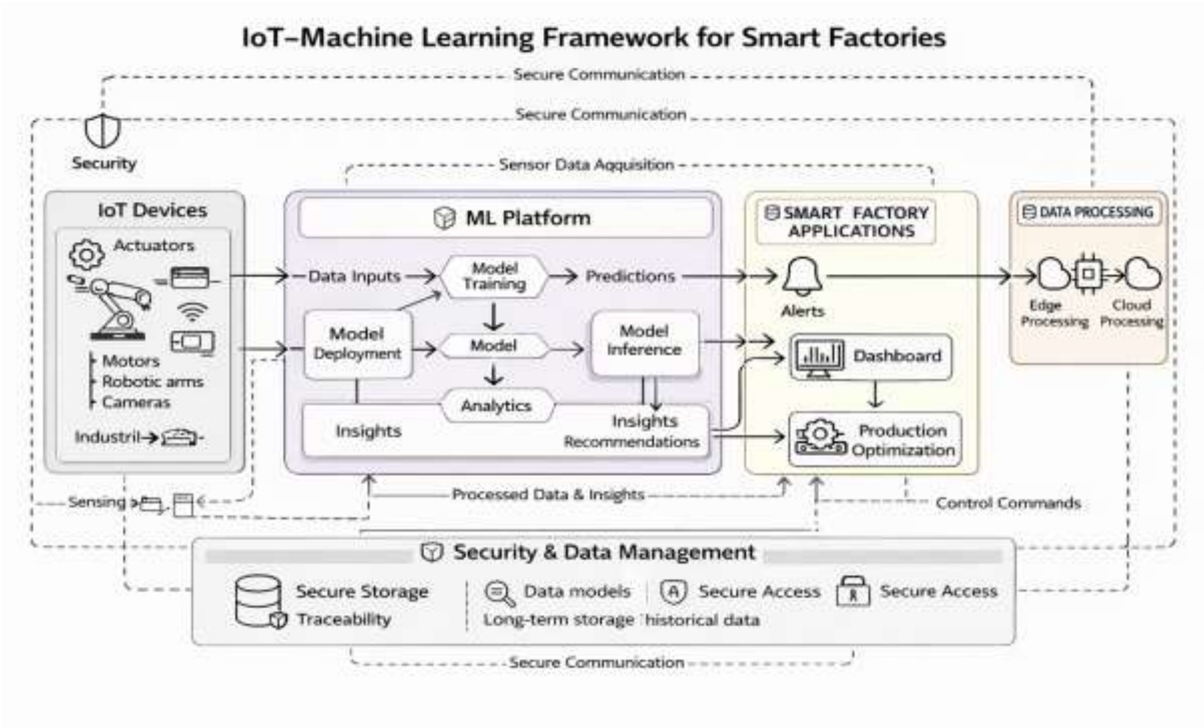

Fig1. IoT–Machine Learning Framework for Smart Factories

Historical data used for training ML models are organized as a dataset [4]

$$D = \{(x_i, y_i)\},\ i = 1,\ldots,N \qquad \text{-- (3)}$$

where D is the dataset, x_i is the input feature vector of the *i*-th sample, y_i is the corresponding target output, and *N* is the total number of samples. This dataset forms the basis for supervised and semi-supervised learning.

Model training is typically formulated as an empirical risk minimization problem [5]

$$\min_\theta (1/N)\ \Sigma_i\ L(y_i, f\theta(x_i)) \qquad \text{-- (4)}$$

In this equation, $L(\cdot)$ is the loss function measuring the difference between the true output y_i and the predicted output $f\theta(x_i)$. The objective is to determine θ such that the average prediction error over all samples is minimized.

10.48047/jocaaa.2022.30.02.26

For latency-critical applications, ML inference is deployed at the edge rather than the cloud [6]

$$t\_edge \ll t\_cloud \qquad -- (5)$$

where t_edge denotes processing latency at the edge device and t_cloud represents cloud processing latency. This condition is essential for real-time fault detection and safety monitoring.

The Table .1 shows comparision of the different ML algorithms in the IoT Enabled Factory framework in Industry 4.0

Table 1. Machine Learning Algorithms and Their Applications in IoT-Enabled Smart Factories

Category	Machine Learning Algorithm	IoT Data Type	Smart Factory Application	Typical Output / Decision
Supervised Learning	Support Vector Machine (SVM)	Vibration, temperature, current	Predictive maintenance, fault diagnosis	Fault class (normal/faulty)
	Random Forest (RF)	Multisensor data	Predictive maintenance, quality prediction	Health state, defect probability
	k-Nearest Neighbors (k-NN)	Sensor feature vectors	Equipment condition monitoring	Similarity-based fault label
	Linear / Logistic Regression	Process parameters, energy data	Energy prediction, quality estimation	Continuous value / class
Unsupervised Learning	k-Means Clustering	Sensor streams	Anomaly detection, machine behavior clustering	Cluster ID, abnormality
	Hierarchical Clustering	Operational data	Machine state grouping	Cluster hierarchy
	Autoencoder (AE)	Vibration, acoustic signals	Anomaly detection, early fault detection	Reconstruction error
Deep Learning	Convolutional Neural Network (CNN)	Images, thermal maps	Quality inspection, defect detection	Defect class / location
	Long Short-Term Memory (LSTM)	Time-series sensor data	Remaining useful life estimation	RUL value
	Gated Recurrent Unit (GRU)	Temporal sensor data	Machine health monitoring	Health score
	Deep Neural Network (DNN)	Multimodal sensor data	Process modeling, energy forecasting	Predicted output
Reinforcement Learning	Q-Learning	Machine states, rewards	Energy optimization, adaptive control	Optimal action
	Deep Q-Network (DQN)	High-dimensional sensor states	Process optimization	Control policy
	Policy Gradient Methods	Continuous control signals	Robotic assembly, scheduling	Optimized policy

10.48047/jocaaa.2022.30.02.26

Probabilistic Models	Hidden Markov Model (HMM)	Sequential sensor data	Fault progression modeling	State transition
	Bayesian Networks	Multisensor uncertainty data	Fault diagnosis, risk analysis	Failure probability
Computer Vision Models	CNN + Transfer Learning	Camera images	Surface defect inspection	Pass/fail decision
	Vision Transformers (ViT)	High-resolution images	Advanced quality inspection	Defect segmentation
Explainable AI (XAI)	SHAP, LIME	Model inputs & outputs	Model interpretability	Feature importance

3. Predictive Maintenance Using Machine Learning

Unsupervised methods like autoencoders and clustering techniques are employed to detect anomalies in the cases when there are few labeled fault data available to identify these abnormalities through the detection of deviations of normal operating behavior [1], [4]. In particular, recent papers focus on the fact that intelligent sensor integration, edge computing, and data-driven reasoning are important factors that can increase predictive maintenance accuracy and scalability in Industry 4.0 settings [2], [3]. Nevertheless, issues concerning data imbalance, model interpretability, real-time deployment, are still under active research, and hybrid, explainable, and adaptive machine learning systems are created to become the main trend of the next-generation smart factories [1], [2]. One of the most used applications of ML in smart factories is predictive maintenance, the purpose of which is to anticipate failures prior to their breakdown [7].

One of the most effective IoT-enabled smart factory applications with machine learning has been predictive maintenance, which allows fault identification in advance and pre-provisioning of maintenance through real-time and historical sensor information analysis. The multisensor data of the machine learning algorithms is trained to predict degradation pattern using the vibration, temperature, current, and acoustic sensors to predict the health and remaining useful life of equipment, thus, minimizing sudden failures and maintenance expenses [1], [2]. Support vector machines and ensemble classifiers are supervised learning models that are also extensively used in fault diagnosis and condition classification, and deep learning models such as long short-term memory networks are capable of capturing temporal interactions in sequential sensor data so that they will remain useful [1], [3].

3.1 Fault Diagnosis and Classification

Support Vector Machines (SVMs) are commonly used for fault classification in rotating machinery and industrial equipment [8]. The optimization problem is expressed as

$$\min(w, b)\ (1/2)||w||^2 + C\ \Sigma_i\ \xi_i \qquad \text{-- (6)}$$

where w is the weight vector defining the decision boundary, b is the bias term, $||w||^2$ enforces margin maximization, C is the penalty parameter, and ξ_i are slack variables representing misclassification errors.

10.48047/jocaaa.2022.30.02.26

The constraint is given by

$$y_i(w^T x_i + b) \geq 1 - \xi_i \, , \; \xi_i \geq 0 \qquad \text{-- (7)}$$

where y_i is the true class label and $w^T x_i + b$ is the decision function output.

3.2 Remaining Useful Life Estimation

Temporal degradation in machinery is modeled using Long Short-Term Memory (LSTM) networks [9]

$$h_t = \mathrm{LSTM}(x_t, h_{t-1}) \qquad \text{-- (8)}$$

Here, h_t is the hidden state at time *t*, x_t is the sensor input at time *t*, and h_{t-1} is the previous hidden state. This structure enables learning long-term temporal dependencies. The predicted output is computed as

$$\hat{y}_t = Wh_t + b \qquad \text{-- (9)}$$

where W is the output weight matrix, b is the bias, and $\hat{y}_t$ denotes the predicted remaining useful life or health indicator.

3.3 Anomaly Detection

Unsupervised anomaly detection is often performed using autoencoders [10]

$$\min\theta \, ||x - g\theta(f_\theta(x))||^2 \qquad \text{-- (10)}$$

In this expression, $f_\theta(x)$ is the encoder that compresses the input data, $g_\theta(\cdot)$ is the decoder that reconstructs the input, and the squared norm represents reconstruction error. High error indicates abnormal behavior.

4. Intelligent Quality Control and Defect Detection

Smart factories built on machine learning Intelligent quality control and defect detection represent a key usage of machine learning in the IoT-enabled smart factory, as the ongoing quality of products has to be measured to produce zero-defect products. IoT sensors and industrial vision generate high amounts of real-time data in the form of images, thermal maps, and process parameters, which are processed by the machine learning models to detect defects and quality deviations in the initial stages of production [11], [13]. Deep learning algorithms and supervised learning methods and especially convolutional neural networks have proven to be very effective in automated visual inspection processes like surface defects detection, dimensional inspection, and categorizing manufacturing defects [12]. These models are trained on the discriminative spatial features using raw images, and they can work well with defect recognition in different lighting conditions and under different operating conditions [11].

Besides vision-based inspection, process-level quality prediction is also implemented based on machine learning models in terms of using sensor measurements along with a final

10.48047/jocaaa.2022.30.02.26

product quality and predicting the quality in order to implement the quality control and process adjustments [11], [13]. According to recent reports, the implementation of intelligent quality control systems into Industry 4.0 infrastructures can considerably enhance the consistency level, decrease the rework rate, scrap rate, and improve the overall productivity of the manufacturing process, whereas the issues of data imbalance, the possibility of generalization of the model, and real-time deployment remain the reasons to research this field further [12], [13].

Machine learning enables automated and real-time quality inspection in smart factories [11]. Convolutional Neural Networks (CNNs) extract spatial features from images as

$$h(l) = \sigma(W(l) * h(l-1) + b(l)) \qquad \text{-- (11)}$$

where h(l) is the feature map at layer l, W(l) is the convolution kernel, * denotes convolution, b(l) is the bias, and $\sigma(\cdot)$ is an activation function.

Defect classification is optimized using cross-entropy loss [12]

$$L\_CE = -\Sigma_k \, y_k \log(\hat{y}_k) \qquad \text{-- (12)}$$

Here, y_k is the true label for class k and $\hat{y}_k$ is the predicted probability.

5. Production Process Optimization

Another important use of machine learning in the smart factories using IoT is producing optimization of the production process, whereby the goal is to enhance productivity, product quality and operational efficiency using the data through control and decision making. Parameters of the processes that IoT sensors constantly monitor include temperature, pressure, feed rate, cutting speed, machine states and all these are analyzed with machine learning models to learn the intricate links between manageable factors and production outputs [14], [15].

Deep neural networks and supervised learning are also widely used to simulate the behavior of the processes and forecast the quality results to be observed in order to identify the suboptimal operating conditions early and provide adaptive parameter tuning [13], [16]. Moreover, the methods of reinforcement learning develop the idea of production control as a sequential decision-making problem, which enables intelligent agents to dynamically adapt to the values of the process parameters and scheduling strategies under the influence of real-time feedback of the manufacturing environment [14], [16].

These types of approaches to learning-based optimization have been effectively used to adaptive machining, robotic assembly, production schedule and real-time process monitoring in Industry 4.0 systems [14], [15]. Even though these benefits exist, issues regarding system stability, safety limitations as well as scalability continue to pose as research problems, and thus, the research question regarding exploring hybrid optimization frameworks where machine learning is combined with domain knowledge and industrial control systems is still open to further investigation [15], [16].

The relationship between process parameters and output quality is modeled as [13]

10.48047/jocaaa.2022.30.02.26

$$q = f\theta(u) + \varepsilon \quad \text{-- (13)}$$

where q denotes output quality, u represents controllable process variables, and ε is a noise term.Reinforcement learning formulates adaptive control as a Markov Decision Process [14]

$$M = (S, A, P, R, \gamma) \quad \text{-- (14)}$$

where S is the state space, A is the action space, P is the transition probability, R is the reward function, and γ is the discount factor.

The objective function is

$$\max\pi\ E[\ \Sigma_t\ \gamma^t\ R(s_t, a_t)\ ] \quad \text{-- (15)}$$

where π is the policy and $R(s_t, a_t)$ is the reward obtained at time *t*.

6. Energy Efficiency and Sustainability

The problem of energy efficiency and sustainability is a primary goal in IoT-enabled smart factories as the cost of energy and environmental regulations are rising. IoT sensors allow monitoring energy consumption within the machines and production systems continuously and machine learning models are used to analyze this data to predict energy demand and detect inefficiencies [17], [18]. Energy consumption forecasting and anomaly detection are highly practiced with the help of the supervised learning and deep learning methods and help with adaptive load management and process optimization [17], [19].

Reinforcement learning techniques also allow controlling the dynamic energy using optimal operation policies, which strike a balance between the productivity and the energy consumption in different conditions [18], [19]. Combination of machine learning and Industry 4.0 technologies leads to decreased energy use, decreased carbon emission, and enhanced sustainability of manufacturing processes though issues related to scalability and real-time implementation are still unsolved research questions [17].

Energy consumption prediction is expressed as [15]

$$\hat{E}(t) = f_\theta(x(t)) \quad \text{-- (16)}$$

where $\hat{E}(t)$ is predicted energy consumption and x(t) is sensor input.

Energy cost minimization is formulated as

$$\min\_u\ \Sigma_t\ E(t) \cdot C(t) \quad \text{-- (17)}$$

where E(t) is energy usage, C(t) is unit energy cost, and u denotes control actions.

Adaptive energy control using Q-learning is defined as [16]:

10.48047/jocaaa.2022.30.02.26

$$Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \max\_a' Q(s', a') - Q(s, a)] \quad \text{-- (18)}$$

where Q(s, a) is the state-action value, α is the learning rate, r is the reward, and s′ is the next state.

7. Safety Monitoring and Human–Machine Interaction

The human-machine interaction and safety surveillance are vital components of the IoT-based smart factories, especially in the areas where automated material handling equipment and collaborative robots are to be used. The environmental and physiological data captured by IoT sensors and wearable devices are analyzed with machine learning models to identify dangerous situations, dangerous behavior, and fatigue in employees in real time [20], [21].

The multimodal learning techniques involve a combination of vision, movement, and biometric measurements in order to enhance the accuracy of safety detection and accident avoidance [20]. The safety systems based on machine learning can allow proactive intervention through the production of alerts or control measures in case a possible danger is detected and thereby mitigate workplace accidents and enhance the safety of operations [21]. In spite of such developments, the problem of robustness, privacy protection, and explanability of the safety-related models of machine learning has become crucial in Industry 4.0 settings [22]. Probably classification is employed in the safety monitoring to identify hazards [17]

$$P(\text{hazard} \mid x) > \tau \rightarrow \text{Alert} \quad \text{-- (19)}$$

where P(hazard | x) is the probability of a hazardous condition given sensor data x, and τ is a safety threshold.

Wearable sensor data are represented as

$$x(t) = [HR(t), SpO_2(t), a_x(t), a_\gamma(t), a\_z(t)] \quad \text{-- (20)}$$

where HR is heart rate, SpO_2 is oxygen saturation, and a_x, a_γ, a_z are acceleration components [18].

8. Supply Chain and Inventory Optimization

Another vital use of machine learning in IoT-enabled smart factories is the supply chain and inventory optimization that will allow implementation of data-based coordination of production, storage, and distribution processes. IoT technologies make real-time monitoring of inventory levels, material flows, and logistics operations and machine learning models process these data to predict demand, make better inventory policy decisions, and make decisions under uncertainty [23], [24].

Demand prediction and inventory level estimation are more typically handled by supervised learning methods, and adaptive ordering, routing, and scheduling methods in dynamic supply chains are aided by the reinforcement learning techniques [24], [25]. Machine learning combined with IoT-based identification systems like RFID also improves the visibility and responsiveness throughout supply chains [26].

10.48047/jocaaa.2022.30.02.26

In spite of these advantages, the issues of data integration, scalability, discontinuity resistance, and continuous operation remain the driving forces behind the development of intelligent, resilient, and sustainable supply chain systems in Industry 4.0 [23], [24]. Inventory dynamics are expressed as [19]

$$I_{t+1} = I_t + O_t - D_t \quad \text{-- (21)}$$

where I_t is inventory level, O_t is order quantity, and D_t is demand.

Demand forecasting minimizes squared prediction error:

$$\min\theta\ \Sigma_t\ (D_t - \hat{D}_t)^2 \quad \text{-- (22)}$$

where $\hat{D}_t$ is predicted demand.

9. Challenges and Future Scope

Despite all the advantages of machine learning-enabled IoT-based smart factories, some obstacles exist in the form of challenges that prevent the widespread introduction of the industrial implementation. The issues of data quality and imbalance, absence of labeled fault data, heterogeneous devices interoperability and computational capabilities of real time edge deployment are critical problems [1], [2], [6].

In addition, model transparency and explainability are also lacking, which limits the confidence of machine learning-based decisions particularly in high-value and safety-critical manufacturing operations [20], [22]. Cybersecurity concerns and privacy of data also make connected and intelligent manufacturing system implementation more complicated [22]. Intelligible and reliable artificial intelligence, federated learning, distributed learning, to safeguard privacy, digital twins integration to make predictive decisions, and energy-saving edge intelligence are probable considerations in the future research under the Industry 4.0 paradigm [1], [6], [21].

Explainability of ML models is critical for industrial adoption. Feature importance can be approximated as [20]

$$\text{Importance}(x_i) = |\ \partial f(x) / \partial x_i\ | \quad \text{-- (23)}$$

Future research will focus on explainable AI, federated learning, digital twins, edge intelligence, and secure ML deployment in smart factories [21].

10. Conclusion

A comprehensive literature review was conducted on the application of Machine Learning (ML) as an enabler for IoT-based Smart Factories within the Industry 4.0 Paradigm; specifically focusing on Predictive Maintenance, Intelligent Quality Control, Optimizing Production Process, Energy Efficiency, Safety Monitoring and Supply Chain Optimization. Using Real Time Sensor Data and Advanced Learning Algorithms, Smart Factories are able to make decisions that are Proactive, Adaptive and Autonomous, which can contribute to Improved Operational Efficiencies, Product Quality and Sustainability.

10.48047/jocaaa.2022.30.02.26

The Literature Review also demonstrated how Supervised, Unsupervised, Deep Learning and Reinforcement Learning Techniques are used in conjunction with IoT Infrastructure to address complex manufacturing challenges. While there has been considerable progress in this area, several challenges including poor Data Quality, Model Explainability, Real-Time Deployment and Cybersecurity continue to pose significant barriers to widespread adoption. Ultimately, it is anticipated that the continued Convergence of IoT, ML and Emerging Industry 4.0 Technologies will Drive the Evolution of Resilient, Sustainable Manufacturing Systems.

References

[1] J. Dalzochio, R. Kunst, E. Pignaton, A. Binotto, S. Sanyal, J. Favilla, and E. Mendes, "Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges," *Computers in Industry*, vol. 123, Art. no. 103298, 2020, doi: 10.1016/j.compind.2020.103298.

[2] T. Zonta, C. A. da Costa, R. da Rosa Righi, J. L. M. Yamin, L. M. S. Goliatt, and E. L. Bezerra, "Predictive maintenance in the Industry 4.0: A systematic literature review," *Computers & Industrial Engineering*, vol. 150, Art. no. 106889, 2020, doi: 10.1016/j.cie.2020.106889.

[3] M. Pech, J. Vrchota, and J. Bednář, "Predictive maintenance and intelligent sensors in smart factory," *Sensors*, vol. 21, no. 4, Art. no. 1470, 2021, doi: 10.3390/s21041470.

[4] A. Cachada, J. Barbosa, P. Leitão, G. Pires, and A. P. Moreira, "Maintenance 4.0: Intelligent and predictive maintenance system architecture," in *Proc. IEEE Int. Conf. Emerging Technologies and Factory Automation (ETFA)*, Limassol, Cyprus, 2018, pp. 139–146, doi: 10.1109/ETFA.2018.8502486.

[5] I. Bisio, C. Garibotto, A. Grattarola, F. Lavagetto, and A. Sciarrone, "Context-aware IoT systems for Industry 4.0 applications," *IEEE Network*, vol. 32, no. 4, pp. 101–107, 2018, doi: 10.1109/MNET.2018.1700338.

[6] B. Elahi and S. A. Tokaldany, "IoT-aided digital twin technology in smart manufacturing," in *Advances in Mathematics for Industry 4.0*, Elsevier, 2021, ch. 14, pp. 291–314, doi: 10.1016/B978-0-12-822410-5.00014-2.

[7] S. Shan, X. Wen, Y. Wei, and Y. Zhang, "Intelligent manufacturing in Industry 4.0: A case study," *Systems Research and Behavioral Science*, vol. 37, no. 4, pp. 679–690, 2020, doi: 10.1002/sres.2712.

[8] C. K. M. Lee, Y. Lv, K. K. H. Ng, W. Ho, and K. L. Choy, "Design and application of IoT-based warehouse management systems," *International Journal of Production Research*, vol. 56, no. 8, pp. 2753–2768, 2018, doi: 10.1080/00207543.2017.1394592.

[9] Y. Mashayekhy, A. Babaei, and X. Yuan, "Impact of Internet of Things on inventory management: A survey," *Logistics*, vol. 6, no. 2, Art. no. 33, 2022, doi: 10.3390/logistics6020033.

10.48047/jocaaa.2022.30.02.26

[10] N. Mostafa, W. Hamdy, and H. Elawady, “Intelligent warehouse management using IoT,” *Egyptian Informatics Journal*, vol. 32, pp. 59–65, 2020, doi: 10.1016/j.eij.2019.11.001.

[11] S. M. Lee, D. Lee, and Y. S. Kim, “Quality management ecosystem for predictive maintenance in Industry 4.0,” *International Journal on Quality Innovation*, vol. 5, no. 1, pp. 1–11, 2019, doi: 10.1186/s40887-019-0034-5.

[12] S. Yin, X. Li, H. Gao, and O. Kaynak, “Data-driven monitoring and quality improvement in manufacturing using machine learning,” *IEEE Transactions on Industrial Informatics*, vol. 18, no. 6, pp. 4216–4226, 2022, doi: 10.1109/TII.2021.3138304.

[13] S. Sader, I. Husti, and M. Daróczi, “Industry 4.0 as a key enabler of total quality management,” *Periodica Polytechnica Social and Management Sciences*, vol. 27, no. 2, pp. 131–140, 2019, doi: 10.3311/PPso.12463.

[14] M. Wollschlaeger, T. Sauter, and J. Jasperneite, “The future of industrial communication in Industry 4.0,” *IEEE Industrial Electronics Magazine*, vol. 11, no. 1, pp. 17–27, 2017, doi: 10.1109/MIE.2017.2649104.

[15] J. I. R. Molano, J. M. C. Lovelle, C. E. Montenegro, and J. J. R. Cueva, “Metamodel for IoT and Industry 4.0 integration,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 9, pp. 709–723, 2018, doi: 10.1007/s12652-017-0469-5.

[16] U. Küpper, T. Herrig, A. Klink, and B. Kuhlenkötter, “Online process monitoring in Industry 4.0,” *Procedia CIRP*, vol. 95, pp. 360–365, 2020, doi: 10.1016/j.procir.2020.01.117.

[17] N. Mohamed, J. Al-Jaroodi, and S. Lazarova-Molnar, “Energy efficiency improvement using Industry 4.0 technologies,” *IEEE Access*, vol. 7, pp. 18008–18020, 2019, doi: 10.1109/ACCESS.2019.2895808.

[18] F. Shrouf, J. Ordieres, and G. Miragliotta, “Energy management in smart factories,” in *Proc. IEEE Int. Conf. Industrial Engineering and Engineering Management (IEEM)*, 2014, pp. 1–5, doi: 10.1109/IEEM.2014.7058722.

[19] M. Elsisi, M. Q. Tran, K. Mahmoud, M. Lehtonen, and M. Darwish, “Deep learning-based energy management for smart buildings,” *Sensors*, vol. 21, no. 3, Art. no. 1038, 2021, doi: 10.3390/s21031038.

[20] A. F. Abate, L. Cimmino, I. Cuomo, A. Esposito, and S. Ricciardi, “Multimodal biometrics for safety in smart factories,” *IEEE Transactions on Industrial Informatics*, vol. 18, no. 12, pp. 9092–9100, 2022, doi: 10.1109/TII.2022.3142590.

[21] Z. Liu, K. Xie, L. Li, and Y. Chen, “Safety management paradigm in Industry 4.0,” *Systems Research and Behavioral Science*, vol. 37, no. 4, pp. 632–645, 2020, doi: 10.1002/sres.2704.

[22] A.-R. Sadeghi, C. Wachsmann, and M. Waidner, “Security and privacy challenges in industrial Internet of Things,” in *Proc. Design Automation Conf. (DAC)*, 2015, pp. 1–6, doi: 10.1145/2744769.2747942.

10.48047/jocaaa.2022.30.02.26

[23] E. Manavalan and K. Jayakrishna, “IoT-embedded sustainable supply chains in Industry 4.0,” *Computers & Industrial Engineering*, vol. 127, pp. 925–953, 2019, doi: 10.1016/j.cie.2018.04.030.

[24] D. Ivanov, S. Sethi, A. Dolgui, and B. Sokolov, “Control theory applications in supply chain management and Industry 4.0,” *Annual Reviews in Control*, vol. 46, pp. 134–147, 2018, doi: 10.1016/j.arcontrol.2018.09.014.

[25] C. Cimini, G. Pezzotta, R. Pinto, and S. Cavalieri, “Industry 4.0 impacts on manufacturing and supply chains,” in *Proc. SOHOMA*, 2019, pp. 1–12, doi: 10.1007/978-3-030-27477-1_9.

[26] E. Elbasani, P. Siriporn, and J. S. Choi, “RFID in Industry 4.0: A survey,” in *Internet of Things for Industry 4.0*, Springer, 2020, ch. 1, pp. 1–24, doi: 10.1007/978-3-030-30367-9_1.