

Machine learning–based predictive control for energy-efficient manufacturing systems

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Abstract. The fact that operational costs and the environmental impact are increasing is what has made energy consumption in manufacturing systems a serious issue. In this paper, a machine learning (ML)-based predictive control model is introduced to enhance energy efficiency in the contemporary manufacturing settings. The offered solution combines predictive models based on data and Model Predictive Control (MPC) to optimize the performance of the systems in real time. Machine learning algorithms are used to predict the energy demand, process dynamics, and disturbances, as well as to make decisions proactively. Industrial case studies confirm the validity of the framework, showing great progress in terms of energy efficiency, productivity, and stability of operations.

Introduction

One of the highest energy consumers in the world is the manufacturing industries which contributes a significant portion of the world electricity consumption, and industrial carbon emission. The growing need to produce, the growth in energy prices and the strict regulations on the environment, have turned energy efficiency into a pressing concern of the contemporary manufacturing system. Such poor use of energy not only increases the cost of operations but also plays a major role in environmental degradation, thus the need to come up with smart and sustainable solutions to manufacturing. With the advent of Industry 4.0, the manufacturing systems are undergoing a paradigm shift towards the digitalization, automation, and interconnectivity. All the technologies that make monitoring and control of industrial processes in real-time possible are the Internet of Things (IoT), cyber-physical systems, big data analytics, and artificial intelligence. These innovations enable the gathering of huge amounts of operation data which can be used to enhance decision-making processes and optimize system performance. This has resulted in an environment that is more adaptive, efficient and responsive to dynamic operating environments in manufacturing environments.[1] Predictive control based on machine learning has become a



promising method to overcome these problems. These systems can also use data-driven modeling techniques with advanced control methods, like Model Predictive Control (MPC), to predict future states of the process and proactively optimize control actions. Machine learning algorithms, such as regression models, neural networks and reinforcement learning methods, process the past and present data to learn the dynamics of a complex system that does not explicitly have mathematical representations. This predictive ability allows the manufacturing systems to consume less energy, reduce variability of the processes and maintain the desired level of performance.[2].

In addition, the new trends in artificial intelligence have depicted much promise in the aspect of energy conservation and efficiency of activities. With AI-based optimization algorithms, intelligent scheduling, load management, and predicting maintenance will be achievable and will minimize energy wastage and more efficient resource utilization. The reports in the studies have claimed that the energy efficiency level has dramatically increased (usually by 15-30 percent) and the reliability of the systems and the throughput has also improved. Such developments highlight the radical place machine learning-based predictive control is in the development of sustainable and energy efficient manufacturing systems [3].

Machine learning (ML) is a recent subject of ongoing research over the past several years to predict energy, optimize it, and automatically control production systems. The increasing availability of industrial data, along with the increasing processing power, has facilitated the creation of data-driven models which can well model even the complicated interactions among process parameters and the use of energy. The models play a vital role in improving operation efficiencies and maintenance of manufacturing practices[4]. Supervised machine learning methods have widely been used to predict the industrial energy consumption considering both the historical and real-time plant data. Algorithms of linear regression, support vector machines (SVM), decision tree and random forest models have been found to be good predictors of energy consumption in various manufacturing processes. These models come in especially well in locations where there is adequate data with known values since they can be trained to identify patterns and relationships among the input variables (machine load, temperature, and rate of production) and the energy consumption.[5]

In addition to traditional supervised methods, deep learning models have received the focus of attention as they can learn nonlinear dependencies and time dependencies. The use of hybrid models such as the Convolutional Neural Network-Long Short-term Memory (CNN-LSTM) networks have particularly proved to be helpful in the description of both spatial and temporal features of industrial data. CNN layers are used to extract features, and LSTM networks deal with the dependencies of the sequences, which prove to be highly applicable in the time-series energy prediction of manufacturing systems. These models are much more accurate than traditional methods particularly in dynamic and highly variable environments.[6] Also, machine learning has been integrated with high-level control techniques, particularly Model Predictive Control (MPC) to enhance the performance of the system. ML-enhanced MPC systems are based on models that are trained to learn how the system will behave in future and use control inputs to optimize over a prediction horizon. It results in better process stability and increased energy efficiency as well as simpler management of nonlinearities, uncertainties and constraints within the system through this integration. Data-driven MPC methods minimize the use of first-principles models, and thus are more versatile to complex industrial systems. Another powerful way of real-time energy optimization is reinforcement learning (RL). Unlike the supervised learning, RL allows systems to experiment with the best possible control policies, when systems interact with the environment. The dynamical utilization of energy in smart manufacturing systems, RL-based controllers can optimize the performance of the system through its constant measuring and adjusting actions based on reward. They are especially useful when dealing with situations that are characterized by

uncertainty, stochastic disturbances, and multi-objective optimization, such as a trade-off between energy efficiency and production throughput.

Although these developments were made, there are still a number of challenges and gaps in research. One of the main shortcomings is the absence of a smooth method to machine learning models and predictive control systems in real-time processes in manufacturing. The existing approaches are primarily utilized individually, and the ML models are applied to prediction only, and are not implemented in closed-loop controls. In addition, other issues that make it impossible to implement in practice are data quality, model interpretability, computational complexity, and scalability. The real-time deployment also requires powerful and effective systems to address the high frequency data streams and dynamic conditions of operations.

Therefore, the need to build joint systems that would integrate machine learning and predictive control in a way that would be not only efficient but also integrated, is urgent. Such structures have to be capable of supporting real-time decision-making, adaptive learning, and good performance in the presence of uncertainty and therefore unleash the potential of intelligent and energy-efficient manufacturing systems.[8]

System Architecture

Framework Overview

The proposed predictive control system is a machine learning implementation with an architecture that is supposed to be a multi-layered one, which includes data acquisition, intelligent modeling, and advanced control capabilities to make manufacturing processes energy-saving. The structure is composed of three important layers with each of the layers playing a particular role in the whole system [Figure 1] [9]. The suggested system is a three-layered system. The Data Acquisition Layer allows real-time monitoring of manufacturing processes using smart sensors and IIoT devices, capturing parameters such as temperature, pressure, vibration, speed, load, and energy consumption, and transmitting data using protocols such as MQTT, OPC-UA or industrial Ethernet and preprocessed to ensure accuracy. The Machine Learning Layer takes advantage of historical and real-time data to develop predictive models using methods such as regression, neural networks and deep learning (e.g. LSTM), predicting energy use and system behavior with performance compared using MAE, RMSE, and R2 and deployed to real-time decision-making. The Predictive Control Layer integrates these predictions with Model Predictive Control (MPC) to optimize operations by minimizing energy usage while maintaining production quality and constraints, enabling proactive control actions such as speed adjustment, scheduling, and load distribution

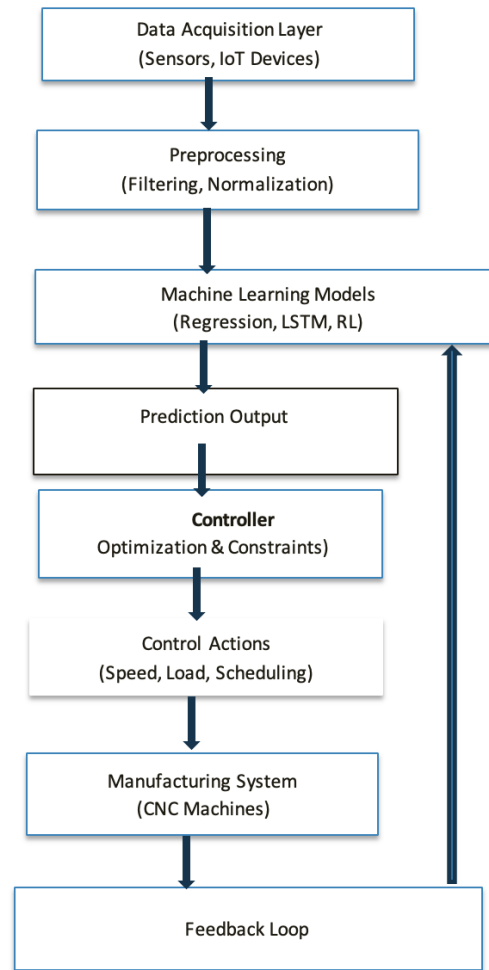


Fig. 1. ML-MPC Framework for Energy-Efficient Manufacturing

Working Principle

The principle of the proposed system is based on the principles of closed-loop operation and data-based approach to facilitate the mechanism of continuous learning and adaptive control to be applied to the environment of dynamic manufacturing environments. The information received by the manufacturing system is captured in real-time by the data acquisition layer in the first step. This information includes the operating conditions of machines, the environmental parameters and measures of energy consumption. The data obtained is then preprocessed and inputted into the machine learning models. This information is then fed to the machine learning layer, which in turn uses the information to make predictions about future system energy consumption and behavior in the next step. Such forecasts not only represent the short-term dynamics but also long-term trends that would be of tremendous value to the system as far as its performance is concerned.

The estimated outputs are sent to the layer of predictive control and the Model Predictive Control (MPC) algorithm is used to calculate the optimal control measures. Each time step is solved by the controller, where an optimization problem is solved, minimizing energy consumption and keeping production targets and system constraints.

After identifying the best control inputs, they are implemented into the manufacturing system. The machine learning models to optimize and enhance are developed in an ongoing loop of monitoring system response and the data as an outcome fed into the machine learning models. This feedback mechanism aids the system to adapt to the change such as machine wear, change in workloads and environmental changes.

Methods of machine learning that have been used.

Machine learning approaches are critical in the contemporary manufacturing since they facilitate predictive control and optimization of energy. The techniques have the ability to provide credible projections, uncover latent trends and assist in making prudent decisions through the use of historical and real-time data. The framework suggested also incorporates some machine learning paradigms, which contribute various roles in the performance of the system, and the energy efficiency of the system. Table 1 shows the summary of machine learning techniques is being used.

Table 1: Summary of Machine Learning Techniques

Technique	Type	Application	Advantage
Linear Regression	Supervised	Energy prediction	Simple, fast
Random Forest	Supervised	Nonlinear modeling	High accuracy
LSTM	Deep Learning	Time-series prediction	Captures temporal data
RL (DQN)	Reinforcement	Control optimization	Adaptive learning

Key Objectives

The main aim of optimization of energy efficiency is to realise a balance between the energy consumption, performance of the production, and economic viability. The main objectives are:

Minimize Energy Consumption

The first goal is to decrease the energy use of machines and manufacture in general. This is possible through the removal of redundant energy loss, optimization of operational timetables and efficient use of resources. Predictive control plans contribute to detecting energy-enormous activities, and proactive change of the parameters.

Quality of Production Maintenance

The quality of products and accuracy of processes should not be sacrificed to the optimization of energy. Precision of dimension, surface and consistency is particularly important in high-precision production. Thus, quality constraints and energy goals should be considered in optimization models.

Decrease in the Cost of Operation

Energy costs are a large percentage of overall manufacturing costs. The utilization of energy and the reduction of peak demand may lead to significant cost reductions. Moreover, energy management helps to save on maintenance and increases the life of equipment.

Sustainability and Environmental Impact

Lower energy usage will directly decrease carbon emissions and environmental impact. This is in line with the principles of global sustainability and regulatory standards in manufacturing practices, which supports the environmentally-friendly industrial performance.

Optimization Parameters

The energy efficiency of the manufacturing systems is based on a number of controllable and uncontrollable parameters. The main variables to be taken into account in the suggested optimization model are

Machine Speed

Speed of machines can greatly affect the energy usage and output of production. High speed can enhance the consumption of energy and wear of equipment and low speed can lower efficiency of operation. The best choice of speed guarantees productivity and energy efficiency.

Idle Time Reduction

Even when the machines are not in use, they use energy. Smart scheduling and predictive maintenance plans are used to reduce the amount of idle time which reduces unnecessary energy use and enhances the overall system use.

Load Distribution

The proper distribution of work among machines helps to avoid the overloading of machines and provides the homogeneity in the consumption of energy. Load balancing strategies prevent energy peaks and increase stability of the system.

Temperature Control

Thermal conditions play a crucial role in processes such as additive manufacturing, casting, and machining. Having the optimal temperatures lowers the energy loss and enhances the efficiency of the processes. High-tech control systems are used to dynamically control heating and cooling systems.

Process Scheduling

The energy efficiency can be greatly enhanced by strategic scheduling operations in terms of energy demand and supply, including the use of off-peak hours. The machine learning models are able to forecast the demand trends and schedule accordingly.

Equipment Condition and Maintenance.

Machines that are not well maintained or damaged are likely to use more energy. Predictive maintenance also makes sure that the equipment is used to the maximum efficiency, thus saving on energy waste and avoiding unexpected breakdowns.

Experimental Setup

The proposed machine learning-based predictive control framework was evaluated using data collected from a smart manufacturing environment consisting of CNC machines and auxiliary systems. IoT-enabled sensors were used to obtain real-time operational parameters including machine speed, load, temperature and power consumption. The data set contains both the historical and live data that were preprocessed through normalization and outlier removal to attain quality and consistency of the data.

The energy optimization problem was defined as a constrained optimization problem and the objective of the energy optimization problem is to minimize the total energy consumption and preserve production efficiency. The optimization takes important constraints into consideration and they include the machine limits, temperature limits and the production needs. The data-driven predictive models were used to model system dynamics, and thus an accurate estimation of the future system behavior can be obtained.

The development and implementation of machine learning models were carried out with the help of Python-based libraries. The data was separated into training and testing set by splitting the data using 70:30. The models were trained to forecast energy consumption and system states, in relation to input parameters. The predictions were incorporated into a Model Predictive Control (MPC) system, which optimizes the control inputs over a finite prediction horizon.

The general methodology will be a closed-loop approach: data acquisition, preprocessing, model training, prediction, optimization using MPC, implementation of control actions, and continuous model updating using feedback. This combined arrangement enables real time observation and dynamic control of the manufacturing operations.

Results and Discussion

The experimental outcomes reveal the usefulness of the proposed ML-MPC framework in enhancing the energy efficiency and system performance. The machine learning models had a high prediction accuracy rate with low error measures in terms of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) and a high level of correlation indicated by a high value of R². Combining machine learning and Model Predictive Control led to the best performance in comparison to traditional control policies. The predictive nature of the system allowed the system to make proactive changes in its control inputs to minimize the unnecessary use of energy and enhance stability in operations.

Quantitative data show that the proposed solution led to a reduction of the energy consumption by about 15-30 per cent, as well as a rise in the efficiency of the system by 20-35 per cent. Also, the peak energy demand was significantly reduced, which also helps to save expenses and load management.

Another outcome is the enhanced adaptability of the system to different operating conditions. Repeated learning and model refinement of the models is aided by the closed-loop feedback mechanism which makes the models robust and reliable in dynamic manufacturing environments. Overall, the findings confirm the notion that the ML-based predictive control system is a feasible solution to achieve energy-saving and intelligent manufacturing systems and both performance and sustainability are significantly enhanced.

Conclusion

The paper discussed a machine learning-based predictive control system to improve the energy efficiency of manufacturing systems. The proposed solution allows predicting the energy consumption and optimizing the control measures proactively by combining data-driven machine learning models with Model Predictive Control (MPC). The framework is effective in overcoming the drawbacks of the traditional control methods because it addresses nonlinearities, uncertainties and dynamic operating conditions.

The findings indicate that the proposed ML-MPC system is capable of significantly improving the performance of the system, which will result in a reduction in system energy consumption of about 15-30 percent, as well as an increase in the efficiency and low cost of operation in the system. Closed-loop architecture has the advantage of continuous learning and adaptability and can therefore be used in real-time industry environments.

Overall, the study highlights the potential of combining machine learning and predictive control as a powerful solution for sustainable and intelligent manufacturing. Future directions can involve real-time deployment, integration with the digital twin technology, and additional improvement using advanced AI techniques to support the next-generation smart factories.

References

- [1] McKenna Patterson, Prashant Singh, Heejin Cho, The current state of the industrial energy assessment and its impacts on the manufacturing industry, Energy Reports, Volume 8, 2022, Pages 7297-7311
- [2] Sahu, U.K., Pradhan, A.K. Discovering the determinants of energy intensity of Indian manufacturing firms: a panel data approach. *Discov Sustain* 5, 139 (2024).
- [3] IEA (2021), Net Zero by 2050, IEA, Paris <https://www.iea.org/reports/net-zero-by-2050>, Licence: CC BY 4.0

- [4] Subhajit Chatterjee, Prince Waqas Khan, Yung-Cheol Byun, Recent advances and applications of machine learning in the variable renewable energy sector, *Energy Reports*, Volume 12, 2024, Pages 5044-5065
- [5] Mohsen Soori, Behrooz Arezoo, Internet of Things and machine learning for energy saving in advanced manufacturing processes: A review, *Cyber-Physical Energy Systems*, Volume 2, Issue 1, 2026, Pages 25-41
- [6] Forootan, M.M.; Larki, I.; Zahedi, R.; Ahmadi, A. Machine Learning and Deep Learning in Energy Systems: A Review. *Sustainability* 2022, 14, 4832. <https://doi.org/10.3390/su14084832>
- [7] Safiullah Khan, Juhi Jannat Mim, Jannatul Fardous Shorna, Md Arif Hasan, Hasibur Rahman Tarek, Md. Aminul Islam, Nayem Hossain, Machine learning for renewable energy advancements: Prospects and emerging techniques, *Energy Reports*, Volume 15, 2026, 109008
- [8] Strielkowski, W.; Vlasov, A.; Selivanov, K.; Muraviev, K.; Shakhnov, V. Prospects and Challenges of the Machine Learning and Data-Driven Methods for the Predictive Analysis of Power Systems: A Review. *Energies* 2023, 16, 4025. <https://doi.org/10.3390/en16104025>
- [9] Sherien Elkateb, Ahmed Métwalli, Abdelrahman Shendy, Ahmed E.B. Abu-Elanien, Machine learning and IoT – Based predictive maintenance approach for industrial applications, *Alexandria Engineering Journal*, Volume 88, 2024, Pages 298-309
- [10] M. Arun, Debabrata Barik, Nashwan Adnan Othman, Seepana Praveenkumar, Kapura Tudu, Investigating the performance of AI-driven smart building systems through advanced deep learning model analysis, *Energy Reports*, Volume 13, 2025, Pages 5885-5899