AI in Industry: Activities of the CINI-AIIS Lab at University of Naples Federico II

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Abstract
Artificial intelligence (AI) is reshaping the manufacturing landscape, offering opportunities for efficiency improvements and innovation. Through Machine Learning (ML) and Deep Learning (DL), AI enables predictive maintenance, anomaly detection, and image analysis in industrial settings. ML algorithms empower systems to learn from data, facilitating predictive maintenance by predicting optimal equipment servicing schedules based on operational conditions. DL techniques, including Convolutional Neural Networks (CNNs), are revolutionizing industrial image analysis by extracting intricate features for quality control and defect detection. Moreover, the integration of DL with natural language processing (NLP) streamlines tasks like document analysis and inventory management. At the University of Naples Federico II's CINI-AIIS Lab, cutting-edge AI projects are underway, showcasing the transformative potential of AI in the industry sector.

Keywords
Predictive Maintenance, Energy Forecasting, Anomaly Detection, Remaining Useful Life.

1. Introduction

Artificial intelligence (AI) is transforming various industries, including the manufacturing sector, by emulating human intelligence to tackle complex challenges. In the industrial domain, AI holds significant promise, enhancing operational efficiency, optimizing processes, and driving innovation. AI-powered systems can analyze extensive datasets to detect anomalies, predict equipment failures, and improve overall productivity. Machine Learning (ML), a subset of AI, enables systems to learn from data and make informed decisions, such as predicting optimal maintenance schedules based on equipment conditions and operational context.

Deep Learning (DL), another ML subset, leverages Artificial Neural Networks (ANNs) to process complex data patterns and make accurate predictions. DL, particularly through Convolutional Neural Networks (CNNs), is revolutionizing industrial image analysis by extracting meaningful features from images for quality control and defect detection. Additionally, DL, combined with Natural Language Processing (NLP), is streamlining tasks like document analysis and inventory management. The versatility of AI underscores its pivotal role in the manufacturing industry, driving efficiency gains and fostering innovation.

In this paper, we showcase AI projects in the industrial sector from the University of Naples Federico II node of the CINI-AIIS Lab, highlighting their innovative contributions.

2. Prediction and Forecasting for railway rolling stock equipment

The manufacturing industry is currently undergoing the so-called Industry 4.0 revolution, characterized by the extensive integration of physical and digital realms within production settings. Key technologies driving this revolution include the Industrial Internet of Things, Big Data, Artificial Intelligence, and advanced telecommunications like 4G and 5G, which profoundly influence the transport sector. These innovations enable the gathering of vast data from diverse onboard devices and equipment installed on train vehicles and along railway tracks.

This wealth of data, acquired through smart sensors and relayed to diagnostic systems either onboard or in control rooms, holds immense potential. By employing appropriate techniques, it can unveil patterns of degradation in components and anticipate failures in a timely manner, facilitating optimal maintenance decisions. Traditionally, players in the railway transport sector have relied on planned maintenance, often resulting in unnecessary actions and inflated operating costs. However, the evolution towards Condition-Based Maintenance (CBM) offers a proactive alternative. CBM, an extension of planned maintenance, assesses equipment conditions through direct measurements, enabling timely repairs or replacements when specific conditions are met.

Predictive Maintenance takes CBM a step further by leveraging monitoring data and effective predictive tech-

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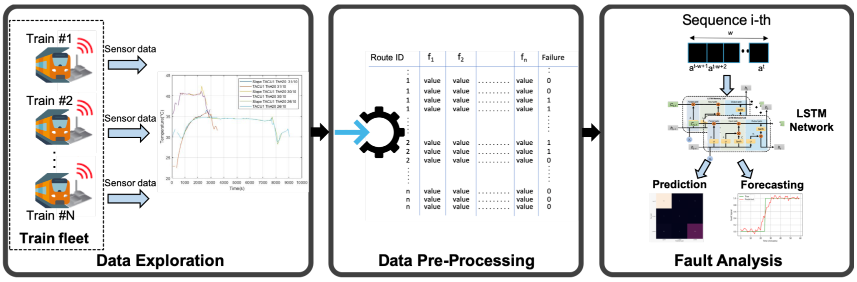

Figure 1: The proposed failure prediction methodology.

niques to anticipate fault occurrences. This approach enables companies to schedule maintenance operations precisely when needed, leading to cost reductions, decreased mean time to failures, and overall profit enhancement. The key advantage lies in conducting maintenance preemptively, averting prolonged downtime without resorting to premature interventions, thus minimizing the unavailability of rolling stock and infrastructure equipment.

Machine Learning (ML) algorithms emerge as powerful tools in maintenance across diverse domains, owing to their support for predictive techniques. ML techniques have been applied extensively, from predicting light bulb failures to early detection of machine failures, rotating machinery failure prediction, and estimating the Remaining Useful Life (RUL) of various assets like hard disks and wind turbines. In the railway domain, ML is gaining prominence in enhancing operations and reliability. However, the efficacy of ML algorithms hinges on selecting the appropriate technique, especially considering the gradual deterioration or sudden failure characteristic of rail systems. Thus, ML approaches for predictive maintenance must account for such data dynamics to ensure accurate failure prediction and forecasting.

We introduced a deep learning-based methodology which enables the prediction and forecasting of failures, allowing for proactive maintenance interventions to be planned before they occur, thereby optimizing both the cost and duration of maintenance activities. Utilizing Long Short-Term Memory (LSTM) networks, an extension of recurrent neural networks (RNN), the methodology is adept at learning long-term dependencies in data that change gradually over time. An overview of the methodology is provided in Figure 1.

The proposed approach analyzes data collected from numerous sensors distributed across the various subsystems of a railway vehicle, with a particular focus on the critical train traction converter cooling subsystem. Operational data from a train fleet spanning several months is examined. The framework employs classic statistical data analysis techniques, such as trend estimation (e.g., Mann-Kendall) and correlation, to uncover relationships between dataset features and failure patterns. Subsequently, LSTM networks are utilized to both predict and forecast failures, offering valuable insights to maintenance personnel responsible for rolling stock equipment.

Our methodology achieves an accuracy exceeding 99% for both prediction and forecasting tasks, surpassing existing ML models and techniques in the predictive maintenance literature. Moreover, the error rates for prediction and forecasting tasks are notably low, with a false alarm rate of approximately 0.4% and a mean absolute error on the order of 10^{-4}. These results are highly promising compared to previous studies. Additionally, the methodology is validated against real-world systems by our industry partner, confirming the soundness of our assumptions and approaches.

3. Forecast and Anomaly Detection in Photovoltaic System

In the context of the global energy landscape, the International Energy Agency (IEA) highlights the pivotal role of photovoltaic (PV) energy in driving the ongoing energy transition, as indicated in the World Energy Outlook 2023 [1]. Despite the adoption of the Stated Policies Scenario (STEPS), it is observed that the utilization rate of solar energy markets lags behind the expanding production capacity of PV technologies (Figure 2).

Recognizing the imperative for a paradigm shift within the PV market, encompassing both domestic and industrial installations, there is a pressing need for active involvement from network and infrastructure stakeholders, energy producers, and consumers [2]. These entities, frequently coalescing into energy communities, aim to foster sustainable energy exchange paradigms, necessitating the development of novel tools. These tools must render photovoltaic production economically viable for energy trading while ensuring environmental sustainability through reductions in energy storage requirements and effective planning for grid load and dispersion/uti-

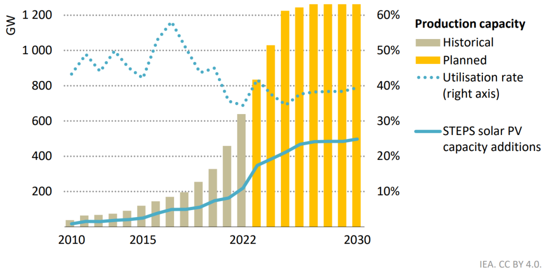

Figure 2: Global solar module manufacturing and solar PV capacity additions in the STEPS, 2010-2030 [1].

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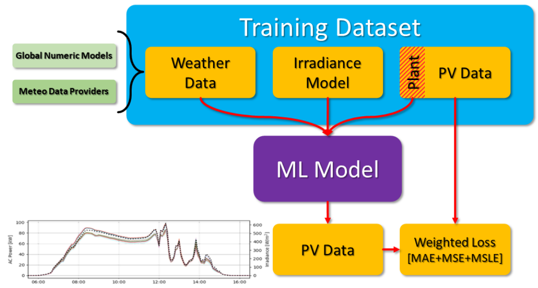

Figure 3: The proposed approach for Power Forecasting. The training dataset is composed by weather data, irradiance model and PV configuration (red-dashed PV Pant Data). Target data is composed by real daily AC Power Production and Solar Irradiance (bottom left graph).

The proposed approach, as presented in Figure 3, entails the integration of a selected provider from among global numerical and commercial models. This choice is informed by preliminary results. The integration involves coupling this provider with a mathematical and physical model of irradiance [3], with the objective of effectively propagating irradiance contributions through suitable machine learning models. Long short-term memory (LSTM) and Transformer Neural Networks (NN) models will be considered, with comparisons drawn against classical machine learning techniques. To optimize the model's performance, an appropriate weighted combination of losses will be employed during the training process. The training is conducted using real data sourced from managed photovoltaic systems situated at five distinct Italian sites. By leveraging this combination of numerical, commercial, and machine learning models, the proposal aims to enhance the accuracy and predictive capability of the system, paving the way for a more effective utilization of solar energy resources.

Preliminary results shows up to 0.536 ± 0.015% mean absolute percentage error (MAPE) on power yield forecasting (99% CI validated) using a seq2seq Transformer architecture.

This result allowed us to test an anomaly detection procedure by comparing the predicted result with the power produced by each individual inverter. When considering a single plant and computing the prediction error, it is possible to put into practice a simple but effective anomaly detection technique as shown in Figure 4.

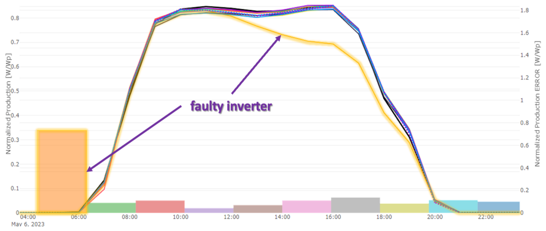

Figure 4: A single day of PV Power production (scaled to Inverter Nominal Power) as continuous lines and the relative model predictions as dotted lines. Highlighted a single faulty inverter showing a transient power loss. The bar plot of the model prediction error for each inverter allows to easily recognize the faulty one by applying a threshold.

Figure 4 shows that an individual inverter has suffered a transient power loss that can be appreciated visually by comparing the predicted vs. produced power curves, but also quantitatively by thresholding the prediction error. It is not yet possible to quantify an unambiguous threshold, and future work is investigating the possibility of a local adaptive approach.

4. Predictive Maintenance in IoT scenarios

We are currently immersed in the Industry 4.0 era, marked by the continual automation of traditional manufacturing and industrial processes through modern smart technologies like *Internet of Things* (IoT) and *Artificial Intelligence* (AI) ([4]). This evolution demands an increasing integration between physical and digital systems in production environments, enabling the collection of vast data from various smart equipment and sensors.

Smart sensors, devices generating data on physical parameters (e.g., temperature, humidity, or vibration speed), offer functionalities ranging from self-monitoring to managing complex processes ([5]).

Analyzing such data yields insights into machinery health and production levels, driving strategic decision-making for benefits like reduced maintenance costs, fewer machine faults, optimized inventory, and increased production. Maintenance procedures are a key focus, given their significant impact on industrial production and service availability. Industries are investing heavily in equipping themselves with the tools for data-driven maintenance strategies.

In the literature, two main approaches support maintenance: *model-driven* and *data-driven* methods, with *hybrid-driven* approaches gaining traction. While model-driven techniques rely on expert theoretical understanding, data-driven techniques leverage the vast information available to detect machinery anomalies ([6, 7]). Hybrid-driven solutions merge model and data fusion ([8, 9]). Maintenance management approaches, as categorized by ([10]), include *Run-to-Failure* (R2F), *Preventive Maintenance* (PvM), and *Predictive Maintenance* (PdM). Our focus is on PdM, which relies on data-driven analysis to predict machinery failures, optimizing maintenance procedures and increasing machine longevity ([11, 12]).

In many domains with complex data, machine learning and deep learning techniques stand out for predictive maintenance ([13, 14, 15]). These approaches use historical datasets to train models for predicting failures, such as *Remaining Useful Life* (RUL) estimation.

However, deploying deep learning in real-world IoT scenarios faces challenges due to computational limitations. Edge/fog computing solutions are favored but influenced by network connectivity ([16]). *Embedded AI* techniques are increasingly proposed for efficient, cost-effective data-driven analysis on industrial equipment hardware ([17]).

This proposal presents a deep learning approach for predictive maintenance, leveraging a *multi-head attention* mechanism for high RUL estimation accuracy and low memory requirements, suitable for hardware implementation. Experimental results demonstrate its effectiveness and efficiency, making it a promising solution for real-world PdM scenarios.

Figure 5 presents a high-level overview of the proposed model architecture for the described PdM task, along with the data analysis pipeline necessary for generating estimated RUL values.

The input comprises historical data from sensors providing crucial information about the monitored machinery's conditions, which includes a temporal component crucial for detecting degradation trends.

Once the input data is processed, it's fed into the model capable of capturing temporal dependencies between features. By setting an appropriate time window, the input data fed into the model forms a matrix of size (T_w, N_x), where T_w represents the length of the input time window and N_x denotes the number of considered features. The model output is a real number representing the remaining useful life of the machinery. The main components of the proposed architecture include: positional encoding block, accounting for the relative or absolute position of the time-steps in the input sequence; the attention module, comprising two sub-layers with residual connections between them: the multi-head attention block and fully connected network module.

The experimental results demonstrate how the proposed approach effectively meets the demands of modern embedded AI applications, particularly benefiting smart manufacturing systems where reliability, low latency, privacy, and low power are critical. These findings have significant management implications for optimizing production line operations.

Future research could explore further applications of the attention mechanism in predictive maintenance. Additionally, investigating what aspects the model prioritizes (i.e., receives more attention) could be insightful, potentially leveraging eXplainable Artificial Intelligence (XAI) tools to provide explanations.

5. Forecasting Remaining Useful Life in Aerospace Maintenance

The aerospace industry is known for its strict safety standards, regulatory requirements, and the importance of efficient maintenance to keep operations running smoothly. While traditional maintenance methods like preventive and reactive maintenance have their drawbacks in terms of cost and accurately predicting failures, predictive maintenance driven by AI and data analytics is a more proactive and cost-effective solution that can help overcome these challenges.

PdM uses data from sensors, operation logs, and maintenance records to monitor equipment health and predict failures. By forecasting the remaining useful life of key components, it prevents unplanned downtime, cuts maintenance costs, and improves safety.

The focus is on using advanced algorithms such as LSTM networks and Transformer models to improve maintenance schedules in the aerospace industry using the C-MAPSS dataset, which contains sensor readings and remaining useful life (RUL) values for turbofan jet engines under different operating conditions. These types of deep learning models have shown great success in understanding intricate time-based patterns and distant connections in data sequences.

The C-MAPSS dataset is highly valued in the research community and widely used. Many researchers consider it a valuable resource for studying intelligent maintenance and machine health prognosis as shown in the figure 6.

The LSTM network, with its gating mechanisms (forget, input, and output gates) and capability to selectively retain or discard information over time, proved adept at modeling long-term dependencies intrinsic to time-series data. Conversely, the Transformer model, originally designed for natural language processing tasks, employed a self-attention mechanism and position-wise

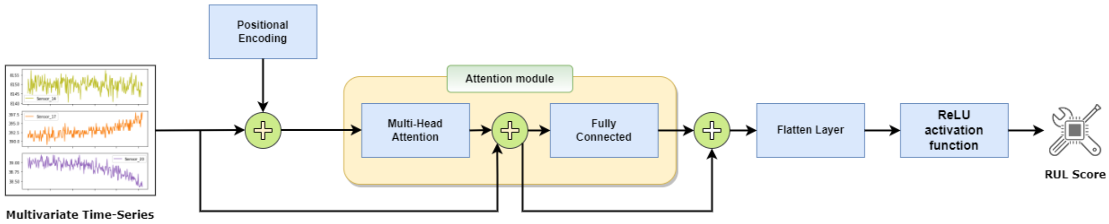

Figure 5: Proposed AI architecture.

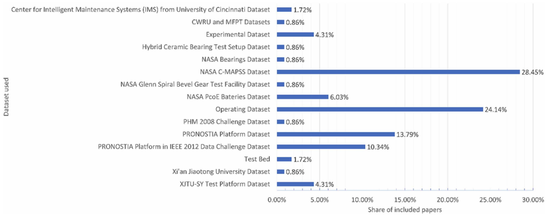

Figure 6: Datasets used for RUL prediction

feed-forward networks to capture distant relationships within the input sequences effectively.

Through rigorous testing and analysis using various metrics like mean absolute error, loss function and R^2 values, our findings show that LSTM networks outperform Transformers in accurately forecasting RUL 1.

Table 1
Comparison of metric results for LSTM and Transformer models

	MAE	Loss	R^2
LSTM	20.51	922.80	0.729
Transformer	29.11	1609.31	0.517

The results analysis indicates that while the Transformer model shows good performance in predicting engine performance, it falls short compared to the LSTM model, likely due to dataset limitations rather than architectural constraints. The Transformer's self-attention mechanism and lack of an explicit recurrent structure like LSTMs may require more diverse data to accurately capture sequential patterns, especially in complex time-series tasks. Understanding and predicting engine performance over time relies heavily on modeling long-term temporal dependencies, which can be challenging with a limited number of representative examples in the dataset. The Transformer's ability to effectively handle such temporal contexts is influenced by the quality and comprehensiveness of the training data it receives. Further research could explore new model architectures, ensemble techniques and optimization strategies to improve model performance and address specific challenges associated with time series data.

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