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ENERGY-AWARE CLASSIFICATION OF MACHINE OPERATING STATES FOR EFFICIENT AND SUSTAINABLE PRODUCTION

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ABSTRACT

The monitoring of machines is becoming more energy efficient as it contributes to better production performance and sustainable production. This paper investigated if machine operating states can be identified based on the commonly collected power consumption characteristics. The operating states analysed were: Production, Standby, MachineOn, Alarm, Loading and Tooling (all publicly available discrete manufacturing). Average, minimum and maximum power consumption were selected as main predictive variables, and machine-state recognition was applied using a Random Forest (RF) Classifier. The overall accuracy of the model was 72.26% and the weighted F1-score was 0.760. Production had the best classification performance, followed by Standby and MachineOn, whereas Alarm and Loading and Tooling were more challenging to classify due to high energy patterns overlapping and low energy frequencies of the classes. The average power was the strongest contributor to classification, while the minimum and maximum power were also contributing information for classification. Non-production states were more likely to have a higher percentage of machine time but a lower percentage of total energy use, as production was responsible for 84.75% of estimated energy use and 41.43% of recorded machine time. The results show that simple power consumption parameters can be used for practical machine state monitoring and to help determine operation parameters that are relevant for enhanced energy management, machine utilization, and sustainable production.

1. Introduction

In today's manufacturing landscape, energy efficiency is a major concern as businesses strive for higher productivity and lower operational expenses, energy wastage, and environmental footprint. The challenge is becoming increasingly relevant as the shift towards digitally integrated production systems, as data is generated continuously by machines, sensors and industrial Internet of Things platforms. In the context of Industry 4.0, new opportunities have emerged to connect energy monitoring to production control, equipment management and sustainability programs. But the value of digitalisation is only realized if it can be used to convert the raw machine data into operational information. The study of energy related Industry 4.0 applications has revealed significant potential for energy efficiency improvements in industry, as well as ongoing problems with data integration, implementation complexity and practical solutions for energy management (da Silva et al., 2020).

The machine level power consumption is especially beneficial, since the use of energy varies depending on production activity, condition of the equipment, and operating state. Electricity reading may be used to give an indication of total consumption, but rarely shows when and why energy is being consumed. By contrast, machine-level energy profiles can differentiate between productive and other (standby, preparation, interruption etc.) non-productive states. In this context, data-driven energy modelling has been found to be a useful tool to correlate energy efficiency and equipment performance and maintenance in Smart Manufacturing environments (Bermeo-Ayerbe et al., 2022). This can be further extended to capture complex nonlinear relationships and patterns that are not represented by conventional analytical methods, through machine-learning techniques (Sarswatula et al., 2022).

An important development in this area is the use of power-consumption characteristics for identifying machine operating states. If a machine is switched from standby to production, loading, tooling or an abnormal condition, then the energy signature can change as well. This information can be used to assist in automatic identification of operational behaviour, without the need for extensive additional sensor installations. To show the usefulness of directly linking energy use with manufacturing activity and production estimation, a machine-learning framework that combines energy profiling with activity-state prediction has been developed (Tan et al., 2021). Likewise, in ultra-precision CNC machining, the energy method for state identification has been demonstrated to be useful and provided information when identifying the machine condition and production state (Xu et al., 2024).

Fault detection and equipment supervision can also be included in energy monitoring. Machine operating conditions can also lead to unique power fluctuations, so that power measurements can be used as a rough estimate of the operating disturbances. The real-time fault identification by power consumption data has proved the effectiveness of monitoring energy data for retrofitted manufacturing equipment so that the unusual condition can be timely captured and the management of the equipment is improved (Selvaraj & Min, 2023). In addition to fault detection, energy waste classification offers another sustainability view: It differentiates required process consumption from avoidable electricity consumption due to inefficient or non-productive operating conditions (Geng et al., 2023).

As AI becomes more embedded in industrial systems, the energy-aware manufacturing gains even more significance. Pattern recognition, operational prediction, adaptive monitoring and data-driven decision support are some of the techniques that can be used to support energy-efficient production using AI-based methods. Recent reviews highlight the increasing significance of AI in enhancing manufacturing energy efficiency and promoting more agile and sustainable manufacturing processes (Abadi et al., 2025). Data analytics can also be leveraged at the operational level to better understand how machines are using, how the production is behaving and which machines have not been used, and provide a chance to manufacturers to optimise how the resources are being allocated and how the process is running (Seyedzadeh et al., 2025). Central findings at the organisational level are that digitalisation enhances monitoring, information availability and decision making capacity, thereby helping to implement energy-management practices.

Nevertheless, a lot of current research concentrates on aspects such as energy forecasting, complicated deep-learning architectures, predictive maintenance, or general digital transformation. Less effort is directed towards simpler, more easily understood, classification of the states of a machine's operation, based on a small number of easily measured power measurements. Routine monitoring methods like those for low complexity environments such as SMEs are still relevant. It may be enough to describe the primary operating conditions by average, minimum and maximum power parameters to delineate major operating conditions and to reveal energy consumption without contributing to production.
With this in mind, the study explored the energy consumption patterns of various machine operating states and examined the feasibility of using energy characteristics based on power for automatic machine state classification. It also investigates the ratio of productive and non-productive operating conditions to maximise the use of the machines and minimise wasteful energy use. The study seeks to develop a practical framework that enables the monitoring of efficient production and more sustainable manufacturing processes by incorporating the operational-state recognition and energy analysis.

2. Materials and Methods

2.1 Research Design and Data Source

Machine energy consumption was analyzed using a quantitative analytical approach, and operating states were classified. The data set in the study is the publicly available data set of discrete manufacturing reported by Atzeni et al. (2023). The main analysis is conducted on Company B since it has operating-state labels for machines along with detailed power consumption.

2.2 Study Variables

The machine operating condition was the outcome variable with 6 categories: Alarm, Standby, MachineOn, Production, Loading, and Tooling. The energy variables measured mainly were average power consumption (power_avg), minimum power consumption (power_min) and maximum power consumption (power_max). In addition, the machine identifier and the time of the observation were recorded to allow for machine and time of observation variability.

2.3 Data Preparation and Descriptive Analysis

The data for this study were screened for missing data, duplicate records, invalid numbers, and for highly extreme measures of power. Consistent timestamping was performed and operating-state categories were created for analysis. Frequency, mean, median, standard deviation, minimum and maximum machine state power consumption were computed for each machine state. These were implemented to ensure a comparison of energy-use patterns under the six operating conditions.

2.4 Machine-State Classification

A random forest classifier was used to classify the machine operating states based on their power consumption. The predictor variables were average, minimum, and maximum power consumption and the target classes were the six operating states. The observations were divided into training and testing sets, the training set was used to train the classifier, while the testing set was used to evaluate the predictive accuracy of the classifier.

2.5 Model Evaluation and Energy Analysis

The accuracy, precision, recall, F1-score, and confusion matrix were used to validate the classification model. The effect of power variable on feature importance was also explored to see how significant the power variable is for machine-state recognition. Also, the energy consumption was compared under productive and non-productive operating conditions. Special focus was paid to the Standby, Alarm, MachineOn, Loading and Tooling states to determine power consumption associated with these conditions, which are not directly related to production. The results were then explained with regards to opportunities for more effective machine monitoring, energy saving due to waste, and production efficiency and sustainability.

3. Results

3.1 Distribution of Machine Operating States

Table 1 shows the machine operating state distribution of the final analytical data set. More than four-fifths of observations were in the Production (41.43%) or Standby (39.48%) state. MachineOn was an incident that happened 11.65% of the time, followed by Alarm, Loading, and Tooling.

Table 1. Distribution of Machine Operating States

Operating state	Observations (n)	Percentage (%)
Production	649,887	41.43
Standby	619,341	39.48
MachineOn	182,708	11.65
Alarm	50,467	3.22
Loading	50,141	3.20
Tooling	16,174	1.03
Total	1,568,718	100.00

3.2 Power Consumption Across Operating States

Table 2 shows that the tooling, machineon, and production sectors have the highest, average, and median average power consumption, respectively, at 11.58, 7.45, and 82.69 kW. Standby was the lowest average power consumption with a median average of 3.09 kW. This large disparity in power demand between Production and the rest of the operating states is also shown in figure 1.

Table 2. Power Consumption Characteristics Across Machine Operating States

Operating state	Mean power (kW)	SD	Median power (kW)	IQR (kW)	Median minimum power (kW)	Median maximum power (kW)
Production	94.88	79.09	82.69	28.44–125.92	43.33	122.46
Tooling	39.17	47.71	11.58	2.97–84.69	6.05	15.79
MachineOn	21.06	27.06	7.45	4.65–22.55	3.70	20.15
Alarm	29.38	40.61	5.24	3.06–59.25	4.37	8.40
Loading	30.45	54.85	5.10	3.30–16.74	4.37	8.14
Standby	5.82	14.57	3.09	2.04–5.19	2.38	4.41

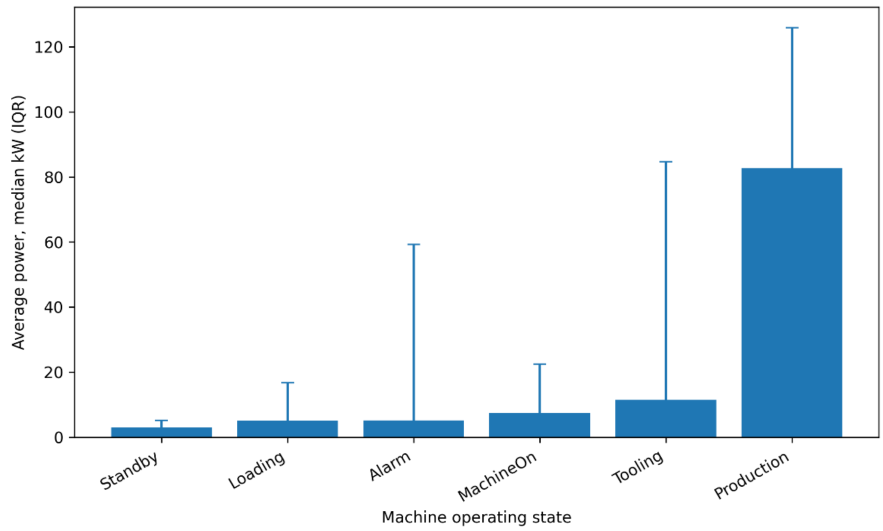

Figure 1. Median Average Power Consumption Across Machine Operating States

3.3 Machine-State Classification Performance

Table 3 shows that the Random Forest classifier achieved an overall accuracy of 72.26%, with a weighted F1-score of 0.760 and a macro F1-score of 0.482. Production achieved the strongest classification performance with an F1-score of 0.860, followed by Standby and MachineOn. Alarm, Loading, and Tooling were comparatively more difficult to distinguish.

Table 3. Random Forest Classification Performance

Operating state	Precision	Recall	F1-score	Test observations
Alarm	0.151	0.337	0.209	10,093
Loading	0.167	0.371	0.231	10,028
MachineOn	0.625	0.760	0.686	36,542
Production	0.924	0.804	0.860	129,978
Standby	0.889	0.696	0.781	123,868
Tooling	0.076	0.342	0.124	3,235

As illustrated in Figure 2, Production, Standby, and MachineOn showed clearer classification patterns, whereas the smaller operating classes exhibited greater overlap with other machine states.

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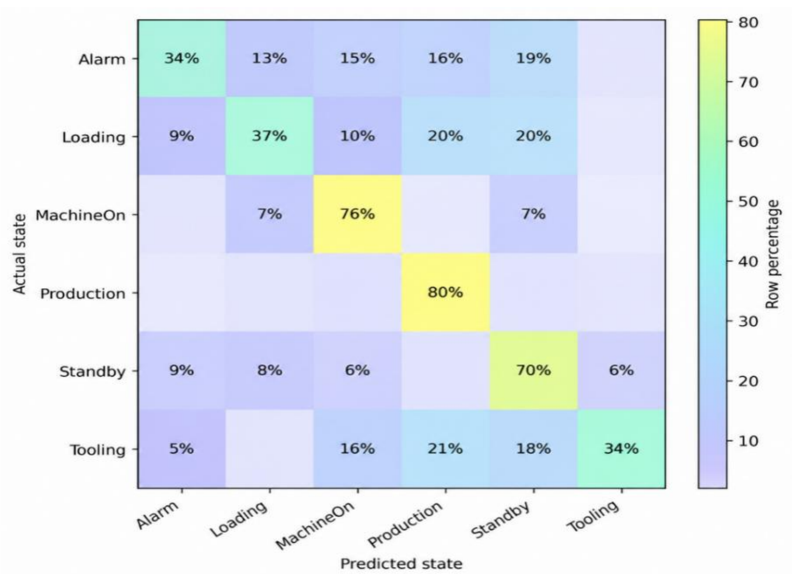

Figure 2. Confusion Matrix for Machine Operating-State Classification

3.4 Importance of Power-Consumption Features

Figure 3 shows the relative contribution of each of the three power variables to classify the states of the machine. Average power was the most important with 40.85% of the total importance. All three energy characteristics supported the recognition of operating state: minimum power contributed 30.63%, and a minimum of 28.52% came from maximum power.

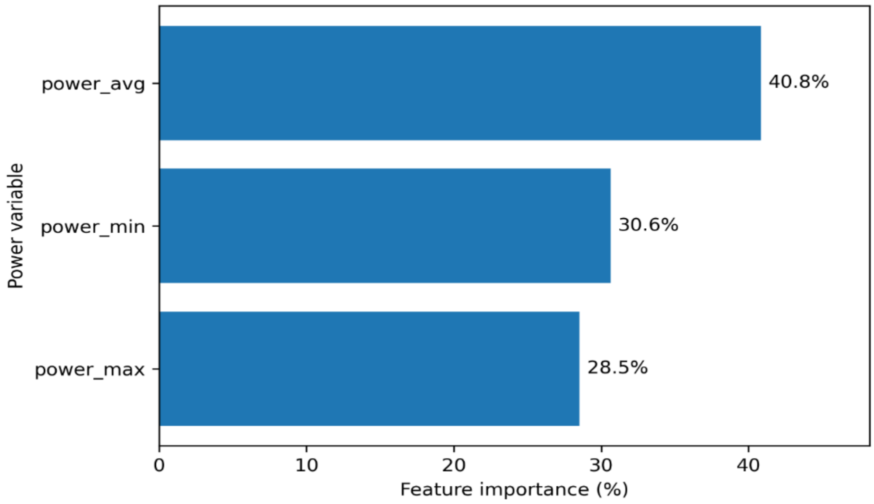

Figure 3. Importance of Power-Consumption Features in Machine-State Classification

3.5 Energy Distribution Across Operating States

Production accounted for 41.43% of the recorded machine time but 84.75% of the estimated energy use as shown in Table 4. By contrast, Standby was 39.48% of machine time, and just 4.96% of total energy. Another 5.29% was used by MachineOn, used to show that energy is being consumed even when production isn't occurring.

Table 4. Operating-Time and Estimated Energy Distribution

Operating state	Time share (%)	Estimated energy (kWh)	Energy share (%)
Production	41.43	1,027,698.86	84.75
Standby	39.48	60,089.13	4.96
MachineOn	11.65	64,141.01	5.29
Alarm	3.22	24,709.44	2.04
Loading	3.20	25,446.73	2.10
Tooling	1.03	10,558.86	0.87
Total	100.00	1,212,644.02	100.00

4. Discussion

The results show that it is possible to use machine power-consumption characteristics to identify operating states in an industrial manufacturing context, which is a viable basis for classification. Despite significant disparity in class frequencies, the Random Forest (RF) classifier was able to attain an overall accuracy of 72.26% and a weighted F1-score of 0.760, demonstrating good predictive ability. Production, Standby, and MachineOn were classified much more accurately than other states, such as Alarm, Loading, and Tooling, suggesting that dominant, yet operationally distinct, states create more stable energy signatures. This finds applications in the broader context of

Machine Learning in Industry 4.0, where a lot of industrial data is collected routinely which can be converted into operational knowledge for process monitoring, prediction and decision making (Mazzei & Ramjattan, 2022).
Significant differences in power consumption were seen between the six machine states. The median average power demand results for Production were higher, at 82.69 kW, which was significantly larger than Tooling (11.58 kW), MachineOn (7.45 kW), Alarm (5.24 kW), Loading (5.10 kW) and Standby (3.09 kW). These differences highlight that the energy measures capture tangible differences in machine behaviour and not simply fluctuations in electricity demand overall. The feature-importance analysis further supports this interpretation, with average power accounting for 40.85% of the model importance, minimum power accounting for 30.63% and maximum power accounting for 28.52%. The contribution of all three variables suggests that the central level and range of power demand are informative for state recognition. This analysis aligns with the findings from the machining study, which showed that process signals can capture unique process signatures and enhance interpretable manufacturing monitoring (Cooper et al., 2024).
The individual states showed that Production had the highest classification performance in terms of F1-score (0.860), precision (0.924) and recall (0.804). Standby and MachineOn achieved relatively high F1-scores of 0.781 and 0.686 respectively. The significance of these results lies in the fact that only three basic power variables can be used to recognize the major productive and non-productive operating conditions. This relatively simple way can be beneficial if a manufacturer needs to monitor in a scalable manner, but doesn't have a lot of sensors in place. Tree-based learning methods have also been shown to be useful for separating different classes of industrial processes from production-related variables, which further validates the wider possible applications of machine-learning classification in manufacturing processes (Polenta et al., 2022).
Alarm, Loading, and Tooling were by contrast significantly lower in their F1-scores. Class imbalance is one reason for their less successful performance, as is overlapping power consumption distributions. Of all the observations, only 1.03% were in the category of Tooling and about 3% were under Alarm and Loading. These states can also include Activities with Heterogeneous machines, where the energy patterns are less distinct than for Continuous Production or Standby. Therefore, power measurement seems to be insufficient for the purpose of recognizing all the states related to the transition or the interruption, with the high degree of accuracy required. Power consumption may then continue to be used as the principle measurement of the monitoring during future classification but may include temporal parameters, machine parameters, or other sensor readings.
The energy distribution also provides important implications for sustainable production. Production used 41.43% of recorded machine time, but accounted for 84.75% of estimated energy consumption, meaning that most energy use was linked to production. However, non-production conditions in total consumed about 58.57% of the machine time and 15.25% of the estimated energy. The remaining time was spent by Standby alone (39.48%) and by MachineOn (11.65%). These states used significantly less power as compared to Production, but their duration is long enough for an identifiable area of operational improvement. The analysis thus indicates the need to take into account not only the instantaneous power demand but also the duration of the machines' non-productive periods. Identification of such states through data is key for applications of machine learning in modern manufacturing systems such as better scheduling, utilization monitoring, and resource allocation (Rai et al., 2021).
In general, the results show that the energy-aware machine-state classification provides a valuable link between intelligent production monitoring and sustainable production management. The method was especially successful in identifying the prevailing Production, Standby and MachineOn states and in providing insight into the distribution of machine time and energy consumption over the operating states. These results should be viewed as indication of opportunities for energy-efficiency, though not as actual energy savings as electricity consumption was not directly measured. Additional validation on other machines, factories, and production settings will enhance generalizability and more operational variables will increase discrimination of less common states. Despite these constraints, the results show that the power readings that are commonly sampled

during operation contain useful operational intelligence to facilitate more efficient and sustainable manufacturing processes.

5. Conclusion

An energy-aware machine operating state classification is a practical solution which enables the combination of efficient and sustainable manufacturing with power monitoring. The analysis showed that there are significant differences in power consumption between the operating conditions (Production vs. Standby). The overall accuracy of the Random Forest classifier was 72.26% and weighted F1-score was 0.760, indicating that basic power variables can be useful for the identification of major machine states. Production, Standby, MachineOn were classified with greater reliability, because the dominant operating conditions had greater energy signatures than did the Alarm, Loading, and Tooling classes. Average power turned out to be the most significant classification feature, along with minimum and maximum power. Production used an estimated 84.75% of the total energy, and recorded 41.43% of the machine time. Discussions of machine time and machine energy utilization reflected that there were more non-production states involving machine time than non-production states involving machine energy, which suggests opportunities for optimizing scheduling and machine utilization. Overall, these results demonstrate the potential of using power consumption information, which is available in many cases, for scalable machine-state monitoring, without the need for highly complex sensing networks. Future work should extend the approach to more uncommon states, include more operation parameters and test it in other machines and manufacturing environments.

References

1. Abadi, M. M. K. F., 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.
2. Atzeni, D., Ramjattan, R., Figliè, R., Baldi, G., & Mazzei, D. (2023). Data-driven insights through industrial retrofitting: An anonymized dataset with machine learning use cases. Sensors, 23(13), 6078. https://doi.org/10.3390/s23136078
3. Bermeo-Ayerbe, M. A., Ocampo-Martinez, C., & Diaz-Rozo, J. (2022). Data-driven energy prediction modeling for both energy efficiency and maintenance in smart manufacturing systems. Energy, 238, 121691.
4. Cagno, E., Accordini, D., Thollander, P., Andrei, M., Hasan, A. M., Pessina, S., & Trianni, A. (2025). Energy management and industry 4.0: Analysis of the enabling effects of digitalization on the implementation of energy management practices. Applied Energy, 390, 125877.
5. Cooper, C., Zhang, J., Ragai, I., & Gao, R. X. (2024). Multi-sensor fusion and machine learning-driven sequence-to-sequence translation for interpretable process signature prediction in machining. Journal of Manufacturing Systems, 75, 288-298.
6. da Silva, F. S. T., da Costa, C. A., Crovato, C. D. P., & da Rosa Righi, R. (2020). Looking at energy through the lens of Industry 4.0: A systematic literature review of concerns and challenges. Computers & Industrial Engineering, 143, 106426.
7. Geng, D., Evans, S., & Kishita, Y. (2023). The identification and classification of energy waste for efficient energy supervision in manufacturing factories. Renewable and sustainable energy reviews, 182, 113409.
8. Mazzei, D., & Ramjattan, R. (2022). Machine learning for industry 4.0: a systematic review using deep learning-based topic modelling. Sensors, 22(22), 8641.
9. Polenta, A., Tomassini, S., Falcionelli, N., Contardo, P., Dragoni, A. F., & Sernani, P. (2022). A comparison of machine learning techniques for the quality classification of molded products. Information, 13(6), 272.
10. Rai, R., Tiwari, M. K., Ivanov, D., & Dolgui, A. (2021). Machine learning in manufacturing and industry 4.0 applications. International Journal of Production Research, 59(16), 4773-4778.
11. Sarswatula, S. A., Pugh, T., & Prabhu, V. (2022). Modeling energy consumption using machine learning. Frontiers in Manufacturing Technology, 2, 855208.

12. Selvaraj, V., & Min, S. (2023). Real-time fault identification system for a retrofitted ultra-precision CNC machine from equipment's power consumption data: a case study of an implementation. International Journal of Precision Engineering and Manufacturing-Green Technology, 10(4), 925-941.
13. Seyedzadeh, S., Christodoulou, V., Turner, A., & Lotfian, S. (2025). Optimising manufacturing efficiency: a data analytics solution for machine utilisation and production insights. Journal of Manufacturing and Materials Processing, 9(7), 210.
14. Tan, D., Suvarna, M., Tan, Y. S., Li, J., & Wang, X. (2021). A three-step machine learning framework for energy profiling, activity state prediction and production estimation in smart process manufacturing. Applied Energy, 291, 116808.
15. Xu, Z., Selvaraj, V., & Min, S. (2024). State identification of a 5-axis ultra-precision CNC machine tool using energy consumption data assisted by multi-output densely connected 1D-CNN model. Journal of Intelligent Manufacturing, 35(1), 147-160.