Precision Mechanics & Digital Fabrication
https://www.acadlore.com/journals/PMDF

Multi-Model AI-Driven Smart Energy Dashboard for Real-Time Monitoring of CNC and Digital Fabrication Energy Consumption

Amit Aylani*, Pushkar Uikey

Department of Computer Engineering, Vidyalankar Institute of Technology, 400037 Mumbai, India

* Correspondence: Amit Aylani (amit.aylani@vit.edu.in)

Received: 07-22-2025 **Revised:** 09-06-2025 **Accepted:** 09-20-2025

Citation: A. Aylani and P. Uikey, "Multi-model AI-driven smart energy dashboard for real-time monitoring of CNC and digital fabrication energy consumption," *Precis. Mech. Digit. Fabr.*, vol. 2, no. 3, pp. 178–188, 2025. https://doi.org/10.56578/pmdf020305.

Abstract: The expensive energy prices and sustainability goals are driving the precision manufacturing facilities to stop their periodic energy reporting to full-time, machine-level reporting that can provide insights into where energy is used, anticipate future-demand and observe unusual behavior in the CNC machining and digital fabrication processes. This paper creates a real-time smart power dashboard, which combines power measurement and production-aware processing to facilitate actionable energy governance on the shop floor. This workflow coordinates time-stamped power data (and optional machine context), cleanses and rebuilds windows of features, and uses a multi-model forecasting layer (autoregressive integrated moving average, additive time-series decomposition, gradient-boosted regression, and long short-term memory (LSTM)) to make short-horizon predictions. A dual protocol based on standardized deviation monitoring and isolation-based outlier detectors detect abnormal consumption with energy windows being clustered into repeatable profiles using clustering to facilitate benchmarking across machines and shifts. The prototype testing demonstrates that the forecasting layer has a best mean absolute percentage error (MAPE) of 8.9, the clustering operation has a conspicuous separation with a silhouette score of 0.742 and the anomaly detection has a precision of 95.7 and a false positive of 2.8 at minimal computing power. Such findings show that the dashboard, as suggested, can be used to provide reliable forecasting, interpretable profiling and low noise alerting that can be used in real-time monitoring. The strategy offers deployable analytics structure that converts raw power streams into decision-ready data and facilitates undertakable efficiency steps by means of energy per job, peak-load exposure, and share of non-productive energy indicators.

Keywords: CNC machining; Digital fabrication; Real-time energy monitoring; Smart manufacturing; Energy forecasting; Anomaly detection; Sustainable manufacturing; Industry 4.0

1 Introduction

The largest end-use of energy is the industrial sector, which accounted for approximately 37% (166 EJ) of total global energy consumption in 2022 [1]. With manufacturers seeking to reduce operating costs and achieve decarbonization targets, the ability to quantify, analyze, and improve energy performance at the machine and process level has become central to sustainable production management [2]. Energy management practices reinforce this shift by formalizing systematic monitoring and continuous improvement through frameworks such as ISO 50001 [2].

This is not often linear or stationary energy behavior in precision mechanics and digital fabrication (PMDF). The operation of CNC machining centers and digitally controlled fabrication equipment in various states start-up, warm-up, standby, auxiliary services, cutting, tool change and transient overloads affect the total footprint of a part differently. There is evidence throughout machining research that non-productive and auxiliary loads may constitute a significant portion of the total demand, such that sustainability benefits may be sensitive not only to the state control and workflow but also to the cutting physics itself [3, 4]. Consequently, the energy monitoring which only report aggregate kWh cannot be used to initiate improvement actions in actual workshop environments.

The grounds have been laid by previous efforts to formulate machine-level energy assessment and other related measurement processes. The benchmarking and diagnosis of the machine tools have been suggested to consider standardized methods of monitoring machine tool energy demand during idle, operating sequences, and machining processes [5, 6]. Monitoring automated monitoring techniques have also shown how the energy indicators can be synchronized with the operations by means of event-stream or controller-linked data, and energy consumption can be treated as actionable instead of purely descriptive [7, 8]. Simultaneously, the wider manufacturing energy modeling literature emphasizes the increased application of prediction and forecasting to aid in scheduling, optimization, and demand response—but the performance is highly dependent on the modeling horizon, system boundary, and quality of the data [9, 10].

Regardless of such advances, there are two practical gaps of CNC and digital fabrication environments. To begin with, most of the implementations are based upon a single algorithm or a single operating regime, but the reality of machine tools has regime switching, which compromises the model robustness when the tools wear out, when parameters change, or when production mix changes. Second, energy analytics are sometimes displayed as off-line research instead of operator-friendly dashboards which integrate the functions of forecasts, patterns of operation segmentation and real-time anomaly notifications [11].

To fill this gap, the current paper suggests a Multi-Model AI-Driven Smart Energy Dashboard to Real-Time Monitoring CNC and Digital Fabrication Energy Consumption, and to bring a proven concept of a multi-model dashboard to the precision manufacturing environment. A multi-model forecasting stack (autoregressive integrated moving average (ARIMA), Prophet, extreme gradient boosting (XGBoost), long short-term memory (LSTM)) operating in a dashboard prototype on a baseline real-time system with a mean absolute percentage error (MAPE) of 8.9% (optimal model) and a dual anomaly system (statistical thresholding + Isolation Forest) with 95.7% accuracy showed that complementary models could be used to produce reliable accuracy and fast decision support with acceptable compute limits. Based on this finding, the current work extends the identical multi-model and dual-detection logic to CNC/digital fabrication signals where machine states and auxiliary subsystems along with transient events are the preeminent contributors to energy variance [12].

Lastly, the suggested dashboard will be adapted to the smart manufacturing and digital-twin trends, in which ongoing monitoring is linked to understandable models and lifecycle enhancement processes. The ISO 23247 family offers a digital twin framework of manufacturing components in a structured form and assists the data-to-model connection type required to fulfill real-time monitoring and optimization of manufacturing systems [13].

1.1 Contributions

This work contributes:

- Real-time energy dashboard architecture developed with CNC and digital fabrication in mind, enabling acquisition, monitoring, forecasting, and alerting functionality to be part of one workflow.
- Multi-model forecasting strategy to enhance robustness over operating regime changes (idle-load changes, and transient spikes).
- An anomaly-detection pipeline that uses interpretable statistical thresholds together with machine-learning anomaly detection of uncommon and complicated abnormal patterns.
- An ISO 50001 energy governance and ISO 23247 digital-twin standards-conscious positioning.

2 Related Work

2.1 Monitoring and Benchmarking Energy in Machine-Tools

Pioneering research defined the means to measure and divide the machine-tool energy in different operational states in order to make energy comparable and usable instead of a single and aggregated number [14]. This basis of measurement underlies subsequent work of AI since semi-supervised and supervised models need uniform labels or state-congruent signals. Research on process-level models indicated further that material removal energy could be associated with variables which are controllable (e.g., operating states, process parameters), and thus optimized under sustainability goals [15]. The connection between machining energy and environmental load was also measured in wider manufacturing research, which encouraged carbon-conscious assessment and decision-making in the CNC-based systems [16].

2.2 The Aspect of Learning-Based Prediction/Forecasting

The prediction of machining energy is being conducted by AI and machine learning more often when non-linear, regime-dependent signals are used. The generic models of energy prediction have been developed using deep learning in machine tools, which suggests that the complex machine behavior can be learned using data-driven representation learning [17]. Other works have shown feasible CNC energy prediction based on machine-learning techniques, which implies that it can be deployed to practice when feature pipelines are matched with controller/sensor measurements [18]. Parsing CNC programs and linking the extracted intent (toolpath operations, transitions) with neural models to anticipate better predictions has also been studied as program-aware learning, which is also applicable in digital fabrication workflows where process intent is represented in explicit form. Regarding the dashboard, strategies of multi-model forecasting strategies proven in real-time energy monitoring demonstrate that integrating models with varying strengths can stabilize performance in varying operating regimes, which inspires an adjustment to CNC/digital fabrication settings [18].

2.3 Anomaly Detection and Physical-Cyber Integration

Anomaly detection is based on AI and is applied to detect abnormal energy signatures associated with faults, drifting or inefficient operating modes. Studies on anomaly detection in time-series indicate that the main requirements of shop-floor environments are the ability to deal with noise, drift, and alarm interpretability. Isolation-based techniques have been demonstrated to be used practically in power anomaly detection and are appealing in manufacturing where labeled fault events are scarce [19]. Simultaneously, digital twin and cyber-physical systems enhance integration by linking live signals with predictive systems and feedback loops; ISO 23247 offers guidance applicable to the structuring of such manufacturing digital twins [20]. The concept of digital energy twins has been further developed in recent work, demonstrating integrated architectures for optimization and decision support using real-time energy intelligence [21].

The current literature tends to consider prediction or anomaly detection as an independent activity but CNC and digital fabrication teams require a unified and live workflow that includes monitoring, forecasting, and warning coupled with the ability to interpret their operations in real-time. The gap in this paper is filled by applying a multi-model AI energy dashboard that is sensitive to CNC and digital fabrication energy traces, robust during regime shifts, and decision-satisfying visualization of sustainable production governance [22].

3 System Workflow

3.1 Data Acquisition and Synchronization

At the supply of the machine, active power Xi (kW) is monitored at an inline energy meter or a power analyzer. In case the three-phase data is available, then the sum of the active power is considered as the primary time series. Machine context (optional). One may mention controller/event indicators (e.g., spindle on/off, axis motion, alarms, job limits) that will help to improve the interpretation of consumption variations. Every signal is identified using a single time stamp index. Nearest-time mapping corrects minor timing errors, and the corrections are resampled to a fixed interval (e.g., minute level) on which real-time dashboards can be shown.

3.2 Data Acquisition and Preprocessing

Active power is recorded at a fixed interval suited to shopfloor dynamics (e.g., minute-level for dashboarding; higher-frequency can be aggregated). Controller signals or event logs are collected when available to support interpretation of energy events (e.g., distinguishing "idle loss" from "processing load"). The pipeline applies conservative, auditable cleaning steps as used in the attached prototype:

- Missing value handling: short gaps are imputed; long gaps are excluded from training windows.
- Outlier screening: extreme sensor spikes are flagged using an interquartile range-based rule; flagged points are retained for traceability unless clearly erroneous.
- Temporal consistency: duplicated timestamps and inconsistent sampling are checked before model fitting.
- Resampling and alignment: energy and context streams are aligned using nearest-time matching and resampled into a stable interval for forecasting.

3.3 Preprocessing and Feature Construction

Preprocessing is designed to preserve traceability:

- Missing values: short gaps are imputed; long gaps are excluded from training windows.
- Outliers: extreme sensor spikes are flagged using an interquartile range rule and removed only when they are clearly measurement errors.
- Resampling: data are resampled to a stable interval; higher-rate streams are summarized into window statistics.
- Windowing: a sliding window is maintained for forecasting inputs and for clustering/anomaly features.

Feature vector. Let $\{X_t\}_{t=1}^{T}$ represent the discrete time-series of power measurements, where X_t denotes the power value at time step t. For each time step t, a feature vector f_t is constructed as follows.

(i) Current and Lagged Power Values: The instantaneous power and its lagged values are defined as:

$$X_t, X_{t-1}, X_{t-2}, \ldots, X_{t-L} \tag{1}$$

where, L is the maximum lag order.

(ii) Ramp Rate: The ramp rate captures short-term variations in power and is computed as:

$$\Delta X_t = X_t - X_{t-1} \tag{2}$$

(iii) Rolling Statistical Features: For a rolling window of size W, the rolling mean and variance are calculated as:

$$\mu_t^{(W)} = \frac{1}{W} \sum_{i=0}^{W-1} X_{t-i} \tag{3}$$

$$\sigma_t^{2(W)} = \frac{1}{W} \sum_{i=0}^{W-1} \left(X_{t-i} - \mu_t^{(W)} \right)^2 \tag{4}$$

(iv) Local Peak Indicator: A binary local peak indicator is defined to identify transient maxima:

$$P_t = \begin{cases} 1, & \text{if } X_{t-1} < X_t > X_{t+1} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

(v) Contextual Indicators: Optional contextual features c_t may include calendar-based or exogenous variables such as hour-of-day, day-type, or seasonal indicators.

(vi) Final Feature Vector: The resulting feature vector at time step t is given by:

$$f_t = \left[X_t, X_{t-1}, \ldots, X_{t-L}, \Delta X_t, \mu_t^{(W)}, \sigma_t^{2(W)}, P_t, \mathbf{c}_t \right] \tag{6}$$

3.4 Multi-Model Forecasting Framework

Because machine energy signals show regime changes (idle $\rightarrow$ ramp $\rightarrow$ processing $\rightarrow$ transitions), forecasting is implemented using four complementary models and then selected based on forward-window performance.

(a) ARIMA: ARIMA models differenced autoregression and moving-average components:

$$\phi(B)(1-B)^d X_t = \theta(B)\varepsilon_t \tag{7}$$

where, B is the backshift operator, d is the differencing order, and ε_t is the error term.

(b) Prophet: Prophet represents the time series as additive components:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \tag{8}$$

where, $g(t)$ is trend, $s(t)$ is seasonality, $h(t)$ is holiday/event effects (if used), and ε_t is noise.

(c) XGBoost: XGBoost learns a boosted ensemble with regularization by minimizing:

$$L(t) = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t\left(x_i\right) \right) + \Omega\left(f_t\right) \tag{9}$$

where, $l(\cdot)$ is the loss, f_t is the added tree at boosting step t, and $\Omega(\cdot)$ penalizes model complexity.

(d) LSTM: LSTM updates memory and hidden state using gates:

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right) \tag{10}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{11}$$

$$h_t = o_t \odot \tanh\left(C_t\right) \tag{12}$$

where, f_t, i_t, o_t are forget/input/output gates, C_t is cell state, h_t is hidden state, and $\odot$ denotes elementwise multiplication.

Training and selection:

Models are trained on historical windows and validated on forward windows (rolling evaluation). The dashboard retains the best-performing model for the chosen horizon (or keeps a ranked set for fallback).

3.5 Hybrid Anomaly Detection

To support both interpretability and pattern sensitivity, anomaly detection is implemented using two detectors.

(a) Z-score (statistical)

A standardized deviation is computed as:

$$Z_i = \frac{X_i - \mu}{\sigma} \tag{13}$$

A point (or residual) is flagged if $\mid Z_i \mid$ lexceeds a threshold (default 2.5). This method supports clear operator interpretation.

(b) Isolation Forest (learning-based)

Isolation Forest detects rare patterns in a multivariate feature space. An anomaly score is computed as:

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{14}$$

where, $E(h(x))$ is expected path length for sample x, n is sample size, and $c(n)$ is the average path length in a binary search tree.

Alert fusion:

Two operational policies are supported:

- OR rule: raise an alert if either detector flags (higher sensitivity).
- AND rule: raise an alert only if both flag (lower false positives).

3.6 Energy-Profile Clustering (Segmentation for Benchmarking)

Energy windows are grouped into profiles using K-means by minimizing within-cluster squared distances:

$$J = \sum_{i=1}^{k} \sum_{x \in c_i} \|x - \mu_i\|^2 \tag{15}$$

where, k is the number of clusters, C_i is cluster i, and μ_i is its centroid. Clustering is performed on window descriptors (mean load, variability, peak load, volatility). Principal component analysis (PCA) may be used for visualization of separation, not as the primary decision layer.

3.7 Evaluation Protocol and Metrics

Forecasting metrics: Performance is reported using:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{16}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{17}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{18}$$

4 Results

This section presents quantitative validation of the dashboard's three core functions: short-horizon forecasting, energy-profile clustering, and anomaly detection. All results are from a controlled prototype evaluation dataset (Section 4.1) used to establish baseline performance before live deployment.

4.1 Forecasting Accuracy

Forecasts were generated with each model for a 24-hour horizon. Table 1 summarizes the mean absolute error (MAE), MAPE, and root mean square error (RMSE) for each model.

Table 1. Performance comparison of forecasting models using mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square errors (RMSEs)

Model	MAE (kW)	MAPE (%)	RMSE (kW)
ARIMA	0.147	12.8	0.203
Prophet	0.132	11.4	0.189
XGBoost	0.119	9.7	0.167
LSTM	0.108	8.9	0.154

Note: ARIMA = autoregressive integrated moving average, XGBoost = extreme gradient boosting, LSTM = long short-term memory.

In the four models, LSTM had the least errors, implying that it better tracked the peaks as well as the short-term ramps than statistical baselines. XGBoost gave the best results in the next best, and it was competitive in all measures. This hierarchy is viable in a dashboard context, as it helps to implement feasible selection criteria: the most effective model can be implemented as the primary predictor, whereas the next-best model can be used as a backup in case of the change in operating conditions.

4.2 Energy-Profile Segmentation (Benchmarking Through Clustering)

Energy windows were grouped using K-means clustering ($K = 2$) to create two consumption profiles that can later represent energy modes when applied to CNC/digital fabrication streams. PCA visualization retained 92.1% variance, indicating the main structure of the energy profiles was preserved in the compact representation.

The clustering results, summarized in Table 2, show a near-balanced distribution between the two clusters, with Cluster 0 accounting for 53.2% of the samples and exhibiting a higher mean power consumption of 1.35 ± 0.59 kW, while Cluster 1 represents 46.8% of the data with a lower mean consumption of 0.83 ± 0.37 kW.

Table 2. Show cluster count and mean consumption

Cluster	Count (%)	Mean Consumption (kW) $\pm$ Standard Deviation (SD)
0	266 (53.2%)	1.35 ± 0.59
1	234 (46.8%)	0.83 ± 0.37

To benchmark household-level energy behavior, PCA-based clustering was applied to the segmented energy profiles. As illustrated in Figure 1, two well-separated clusters emerge, corresponding to high- and low-consumption households, while preserving 92.1% of the original variance.

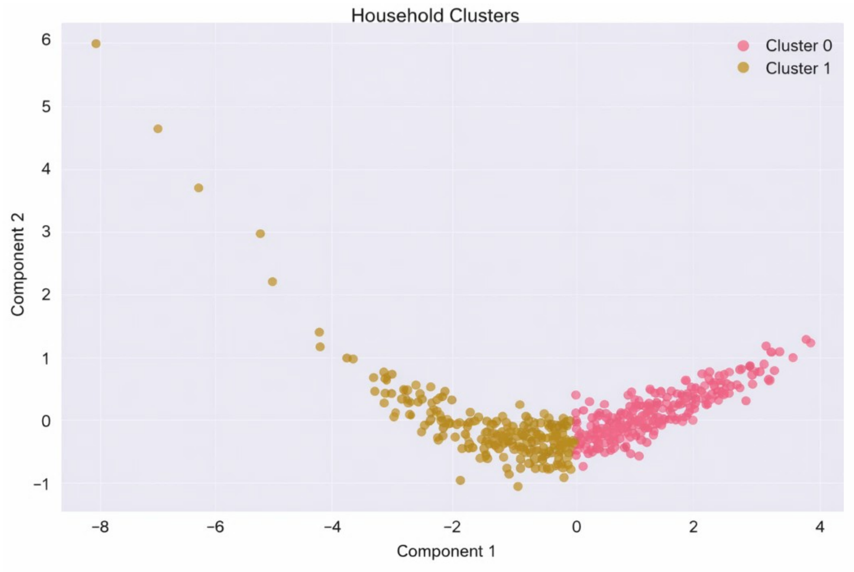

Figure 1. Household clustering analysis using principal component analysis (PCA) showing two distinct clusters

Note: High consumption households (Cluster 0—pink, 266 households) and low-consumption households (Cluster 1—brown, 234 households) with 92.1% variance preserved through dimensionality reduction.

Figure 2 shows the hourly weekday and weekend power consumption patterns, revealing clear behavioral differences. Weekday consumption displays two peaks during the morning (06:00–08:00) and evening (18:00–20:00) hours, while weekend consumption peaks later in the evening (19:00–20:00), indicating more flexible operational schedules.

The clustering quality was strong with a silhouette score of 0.742, showing clear separation between the two energy profiles. For CNC and digital fabrication deployment, these profiles provide a direct benchmarking mechanism: profiles can later be mapped to machine behaviors such as idle-dominant, auxiliary-heavy, or production-dominant energy modes depending on the feature composition and window definition.

4.3 Anomaly Detection Performance

Abnormal events were detected using the hybrid anomaly strategy (Z-score thresholding combined with Isolation Forest).

As summarized in Table 3, the proposed detection framework achieved a precision of 95.7%, a recall of 89.6%, and an F1-score of 92.5% on the test dataset, while maintaining a low false positive rate of 2.8%. The performance indicates that the dashboard can flag abnormal consumption with high reliability while keeping nuisance alarms low. This is important for manufacturing use because alarm fatigue reduces adoption; a low false-positive rate supports operator trust and practical deployment.

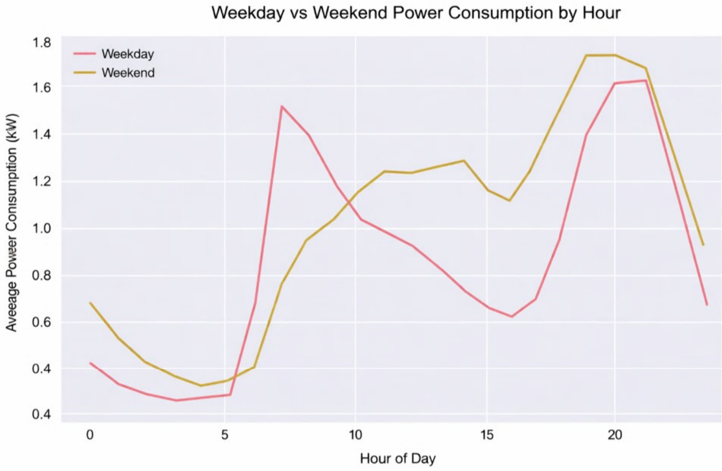

Figure 2. Weekday vs weekend consumption patterns

Note: It shows distinct behavioral differences: weekend consumption (orange) peaks later (19–20 h at 1.9 kW) compared to weekday dual peaks (pink) at 6–8 h and 18–20 h (1.7–1.8 kW).

Table 3. Anomaly detection performance on test data

Metric	Value
Precision	95.7%
Recall	89.6%
F1-score	92.5%
False Positive Rate	2.8%

4.4 Interpretable Demand Patterns

The profiles revealed different energy behaviour with respect to weekends and weekdays. Two weekday peaks were seen at 6–8 h (approximately 1.7 kW) and 18–20h (approximately 1.8 kW) but weekends had a more sustained evening peak at 18–22h (approximately 1.9 kW). This is the evidence that the forecasting layer is learning structured demand behavior, as opposed to responding to short-term noise. In relocating to CNC/digital fabrication environments, similar behaviour under structure is identified as shift cycles, planned production blocks, warm-up time, and patterns of batch start/stop, the environments where real-time monitoring would be most useful to the operations.

5 Discussion and Implications

5.1 Meaning of the Validation Results for CNC and Digital Fabrication

The findings validate the fact that the proposed dashboard pipeline has the potential to provide the three indicators necessary in energy governance in precise manufacturing: predictable short-horizon behavior, consistent grouping of energy patterns, and consistent identification of abnormal consumption patterns. The accuracy of the forecasts was as good as possible, at best-case MAPE of 8.9%, the separation in clustering was strong and silhouette was 0.742, the accuracy of the anomaly detection was 95.7% using a low false-positive rate of 2.8%. Collectively, these results show that the system will be able to go beyond the visualization-only dashboards and assist the decision-making process with the forecasts, profile-based benchmarking, and alerting.

5.2 Performance and Operational Interpretation of Performance Forecasting

Among all the models, LSTM was the most overall accuracy (MAE 0.108 kW; RMSE 0.154 kW; MAPE 8.9%) model. The practical significance of this observation lies in CNC and digital fabrication procedures in which recurring yet not identical periods of energy usage contain warm-up, standby, acceleration ramps, machining/processing and high frequency switching. In such a case, sequence-based models can trace ramps and peak behaviour in a more stable manner compared to only statistical baselines. At the same time, the implication of the multi-model approach of the study to a direct shopfloor is as follows: diverse machines and diverse job mixes generate diverse dynamics and the best model may change with time. Using ARIMA/Prophet as a baseline and then adding it to XGBoost/LSTM will give a good forecasting layer which can be readily made available in a workshop without the need to assume one best model in all regimes. The case of PMDF usage is that forecasting output can be a projected energy envelope. Operators can easily notice abnormal increases in their consumption at the first stage before it becomes a major spike by comparing the actual consumption and what the band expected to consume. This proves to be quite useful in detecting minor deviations that are hard to notice such as increased consumption of the auxiliaries, unexpected idle losses or slow inefficiency that occurs as a result of a worn-out tooling or incorrectly set parameters.

5.3 Clustering and Benchmarking of Machining and Fabrication Cells in Terms of Energy

The two-profile cluster indicated a clear distinction in terms of higher and lower consumption groups. Although the validation set was not recorded on machine tools the result shows a significant fact: the pipeline can convert raw time-series power traces into consistent, reproducible consumption profiles. This is important to CNC machining and digital fabrication since the only overall number that prompts any action to improve is not the sole number but rather the ability to know what operating mode prevails and how that mode is regularly found in every shift, job and all assets.

The identified profiles can be viewed as practical operating modes when the same logic of clustering is used in machining centers and fabrication cells. The profile of idle or standby-dominated behavior with a large proportion of non-productive energy might correspond to one profile and production-dominant behavior with more constant duty cycles of cutting or fabrication to another. Other clusters may also occur in richest datasets, including transition-heavy, which are those organized by frequent ramps and tool changes, and auxiliary-heavy, which are those organized by coolant, compressed air, extraction fans, or heaters controlling the base load.

This is a profile view which can be benchmarked and acted upon by the operators. Machines or schedules that recurrently find themselves in the high-loss profile are direct objects of scheduling modifications, standby more stringent strategies, and auxiliary optimization. The score of silhouette is strong, which shows that the separation is not accidental, it is robust enough to be used as an operational measure instead of a single exploration analysis, and the process of monitoring whether interventions change operations to more efficient profiles can continue.

5.4 Anomaly Detection and Its Connection with Precision-Quality Risk

The hybrid anomaly approach provided high accuracy with the low rate of false-positives that is critical in manufacturing since constant nuisance alarms soon decrease the level of trust and utilization. In digital fabrication and CNC machining, abnormal energy signature is usually an indicator of events that can adversely impact efficiency and quality as well as energy. Depending on the tool wear, chatter and mechanical misalignment, sudden spindle load peaks, abnormal warm-up behaviour, creeping increases in the baseline power provided by auxiliary systems, or abnormal sporadic transients can all be manifested as deviations to expected energy behaviour. Equally, compressed air systems leakage or abnormal duty cycles can result in consistent energy drift that can be easily ignored unless automated measurement is employed.

The two-way practice enables two complementary requirements in the shop floor. Statistical thresholding generates simple alarms that are simple to understand and confirm, whereas the Isolation Forest layer identifies multivariate patterns that are irregular and can not necessarily have a single large spike. This can be useful especially in the manufacture of precision products since not every problem of concern manifests as an extreme outlier, but rather as consistent moderate deviation that builds energy per part and can lead to a poor dimensional stability or surface finish over time.

5.5 Converting the Outputs of the Dashboard into Sustainability Key Performance Indicators

As soon as the cycle boundaries are provided to use CNC and digital fabrication operations, the dashboard results could be converted to sustainability indicators which could be directly used to monitor and improve. This can be estimated by summing up the power over each cycle window to compare tools, programs, materials, and shifts. Ratio of idle-energy may be calculated by dividing the idle and standby energy by the total cycle energy, which measures waste that has been missed in aggregate kWh reporting. Peak-load indicators, including maximum power and peak frequency per shift, can be used to control demand charges and lessen the burden on the electrical infrastructure.

Moreover, the frequency of anomaly events per shift or batch can be referred to as the energy stability index that could present a convenient proxy of process stability and maintenance demands. The distribution metrics of profile can show the percentage of time handled in each energy cluster to indicate whether activities are mostly productive or non-productive. These indicators combined render the operation of real-time monitoring operationally valuable: the system does not just report the aggregate consumption but helps sustain the improvement over time by indicating the areas where energy is being wasted, when it is not acting as expected, and by which recurrent profiles are dominating the performance.

5.6 Practical Limitations of the Current Validation and Expected Changes in CNC Deployment

The present validation has been conducted on a dataset of a clean and complete resolution, which is of an hourly resolution, which is helpful in proving that the forecasting, clustering and anomaly logic all work correctly under a controlled setting. Nevertheless, when implementing the system in CNC machining and digital fabrication, there will be two viable differences that need to be tackled during the implementation.

To start with, machining and fabrication equipment have more-frequency dynamics. Short transitions, spindle ramps, tool changes, and short auxiliary bursts might need finer sampling or event-sensitive aggregation because peaks and short-term anomalies will no longer be smoothed. Second, energy behavior of machine-tools is highly state dependent. It will be enhanced by adding controller-generated state labels or trusted event labels with the goal of making the model more interpretable and less confused in the idle regime and the processing regime (when there is mix of different jobs and materials within a single shift).

The current findings are, therefore, to be taken as a testament to pipeline capability and not the ultimate CNC field analysis. The fundamental analytics stack forecasting, profiling and anomaly detection have been demonstrated to be robust in their baseline testing, the next thing is to test them on actual CNC and digital fabrication power streams with explicit cycle and state data.

5.7 Future Work

One of the first actions is the validation of the dashboard with actual machine-tool energy streams of CNC equipment with at least one digital fabrication asset. This will involve obtaining continuous power readings in diverse jobs, materials, as well as shift conditions that also include optional controller tags where the same is feasible. These tests will enable the forecasting and the anomally components to be tested with realistic variation in production and to ensure that performance is not affected as the operating regimes vary frequently.

The next stage of development will be state-aware energy accounting to ensure that consumption is broken down into states that are meaningful to the operating state of the equipment, including, standby, warm-up, transitions, processing or cutting, and auxiliary loads. This will allow reporting of idle-energy ratio directly and also allow diagnosing waste better by relating losses to where a particular machine was and not viewing energy as an overall aggregated signal.

It will also be extended to the dashboard to report manufacturing sustainability metrics that can be used directly to improve the shop-floor. These will consist of energy per part or job within cycle limits, energy intensity by state to measure the proportion of non-productive consumption, peak-load indexes that are useful in demand control, and an energy stability index that is specified in terms of anomaly frequency per shift or batch. The indicators will be measured prior to and after at least one practical intervention, e.g., the improvement of standby policies, the modification of schedules to avoid idle times, or the optimization of the utilization of the auxiliary subsystems.

The drill-down reasoning that will support anomaly output in order to increase interpretability will include the association of abnormal signatures with likely causes, such as long standby, repeated ramp cycles, and auxiliary base-load drift and irregular bursts of load related to tool wear or mechanical failure. This interpretability is to be provided with the intention of boosting operator confidence and reducing the time between alerting and corrective action.

Lastly, the dashboard will be escalated to a one-machine perspective to a small work-cell deployment which can support multi-asset monitoring and benchmarking. This action will permit comparisons between machines and shifts and will facilitate a gradual movement in the direction of the digital-twin type of monitoring and optimization. Robust mechanisms that add a stable system to long-term reliability will be added to real production setting, such as periodic retraining triggers, horizon-dependent model selection, and lightweight fallback rules that stabilize the system during concept drift, tooling changes, and job-mix variation.

6 Conclusion

The present multi-model smart energy dashboard paper developed a multi-model digital energy monitoring and control dashboard intended to be used in monitoring real-time energy usage in CNC machining and digital fabrication setting. The strategy under consideration unites five functional operations in one workflow: synchronized uptake of machine-level energy signals, transparent preprocessing and feature construction, short-horizon forecasting with various and complementary models, hybrid anomaly detection to detect abnormal energy signatures, and clustering-based energy profile to benchmark and interpret operation.

The results of the validation show that the pipeline can be used in the continuous monitoring of practical environment. The forecasting layer showed good short-horizon prediction, the clustering phase generated energy profiles that were easily separable and could be used to support repeatable benchmarking and the anomaly detection logic generated dependable alerts with minimal false alarm propensity. Combined, these results justify the purpose of the dashboard as an operational energy-intelligence tool that does not just visualize but outright offers insights on decisions that can be used in energy governance and efficiency optimization in precision manufacturing.

Author Contributions

Conceptualization, A.A.; methodology, A.A.; formal analysis, A.A.; writing—original draft preparation, A.A.; writing—review and editing, P.U.; supporting contributions, P.U.; All authors have read and approved the final manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] International Energy Agency, "Energy efficiency 2022," 2022. https://doi.org/10.1787/679f39bd-en

[2] International Organization for Standardization, "ISO 50001: 2018—Energy management systems—Requirements with guidance for use," Geneva, Switzerland, 2018.

[3] A. Vijayaraghavan and D. Dornfeld, "Automated energy monitoring of machine tools," *CIRP Ann. Manuf. Technol.*, vol. 59, no. 1, pp. 21–24, 2010. https://doi.org/10.1016/j.cirp.2010.03.042

[4] T. Behrendt, A. Zein, and S. Min, "Development of an energy consumption monitoring procedure for machine tools," *CIRP Ann. Manuf. Technol.*, vol. 61, no. 1, pp. 43–46, 2012. https://doi.org/10.1016/j.cirp.2012.03.103

[5] S. Kara and W. Li, "Unit process energy consumption models for material removal processes," *CIRP Ann. Manuf. Technol.*, vol. 60, no. 1, pp. 37–40, 2011. https://doi.org/10.1016/j.cirp.2011.03.018

[6] M. F. Rajemi, P. T. Mativenga, and A. Aramcharoen, "Sustainable machining: Selection of optimum turning conditions based on minimum energy considerations," *J. Clean. Prod.*, vol. 18, no. 10–11, pp. 1059–1065, 2010. https://doi.org/10.1016/j.jclepro.2010.01.025

[7] Y. He, P. Wu, Y. Li, Y. Wang, F. Tao, and Y. Wang, "A generic energy prediction model of machine tools using deep learning algorithms," *Appl. Energy*, vol. 275, p. 115402, 2020. https://doi.org/10.1016/j.apenergy.2020.115402

[8] J. Du, Y. Wang, and Z. Ji, "Energy consumption forecast model of CNC machine tools based on support vector regression optimized by improved artificial hummingbird algorithm," *Proc. Inst. Mech. Eng. I*, vol. 238, no. 10, pp. 1857–1871, 2024. https://doi.org/10.1177/09596518241247861

[9] C. Li, Y. Tang, L. Cui, and Q. Yi, "Quantitative analysis of carbon emissions of CNC-based machining systems," in *the 10th IEEE International Conference on Networking, Sensing and Control*, Évry, France, 2013, pp. 869–874. https://doi.org/10.1109/ICNSC.2013.6548852

[10] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*. Hoboken, NJ, USA: Wiley, 2015. https://doi.org/10.1111/jtsa.12194

[11] S. J. Taylor and B. Letham, "Forecasting at scale," *Am. Stat.*, vol. 72, no. 1, pp. 37–45, 2018. https://doi.org/10.1080/00031305.2017.1380080

[12] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.*, San Francisco, CA, USA, 2016, pp. 785–794. https://doi.org/10.1145/2939672.2939785

[13] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997. https://doi.org/10.1162/neco.1997.9.8.1735

[14] F. T. Liu, K. M. Ting, and Z. H. Zhou, "Isolation forest," in *the 8th IEEE International Conference on Data Mining*, Pisa, Italy, 2008, pp. 413–422. https://doi.org/10.1109/ICDM.2008.17

[15] L. Mascali, D. S. Schiera, S. Eiraudo, L. Barbierato, R. Giannantonio, E. Patti, L. Bottaccioli, and A. Lanzini, "A machine learning-based anomaly detection framework for building electricity consumption data," *Sustain. Energy, Grids Networks*, vol. 36, p. 101194, 2023. https://doi.org/10.1016/j.segan.2023.101194

[16] International Organization for Standardization, "ISO 23247-1: 2021—Automation systems and integration—Digital twin framework for manufacturing—Part 1: Overview and general principles," Geneva, Switzerland, 2021.

[17] J. L. Diaz C. and C. Ocampo-Martinez, "Non-centralised control strategies for energy-efficient and flexible manufacturing systems," *J. Manuf. Syst.*, vol. 59, pp. 386–397, 2021. https://doi.org/10.1016/j.jmsy.2021.02.004

[18] X. Xu, L. Wang, and S. T. Newman, "Computer-aided process planning—A critical review of recent developments and future trends," *Int. J. Prod. Res.*, vol. 24, no. 1, pp. 1–31, 2011. https://doi.org/10.1080/0951192X.2010.518632

[19] X. J. Jiang and D. J. Whitehouse, “Technological shifts in surface metrology,” *CIRP Ann. Manuf. Technol.*, vol. 61, no. 2, pp. 815–836, 2012. https://doi.org/10.1016/j.cirp.2012.05.009

[20] A. Ampara and P. T. Mativenga, “Critical factors in energy demand modelling for CNC milling and impact of toolpath strategy,” *J. Clean. Prod.*, vol. 78, pp. 63–74, 2014. https://doi.org/10.1016/j.jclepro.2014.04.065

[21] L. Zhou, J. Li, F. Li, Q. Meng, J. Li, and X. Xu, “Energy consumption model and energy efficiency of machine tools: A comprehensive literature review,” *J. Clean. Prod.*, vol. 112, pp. 3721–3734, 2016. https://doi.org/10.1016/j.jclepro.2015.05.093

[22] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, “Digital twin-driven product design, manufacturing and service with big data,” *Int. J. Adv. Manuf. Technol.*, vol. 94, no. 9–12, pp. 3563–3576, 2018. https://doi.org/10.1007/s00170-017-0233-1