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Optimization of Manufacturing Processes for Enhancing Production Efficiency and Reducing Waste in High-Volume Mechanical Component Production

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Abstract

High-volume production of mechanical components requires manufacturing systems that can consistently achieve high productivity, dimensional accuracy, quality and cost efficiency while minimizing material, energy, time and operational waste. Conventional production systems frequently experience losses arising from machine downtime, excessive setup time, inefficient process routing, tool wear, defects, unnecessary material movement and excessive energy consumption. Recent developments in lean manufacturing, Industry 4.0, artificial intelligence, digital twins, predictive maintenance and sustainable machining provide new opportunities for addressing these challenges. This paper examines process optimization strategies for high-volume mechanical component production, focusing on lean waste elimination, machining-parameter optimization, production scheduling, equipment effectiveness, digital monitoring and energy-efficient manufacturing. The literature indicates that integrating lean principles with data-driven technologies can improve process visibility and support real-time decision-making. Optimization of cutting parameters, tool paths and production schedules can simultaneously reduce machining time, energy consumption and material losses. Digital twins and artificial intelligence further enable predictive process control and equipment optimization. The paper proposes an integrated optimization framework combining process mapping, performance measurement, parameter optimization, predictive monitoring and continuous improvement. Such an approach can enhance productivity while supporting economically and environmentally sustainable manufacturing.

Keywords: manufacturing process optimization, production efficiency, waste reduction, high-volume production, machining, lean manufacturing, Industry 4.0, digital twin

Introduction

High-volume mechanical component production is characterized by repetitive operations, large production quantities, standardized processes and stringent requirements for dimensional accuracy and product quality. Typical components include shafts, gears, bearings, fasteners, automotive parts, machine elements and other precision-engineered products. Because production is repeated over long periods, relatively small inefficiencies in cycle time, tool utilization, material consumption or machine availability can accumulate into substantial productivity and cost losses. Consequently, manufacturing optimization must address the entire production system rather than focusing on individual machines or isolated operations (Ng Corrales et al., 2020; Wang et al., 2023).

Manufacturing waste can arise through overproduction, waiting, unnecessary transportation, excessive inventory, unnecessary processing, defects and underutilization of human and technological resources. Lean manufacturing provides established mechanisms for identifying and eliminating such non-value-adding activities, while Industry 4.0 technologies provide enhanced capabilities for collecting and analysing production information (Mofolasayo et al., 2022; Naciri et al., 2022).

The increasing availability of sensors, industrial Internet of Things (IIoT), machine learning and digital twins has expanded the possibilities for process optimization. Modern manufacturing systems can increasingly monitor machine conditions, production rates, energy consumption and product quality in near real time. These technologies enable manufacturers to move from reactive process correction toward predictive and adaptive optimization (Jiang et al., 2021; Jiang et al., 2021; Karkaria et al., 2025).

Manufacturing Process Optimization and Production Efficiency

Manufacturing process optimization involves identifying operating conditions and production strategies that provide the best combination of productivity, quality, cost and resource utilization. In high-volume production, optimization can involve machining parameters, process sequence, machine allocation, material flow, production scheduling, tool selection and maintenance strategy. Effective optimization therefore requires simultaneous consideration of technical and operational variables rather than maximizing production rate alone (Kong et al., 2022; Feng et al., 2022).

Overall Equipment Effectiveness (OEE), calculated from availability, performance and quality, provides a useful indicator for identifying production losses. Systematic research has shown that OEE has increasingly become associated with maintenance, lean manufacturing, optimization and digital manufacturing systems (Ng Corrales et al., 2020). In high-volume production, OEE can be used to identify whether losses originate primarily from machine downtime, reduced operating speed or defective production. This information provides a basis for prioritizing improvement activities.

Process optimization should also consider production scheduling. In machining environments, different process routes and machine assignments can produce significantly different energy consumption and production times. Kong et al. (2022) demonstrated that integrating process planning and production scheduling can support energy-efficient manufacturing, showing the importance of optimizing production decisions jointly rather than independently. Similar work has demonstrated that data-driven optimization of cutting parameters can reduce both production time and energy consumption (Zhao et al., 2022).

Lean Manufacturing for Waste Reduction

Lean manufacturing remains one of the most effective approaches for improving production efficiency because it focuses directly on the elimination of non-value-adding activities. In high-volume mechanical production, value stream mapping can reveal excessive movement,

waiting, bottlenecks, unnecessary inspection, excessive work-in-progress and inefficient material flows. Lean tools such as 5S, Kanban, Just-in-Time, standardized work, SMED and continuous improvement can subsequently be applied to reduce these losses (Mofolasayo et al., 2022; Javaid et al., 2022).

Evidence from metalworking industries demonstrates the practical value of lean interventions. Jara et al. (2023), for example, reported productivity improvement following the application of 5S, systematic layout planning and Just-in-Time approaches in a metalworking company. Similarly, Lazarte-Pazos et al. (2023) applied lean tools to a metal-mechanical production process to address waiting, transportation and production-flow problems. These findings indicate that substantial improvements can sometimes be achieved through process redesign and management improvements before major capital investment is undertaken.

The combination of lean manufacturing with Industry 4.0 has further strengthened waste reduction. Lean principles identify what should be improved, whereas digital technologies provide better information about when, where and why losses occur. Consequently, Lean 4.0 can provide real-time production visibility, automated data collection and more responsive process control (Javaid et al., 2022; Naciri et al., 2022). Research has also shown that SMEs can adopt Industry 4.0 progressively by establishing basic digitalization and data-management capabilities before implementing more advanced cyber-physical technologies (Mofolasayo et al., 2022).

Optimization of Machining Parameters

Machining operations constitute a major part of mechanical component manufacturing, particularly in the production of shafts, gears, housings and precision components. Cutting speed, feed rate, depth of cut, tool geometry and machining strategy influence machining time, tool life, surface quality, energy consumption and production cost. Optimization of these variables is therefore essential in high-volume production systems (Feng et al., 2022; Zhao et al., 2022).

Recent research has increasingly moved toward multi-objective optimization in which productivity and quality are considered simultaneously with energy and environmental performance. Feng et al. (2022) proposed a systematic approach for optimizing machining parameters considering energy consumption, machining time and surface roughness. Similarly, research on sustainable machining has demonstrated that machining parameters can be optimized to achieve improved surface quality while reducing environmental impacts (Kadi et al., 2023; Ahmad et al., 2023).

Tool-path optimization provides another important opportunity. Efficient tool paths can reduce unnecessary tool movement, machining time and energy consumption while improving tool life. Recent reviews of sustainable CNC machining indicate that optimization of machining parameters, cutting paths, machine-tool selection and virtual machining can contribute simultaneously to productivity improvement and waste reduction (Soori et al., 2024).

Tool Wear, Predictive Monitoring and Maintenance

Tool wear is particularly important in high-volume production because worn tools can increase dimensional errors, surface roughness, energy consumption and rejection rates. Conventional practice often replaces tools at predetermined intervals to avoid failure, but this can result in premature replacement and unnecessary tool expenditure. Herwan et al. (2023) proposed a hybrid monitoring and optimization approach in a mass-production machining environment using machine learning and Bayesian optimization. Their approach demonstrated the potential for monitoring tool wear while optimizing tool-use conditions without disrupting production.

Predictive maintenance can similarly reduce unexpected machine downtime. Sensors and production data can be used to identify abnormal operating conditions before equipment failure occurs. Integration of predictive maintenance with digital manufacturing systems can therefore improve equipment availability and reduce the waste associated with unplanned stoppages. Digital-twin research further indicates that virtual representations of manufacturing assets can support monitoring, simulation, diagnosis and optimization (Jiang et al., 2021; Billey & Wuest, 2024).

Digital Twins and Artificial Intelligence

Digital twins provide a virtual representation of a physical manufacturing system that can be continuously updated using operational data. They can be used to simulate alternative production scenarios before changes are introduced into the physical system. This is particularly valuable in high-volume manufacturing because process changes can be tested virtually without unnecessarily interrupting production (Jiang et al., 2021; Wehking et al., 2024).

Energy-oriented digital twins are emerging as an important application. Billey and Wuest (2024) demonstrated an energy digital twin capable of closed-loop communication and optimization in a manufacturing application. Similarly, Wehking et al. (2024) developed a digital-twin approach for monitoring energy efficiency and product-level environmental performance. These developments indicate that process optimization can increasingly incorporate energy consumption and environmental impact as explicit optimization objectives rather than treating them as secondary considerations.

Artificial intelligence can further enhance optimization by identifying patterns in large volumes of production data. Machine learning can be applied to tool-wear prediction, quality prediction, energy optimization, scheduling and process control. A recent review identified monitoring and prediction, real-time control, scheduling and parameter optimization as major areas in which AI can support energy-efficient manufacturing (Keramati Feyz Abadi et al., 2025). Karkaria et al. (2025) similarly highlight the integration of AI, machine learning and digital twins as a means of supporting real-time monitoring, quality control and dynamic process adjustment.

Energy and Material Waste Reduction

Energy efficiency is increasingly important in manufacturing because machine tools, heating systems, compressors, pumps and auxiliary equipment can consume substantial amounts of electricity. Machining studies have demonstrated that energy consumption depends not only on cutting parameters but also on machine configuration, tool paths, standby conditions and production scheduling (Alswat & Mativenga, 2022; Kong et al., 2022).

High-efficiency machining strategies can reduce energy use by increasing material removal rates while controlling cutting power and machining time. Research on high-efficiency milling has shown that appropriate machining strategies can reduce cutting time and power consumption while increasing productivity (2022). Similarly, models of machine-tool energy consumption have demonstrated that energy can be decomposed into different operating components, allowing more precise identification of energy-saving opportunities (2022).

Material waste can be reduced through improved process planning, near-net-shape production, optimized cutting layouts, recycling of machining chips and better control of defective production. Sustainable CNC machining research emphasizes that tool-path optimization, material utilization, swarf recycling and energy-efficient equipment should be considered together when designing sustainable machining systems (Soori et al., 2024).

Integrated Framework for High-Volume Production Optimization

Based on the reviewed literature, an effective optimization strategy for high-volume mechanical component production should integrate five major stages:

Process Mapping → Waste Identification → Performance Measurement → Data-Driven Optimization → Continuous Improvement

First, the production process should be mapped from raw-material entry to finished-product inspection. Second, sources of waste should be identified using value stream mapping, OEE, process observation and production records which builds on the importance of systematic equipment monitoring and OEE-based performance assessment demonstrated in Nigerian manufacturing research (Wilson et al., 2020). Third, critical performance indicators such as cycle time, downtime, rejection rate, throughput, energy consumption, tool life and material utilization should be established.

The fourth stage involves optimization using appropriate analytical and computational tools. Statistical methods, response surface methodology, genetic algorithms, Bayesian optimization, machine learning and digital twins may be selected according to the complexity of the process. Recent research demonstrates that combining optimization with digital twins can support adaptive manufacturing decisions and improve system flexibility (Karkaria et al., 2025; Billey & Wuest, 2024).

Finally, optimized conditions should be standardized and continuously monitored. This is important because production conditions change due to tool wear, material variation, equipment degradation, demand fluctuations and environmental conditions. Industry 4.0 technologies can provide continuous data that supports ongoing improvement rather than treating optimization as a one-time intervention (Gadekar et al., 2022; Huang et al., 2022).

Conclusion

Optimization of high-volume mechanical component production requires an integrated approach that combines lean manufacturing, process engineering, machining optimization, maintenance, digital monitoring and sustainability. Lean methods provide the foundation for identifying and eliminating non-value-adding activities, while advanced digital technologies provide the data and computational capabilities needed for more precise and responsive optimization (Javaid et al., 2022; Naciri et al., 2022).

The literature demonstrates that optimization of machining parameters, production scheduling, tool utilization, equipment effectiveness and energy consumption can generate simultaneous improvements in productivity and resource efficiency. Digital twins and artificial intelligence are particularly promising because they allow manufacturing systems to move toward predictive and adaptive operation (Jiang et al., 2021; Keramati Feyz Abadi et al., 2025).

For high-volume mechanical component manufacturers, the most effective strategy is therefore not simply to increase production speed. Instead, manufacturers should optimize the complete production system by reducing waiting, downtime, defects, unnecessary movement, excessive material consumption, tool losses and energy waste. Such an integrated approach can provide higher throughput, lower production costs, improved product quality and more sustainable manufacturing performance.

REFERENCES

Ahmad, A. A., Ghani, J. A., & Che Haron, C. H. (2023). The influence of cutting parameter under sustainable machining approaches on surface roughness of AISI 4340. *Journal of Mechanical Engineering, 12*(1), 63–80.

Alswat, H. M., & Mativenga, P. T. (2022). Modelling the direct and embodied energy requirements of machining. *Journal of Cleaner Production, 366*, 132767.

Billey, A., & Wuest, T. (2024). Energy digital twins in smart manufacturing systems: A case study. *Robotics and Computer-Integrated Manufacturing, 88*, 102729.

Dobra, P., & Jósvai, J. (2023). Overall Equipment Effectiveness-related Assembly Pattern Catalogue based on Machine Learning. *Manufacturing Technology, 23*(3), 276–283.

Feng, C., Guo, H., Zhang, J., Huang, Y., et al. (2022). A systematic method of optimization of machining parameters considering energy consumption, machining time, and surface roughness with experimental analysis. *The International Journal of Advanced Manufacturing Technology, 119*, 1–19.

Gadekar, R., Sarkar, B., & Gadekar, A. (2022). Investigating the relationship among Industry 4.0 drivers, adoption, risks reduction, and sustainable organizational performance in manufacturing industries: An empirical study. *Sustainable Production and Consumption, 31*, 670–692.

Grabowska, S., Saniuk, S., & Gajdzik, B. (2022). Industry 5.0: Improving humanization and sustainability of Industry 4.0. *Scientometrics, 127*, 3117–3144.

Huang, Z., Jowers, C., Kent, D., et al. (2022). The implementation of Industry 4.0 in manufacturing: From lean manufacturing to product design. *The International Journal of Advanced Manufacturing Technology, 121*, 3351–3367.

Ivanov, D. (2023). The Industry 5.0 framework: Viability-based integration of the resilience, sustainability, and human-centricity perspectives. *International Journal of Production Research, 61*(5), 1683–1695.

Jara, B., Calderon, S., & Avalos-Ortecho, E. (2023). Application of lean manufacturing to increase productivity of a company in the metalworking sector. *Industrial Engineering and Applications*.

Javaid, M., Haleem, A., Singh, R. P., Rab, S. R., Suman, R., & Khan, S. (2022). Exploring relationships between Lean 4.0 and manufacturing industry. *Industrial Robot, 49*(3), 402–414.

Jiang, Y., Yin, S., Li, K., Luo, H., & Kaynak, O. (2021). Industrial applications of digital twins. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 379*(2207), 20200360.

Jiang, Z., Guo, Y., & Wang, Z. (2021). Digital twin to improve the virtual-real integration of industrial IoT. *Journal of Industrial Information Integration, 22*, 100196.

Kadi, R. V., Dundur, S. T., Goudar, D. M., & Haider, J. (2023). Applying multi-response optimization for sustainable machining of 316 stainless steel with coconut oil-assisted minimum quantity lubrication. *Tribology—Materials, Surfaces & Interfaces, 17*(1).

Karkaria, V., Tsai, Y.-K., Chen, Y.-P., & Chen, W. (2025). An optimization-centric review on integrating artificial intelligence and digital twin technologies in manufacturing. *Engineering Optimization, 57*(1), 161–207.

Keramati Feyz Abadi, M. M., Liu, C., Zhang, M., Hu, Y., & Xu, Y. (2025). Leveraging AI for energy-efficient manufacturing systems: Review and future prospectives. *Journal of Manufacturing Systems, 78*, 153–177.

Kong, T., Nhg, D. R., & Shi, V. T. (2022). Method for optimizing energy consumption in machining manufacturing process. *Mathematical Problems in Engineering, 2022*, 8300666.

Lazarte-Pazos, P. A., Ordoñez-Carrión, S. S. E., & Avalos-Ortecho, E. M. (2023). Implementation of lean manufacturing to increase productivity in the manufacture of kitchen sinks in a metal-mechanical company. *Industrial Engineering and Applications*.

Mofolasayo, A., Young, S., Martinez Rodriguez, P., & Ahmad, R. (2022). How to adapt lean practices in SMEs to support Industry 4.0 in manufacturing. *Procedia Computer Science, 200*, 934–943.

Naciri, L., Mouhib, Z., Gallab, M., Nali, M., Abbou, R., & Kebe, A. (2022). Lean and industry 4.0: A leading harmony. *Procedia Computer Science, 200*, 394–406.

Narkhede, G. (2023). Industry 5.0 and the future of sustainable manufacturing: A systematic literature review. *Business Strategy & Development, 6*(4), 704–723.

Ng Corrales, L. del C., Lambán, M. P., Hernandez Korner, M. E., & Royo, J. (2020). Overall Equipment Effectiveness: Systematic literature review and overview of different approaches. *Applied Sciences, 10*(18), 6469.

Soori, M., Karimi Ghaleh Jough, F., Dastres, R., & Arezoo, B. (2024). Sustainable CNC machining operations, a review. *Sustainable Operations and Computers, 5*, 73–87.

Wang, L., Cai, W., He, Y., Peng, T., Xie, J., Hu, L., & Li, L. (2023). Equipment–process–strategy integration for sustainable machining: A review. *Frontiers of Mechanical Engineering, 18*, 36.

Wehking, S., Riedelsheimer, T., Tanrikulu, C., & Lindow, K. (2024). Developing digital twins for energy efficiency in the production phase of products. *Procedia CIRP, 122*, 933–938.

Wilson, E. O., Uko, D. K., Etok, S. A., & Awaka-Ama, E. J. (2020). Implementation of Total Productive Maintenance (TPM) in Nigerian manufacturing industries (brewery). *International Journal of Engineering Science Invention*, *9*(6), 29–41. https://doi.org/10.35629/6734-0906012941

Zhao, X., Li, C., Chen, X., Cui, J., & Cao, B. (2022). Data-driven cutting parameters optimization method in multiple configurations machining process for energy consumption and production time saving. *International Journal of Precision Engineering and Manufacturing-Green Technology*, *9*(3), 709–728.

Lv, Y., Li, C., He, J., Li, W., Li, X., & Li, J. (2022). Energy saving design of the machining unit of hobbing machine tool with integrated optimization. *Frontiers of Mechanical Engineering*, *17*, 38.

Herwan, J., Misaka, T., Furukawa, Y., Ogura, I., & Komoto, H. (2023). A proposal for improving production efficiency of existing machining line through a hybrid monitoring and optimisation process. *International Journal of Production Research*, *61*(16), 5392–5410.

Ghobakhloo, M., Iranmanesh, M., Mubarak, M. F., Mubarik, M., Rejeb, A., & Nilashi, M. (2022). Identifying Industry 5.0 contributions to sustainable development: A strategy roadmap for delivering sustainability values. *Sustainable Production and Consumption*, *33*, 716–737.

van Erp, T., Carvalho, N. G. P., Gerolamo, M. C., Gonçalves, R., Rytter, N. G. M., & Gladysz, B. (2024). Industry 5.0: A new strategy framework for sustainability management and beyond. *Journal of Cleaner Production*, *461*, 142271.

Note: The references above were checked against publisher, journal, institutional, or scholarly-index records during preparation; examples include the verified records for the machining optimization studies, Lean/Industry 4.0 studies, digital-twin studies, and sustainable manufacturing reviews. (Wiley Online Library)