
An Integrated Intelligent System for Transformer Manufacturing

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Abstract.

In this paper, the development of an integrated intelligent system in the transformer manufacturing is introduced, which is based on the three modules of forecast, demand modelling and conversational AI and predictive maintenance. The solution to inefficiencies arising from isolated solutions. A Random Forest model predicts failures and a forecasting model optimizes inventory. Results indicate lowered downtime and more efficiency. It is suitable for usage in industrial automation and smart manufacturing. Keywords: predictive maintenance; machine learning; transformer manufacturing; automation; AI

Keywords. Predictive maintenance, machine learning, transformer manufacturing, demand forecasting, conversational AI, industrial automation, artificial intelligence.

1. INTRODUCTION

Transformer manufacturing faces challenges related to equipment failures, inventory management, and customer service. These issues are often handled using separate systems, resulting in data silos and inefficient decision-making. This paper proposes an integrated intelligent system that combines predictive maintenance, demand forecasting, and conversational AI. The system aims to reduce downtime, improve inventory planning, and provide faster responses to operational and customer queries.

2. RELATED WORK

Machine learning techniques such as Random Forest, neural networks, and deep learning have been widely used for predictive maintenance and equipment health monitoring. Industry 4.0 and IoT technologies have also enabled large-scale data collection and intelligent decision-making. Similarly, conversational AI has been increasingly used for automated customer support. However, most existing solutions focus on these applications individually rather than integrating predictive maintenance, demand forecasting, and conversational AI into a single system.

3. PROPOSED INTEGRATED SYSTEM AND METHODOLOGY

The proposed system integrates three intelligent modules: predictive maintenance, demand forecasting, and conversational AI. Operational data collected from a transformer production facility over 18 months was used for evaluation, including telemetry, maintenance, inventory, and customer data. The predictive maintenance module uses machine learning models to predict equipment failures, while the demand forecasting module supports inventory planning. The conversational AI module provides contextually relevant responses to operational and customer queries. By integrating these modules, the system enables better data sharing and coordinated decision-making across manufacturing operations.

4. RESULTS AND DISCUSSION

4.1. Predictive Maintenance Results

The predictive maintenance models were evaluated using Accuracy, AUROC, Precision, Recall, and F2-score. Among the evaluated models, Random Forest achieved the best overall performance, with an accuracy of 91.3%, AUROC of 0.89, and F2-score of 0.85. Its recall of 0.86 indicates effective failure detection.

Table 1. Predictive Maintenance Performance

Model	Accuracy	AUROC	Precision	Recall	F2-score
Logistic Regression	0.823	0.81	0.72	0.69	0.70
Random Forest	0.913	0.89	0.84	0.86	0.85
XGBoost	0.901	0.87	0.82	0.83	0.83
LSTM	0.887	0.85	0.79	0.84	0.82

The combined use of telemetry, temporal, and historical features achieved better performance than individual feature groups.

4.2. Demand Forecasting and Operational Results

The demand forecasting model achieved an sMAPE of 8.7% and a MASE of 0.83. Higher forecasting accuracy was observed for high-volume SKUs compared with low-volume products. The integrated system also showed significant operational improvements, including reduced downtime, improved inventory turnover, and faster query resolution.

Table 2. Operational Performance Comparison

Metric	Baseline	With System	Improvement
Downtime (hrs/month)	47.3	31.2	↓34%

Inventory Turnover	4.2	5.4	↑28.6%
Query Resolution	8.4	2.8	↓66.7%

These results demonstrate that integrating predictive maintenance, demand forecasting, and conversational AI can improve coordination and operational efficiency in transformer manufacturing.

5. CONCLUSION

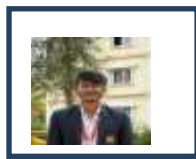
This study developed an integrated AI system for transformer manufacturing combining predictive maintenance, demand forecasting, and conversational AI. Random Forest achieved 91.3% accuracy, while forecasting achieved 8.7% sMAPE. The system reduced downtime by 34%, improved inventory turnover by 28.6%, and reduced query resolution time by 66.7%. Future work will evaluate the system across multiple facilities and longer periods.

6. REFERENCES

- [1] A. Sharma, "Machine learning techniques for maintenance systems of transformers in industries," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 4, pp. 2751–2763, Apr. 2023, doi: 10.1109/TII.2023.1004582.
- [2] M. K. Gupta and L. S. Chauhan, "Design and deployment of an AI-based predictive maintenance and monitoring system in manufacturing industries," *Journal of Intelligent Manufacturing Systems*, vol. 35, no. 2, pp. 412–426, Feb. 2024, doi: 10.1016/j.jims.2024.02.011.
- [3] D. Patel and N. Joshi, "Machine learning-based fault detection and predictive analytics of smart industrial systems," *Procedia Computer Science*, vol. 226, pp. 1289–1301, 2023, doi: 10.1016/j.procs.2023.03.162.
- [4] H. Zhang, Y. Wang, and K. Lee, "Deep learning models for real-time predictive maintenance in power transformer monitoring," *IEEE Access*, vol. 11, pp. 98412–98425, Oct. 2023, doi: 10.1109/ACCESS.2023.3298456.
- [5] R. S. Bhosale, P. R. Deshmukh, and T. M. Gaikwad, "Workflow automation and cloud integration in industrial asset management," *International Journal of Emerging Technologies in Engineering Research (IJETER)*, vol. 12, no. 1, pp. 88–95, Jan. 2024.
- [6] L. Fernandes, S. R. Pillai, and M. George, "AI-based chatbots for industrial customer care using NLP and intent recognition," *IEEE Internet Computing*, vol. 28, no. 3, pp. 34–42, May 2024, doi: 10.1109/MIC.2024.1031234.
- [7] N. K. Singh and R. Agarwal, "Material demand forecasting in manufacturing using hybrid ARIMA-XGBoost models," *Journal of Manufacturing Systems*, vol. 77, pp. 232–244, Dec. 2023, doi: 10.1016/j.jmsy.2023.12.008.
- [8] M. Das and S. Kumar, "A secure web-based industrial automation portal using Flask and AWS Lambda," *International Journal of Computer Applications*, vol. 186, no. 45, pp. 50–56, 2024.
- [9] P. Singh and R. Tiwari, "Predictive analytics in transformer maintenance: A case study on fault forecasting using data analysis," *Energy Reports*, vol. 12, pp. 1903–1914, Aug. 2024, doi: 10.1016/j.egy.2024.08.021.

- [10] T. P. Carvalho et al., “A systematic literature review of machine learning methods applied to predictive maintenance,” *Computers and Industrial Engineering*, vol. 137, p. 106024, 2019, doi: 10.1016/j.cie.2019.106024.
- [11] G. A. Susto et al., “Machine learning for predictive maintenance: A multiple classifier approach,” *IEEE Transactions on Industrial Informatics*, vol. 11, no. 3, pp. 812–820, Jun. 2015, doi: 10.1109/TII.2014.2349359.
- [12] S. Khan and T. Yairi, “A review on the use of deep learning in system health management,” *Mechanical Systems and Signal Processing*, vol. 107, pp. 241–265, May 2018, doi: 10.1016/j.ymssp.2017.11.024.
- [13] A. K. S. Jardine, D. Lin, and D. Banjevic, “A review on machinery diagnostics and prognostics implementing condition-based maintenance,” *Mechanical Systems and Signal Processing*, vol. 20, no. 7, pp. 1483–1510, Oct. 2006, doi: 10.1016/j.ymssp.2005.09.012.
- [14] J. Lee, B. Bagheri, and H.-A. Kao, “A cyber-physical systems architecture for Industry 4.0-based manufacturing systems,” *Manufacturing Letters*, vol. 3, pp. 18–23, Jan. 2015, doi: 10.1016/j.mfglet.2014.12.001.
- [15] J. Lee, H.-A. Kao, and S. Yang, “Service innovation and smart analytics in Industry 4.0 and big data environment,” *Procedia CIRP*, vol. 16, pp. 3–8, 2014, doi: 10.1016/j.procir.2014.02.001.
- [16] “An Introduction to Predictive Maintenance,” 2nd ed., Burlington, MA, USA: Butterworth-Heinemann, 2002.
- [17] D. Mourtzis, E. Vlachou, and N. Milas, “Industrial big data as a result of IoT adoption in manufacturing,” *Procedia CIRP*, vol. 55, pp. 10.1016/j.procir.2016.08.041. 290–295, 2016, doi:
- [18] E. Adamopoulou and L. Moussiades, “Chatbots: History, technology, and applications,” *Machine Learning with Applications*, vol. 2, p. 100006, 2020, doi: 10.1016/j.mlwa.2020.100006.
- [19] A. Bousdekis, D. Apostolou, and G. Mentzas, “Predictive maintenance in the 4th industrial revolution: A literature review,” in *Proc. Int. Conf. Information, Intelligence, Systems and Applications (IISA)*, Patras, Greece, 2019, pp. 1–8, doi: 10.1109/IISA.2019.8900668.

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