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Artificial Neural Network-Based Decision Support Tool for Identifying Operational Causes of Energy Consumption Anomalies in Production Lines

Annalisa Santolamazza*, Vito Introna*

** Department of Enterprise Engineering, Tor Vergata University of Rome, Rome, Italy (annalisa.santolamazza@uniroma2.it, vito.introna@uniroma2.it)*

Abstract: Energy management is a critical challenge for industries that rely on energy-intensive production lines, where inefficiencies can increase costs and waste. This study introduces a practical decision support tool, based on Artificial Neural Networks, designed to monitor energy consumption and identify the operational causes of anomalies. By analyzing data from production lines, the tool helps identify inefficiencies linked to factors like downtime, production speed, and defect rates. The proposed system has been tested on a real case study, showing the ability to detect different issues such as energy waste during unproductive periods or excessive consumption tied to high defect rates. Thus, it also highlights how managerial decisions, such as planned stoppages during cleaning or maintenance, can significantly affect energy efficiency. By making these insights clear, the system helps companies make smarter choices to optimize energy use and reduce waste.

Keywords: Smart manufacturing systems; Sustainable Manufacturing; Industry 4.0; Energy Management.

1. INTRODUCTION

For energy-intensive industries, effective energy monitoring and optimization are critical to minimizing waste, reducing costs, and achieving compliance with increasingly stringent environmental regulations. However, implementing effective energy management demands significant effort in data collection and analysis. The sheer volume of data, combined with the limited availability of human resources dedicated to energy management tasks, often poses major obstacles to its adoption within companies.

To address these challenges, advanced tools, including software powered by machine learning techniques, play a crucial role. These technologies can enable efficient, yet highly accurate, energy control, making the process more accessible and manageable. Moreover, by leveraging digital tools and data-driven approaches, manufacturers can gain deeper insights into energy consumption patterns, identify inefficiencies, and optimize resource utilization (Introna et al., 2024; Li et al., 2023).

On the other hand, the interdependence between energy consumption and operational performance is clear. Anomalies in energy performance can stem from operational factors, such as unplanned downtime, suboptimal machine speeds, or high defect rates, thus the accurate identification of root causes in production context for energy consumption deviations is often difficult (An et al., 2022; Benedetti et al., 2014).

To provide a solution to this issue in this paper a comprehensive methodology for developing a decision support system based on Artificial Neural Networks (ANN) is presented. The aim of the proposed tool is to monitor energy-intensive production lines and identify operational causes of energy consumption anomalies to give energy management personnel actionable insights to optimize the system's behavior.

The paper is structured as follows: Section 2 describes the background on energy consumption control techniques and the connection between energy and production efficiency, Section 3 describes the methodological approach proposed to develop the decision support system, Section 4 shows the results of the application of the proposed methodology on a real case study to test its effectiveness, and Section 5 concludes the paper with some final considerations and the description of future developments.

2. BACKGROUND

2.1 Energy consumption control

Energy management in complex industrial systems requires robust techniques for characterizing, predicting, and controlling energy consumption. These techniques fall into two primary categories: engineering approaches and data-driven methods, each offering distinct advantages and limitations.

Engineering approaches use physical equations to model energy consumption, offering precise insights into energy flows by directly linking usage to physical processes. However, they require extensive knowledge of the system and detailed inputs, which can limit their practicality in complex or dynamic systems. Data-driven approaches, on the other hand, focus on analyzing historical data to identify patterns and relationships between energy consumption and influencing factors. These methods are particularly suited for modelling complex system's behavior (Kim et al., 2022).

Among data-driven techniques, artificial intelligence has gained prominence for their ability to solve complex problems and process nonlinear relationships (Himeur et al., 2021). Anomaly detection in energy performance has been achieved using both unsupervised and supervised approaches, with ANNs being particularly effective due to their adaptability and predictive accuracy. Indeed, ANNs have been implemented

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for various purposes, such as optimizing energy use, forecasting energy consumption, and managing renewable energy integration in smart grid environments (Ahmad et al., 2022; Shahid et al., 2025; Tesch Da Silva et al., 2020).

2.2 Relationship between energy consumption and operation efficiency

The relationship between Overall Equipment Effectiveness (OEE) and energy consumption is a critical area of study in energy-intensive industries. OEE, which measures the efficiency of equipment in terms of availability, performance, and quality, directly impacts energy utilization (Schiraldi & Varisco, 2020).

Scientific research has shown that efficiency losses captured by OEE metrics often lead to increased energy consumption, even when production volumes remain constant (An et al., 2022; Benedetti et al., 2014; Hasan & Trianni, 2023). For example, downtime due to failures or setups often results in machinery consuming energy without productive output. Slowdowns prolong the time required to complete production tasks, not only delaying production but also increasing specific energy consumption. Moreover, defective products lead to rework or scrapping, requiring additional energy to meet production targets. Even when reworking defective units at normal operational speeds, energy usage per unit of acceptable output increases, reducing overall energy efficiency.

Existing energy monitoring systems tend to focus on energy consumption as an aggregate metric, lacking the ability to identify root causes of detected anomalies or correlate them with specific operational conditions. Such systems provide high-level overviews but do not enable manufacturers to determine the causes of inefficiencies, especially in complex, energy-intensive production lines where varying product types and operational changes can obscure patterns of energy use.

3. METHODOLOGY

3.1 Methodology overview

The proposed methodology for developing a decision support tool to identify the operational causes of energy consumption anomalies in production lines follows a structured workflow as illustrated in Figure 1.

3.2 Data acquisition

The first step involves gathering energy consumption data, operational and ambient conditions data from the selected production line. Operational data includes finished products, defective products, planned and unplanned downtimes, production speed. Ensuring the availability of high-quality, reliable data for both energy and production is a prerequisite for the subsequent steps.

To ensure that the model can generalize to all production scenarios, the data must comprehensively represent every possible operating condition of the production line. This includes variations due to different types of products processed, changes in production speeds, and the occurrence of planned or unplanned downtimes.

Energy data, often recorded at a high frequency (such as 5-minutes intervals or at most hourly intervals), must be combined with production data, which are typically recorded at lower frequency, such as per shift or batch. For this reason, an 8-hour production shift could be selected as the reference temporal scale.

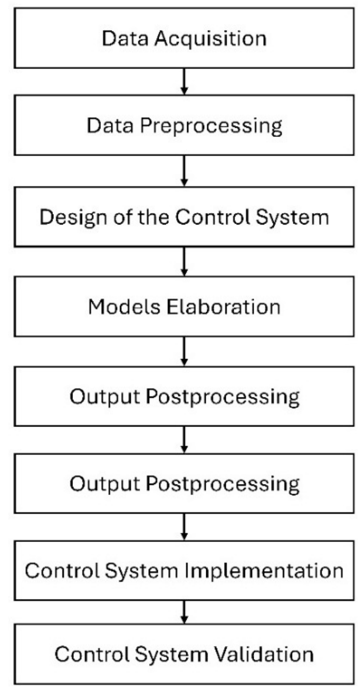

Figure 1. Methodology for the development of the control system.

3.3 Data preprocessing

During this phase energy and operational datasets need to be synchronized to the same temporal scale and the resulting dataset has to be cleaned eliminating incomplete, duplicate, or erroneous records. Categorical variables such as production types or speed classes need to be encoded into binary vectors and numerical data are normalized to maintain uniformity.

After a careful assessment to ensure that the dataset gives a balanced representation of all production conditions, the dataset is ready for input into the machine learning models.

3.4 Design of the control system

The control system is designed to monitor and diagnose energy consumption anomalies. In order to do so multiple ANN models need to be created using different inputs while maintaining the same output, i.e. the energy consumption of the line.

Indeed, by changing the inputs of each ANN model the resulting predicted energy consumption will be normalized in regard to those inputs. Through the comparison among these different ANN models, it is therefore possible to identify the variables that are responsible for the energy performance deviation.

The inputs for the different ANN models are reported in Table 1. Here, "adjusted operating time" is a theoretical measure calculated by subtracting only the duration of planned projects or qualification trials (which do not yield commercial production) from the total operating time.

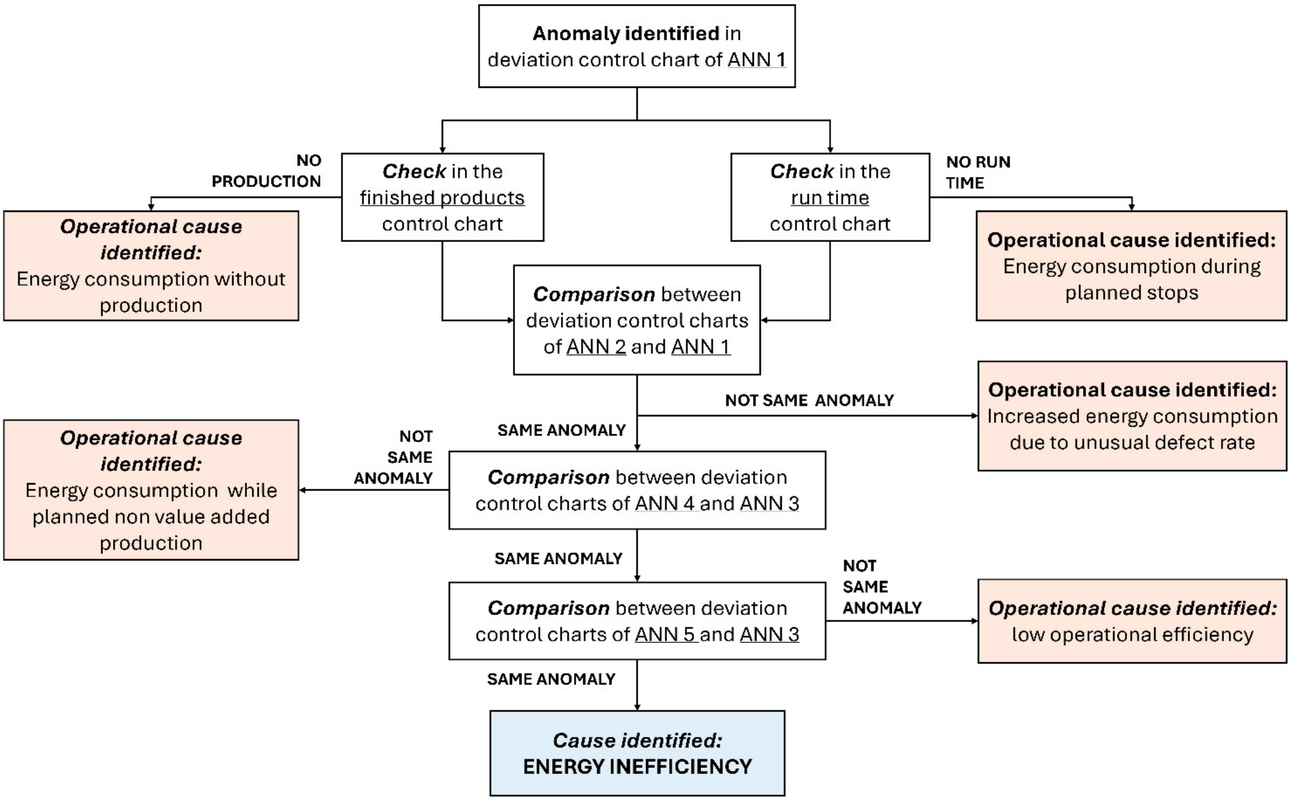

Figure 2. Schematic representation of the control system logic.

In contrast, the established variable "net operating time" represents the actual operating time, excluding all downtime periods and accounting solely for productive operations.

Table 1. Inputs for the different ANN models.

ANN model	Inputs
ANN 1	Product type; finished products
ANN 2	Product type; total processed products
ANN 3	Product type; operating time
ANN 4	Product type; adjusted operating time
ANN 5	Product type; net operating time

A decision tree prototype, in Figure 2 has been developed as a systematic approach to identify energy consumption anomalies and their corresponding operational causes by analyzing deviation control charts for each ANN model and control charts for relevant operational variables in an organized manner. The main causes analyzed for anomalies in energy consumption behavior are:

- Unusual defect rate
- Planned projects or qualification trials that result in non-commercial production
- Planned downtime with energy consumption
- Low operational efficiency

Thus, control charts are analyzed in hierarchical order, allowing for a direct comparison between the out-of-control points observed on the deviation control chart and the trends seen in the control charts. If no match is found in the first control chart, the process moves to the next one in the hierarchy, continuing the analysis until some correspondence is identified.

The process begins by detecting an energy consumption anomaly using the primary deviation control chart, the one for model ANN 1, indicating when actual energy consumption deviates from the expected predicted value using the number of finished products and their type.

The identified deviation is analyzed through two primary control checks using the control charts for the number of finished products and the run time. By using the finished products control chart, it is possible to associate that deviation with an energy consumption without production, whereas using the second control chart the anomaly can be associated with unusual energy consumption during planned downtime.

If the first checks are negative, the process continues with a comparison between the deviation control charts for models ANN 2 and ANN 1. If the control chart for model ANN 2 does not show the same anomaly as the one for ANN 1, it means that the reason for the anomaly in energy consumption is an unusual defect rate.

If the reason for the anomalous energy consumption is still unidentified, the comparisons between the deviation control charts for models ANN 4 and ANN 3 can rule out the use of energy for tests and product qualifications if the same anomaly is in both control charts. Furthermore, the last comparison is between the deviation control charts for models ANN 5 and ANN 3 and can help assess whether the anomaly is attributable to low operational efficiency. If ANN 3 exhibits the anomaly but ANN 5 does not, it suggests that inefficiencies in the production process are the primary cause.

If none of the above controls were positive it means that anomalous energy performance is not connected to these operational causes. Thus, the reasons for inefficiency are truly to be ascribed to the production line (e.g. changes in set points, components, maintenance effectiveness, etc.).

This structured approach ensures a clear connection between deviations in energy consumption and the operational factors responsible for them, enabling a targeted diagnosis of inefficiencies and supporting efforts to improve the energy performance of production lines.

3.5 Models elaboration

At this stage, ANN models are trained using the defined inputs. The chosen architecture for the ANN models is a Multilayer feedforward Perceptron (MLP). To ensure an optimal architecture, the number of neurons in the hidden layer of each model is defined through experimentation using the value of Mean Squared Error (MSE) as optimization value.

3.6 Output postprocessing

The output generated by the trained ANNs is further processed to facilitate the identification of anomalies and their root causes. This involves:

- Evaluation of the deviations between real and predicted energy consumption
- Implementation of control charts for the deviations to highlight anomalies in energy consumption
- Implementation of control charts for each operational variable to analyze their trends and variability during the monitoring period

3.7 Control system implementation

The validated models and processed outputs are implemented into the control system, allowing real-time control of the production line energy performance. This system integrates deviation analysis to identify energy consumption anomalies thought deviation charts and an automatic root cause diagnosis, cross-referencing deviations with control charts of operational variables to identify the primary causes of inefficiencies.

3.8 Control system validation

The final phase involves validating the implemented control system to ensure its robustness and accuracy.

This validation uses additional data from a following time period to verify the system's ability to identify energy anomalies and assess the accuracy of root cause diagnoses.

4. CASE STUDY APPLICATION

4.1 Case study description

The proposed methodology has been tested on a real case study involving an industrial production line, where the primary energy consumption is attributed to glue melters, three-phase motors, and vacuum fans.

The production line is active for three shifts per day, seven days a week, producing four different types of products. The four types of products are characterized by a different production speed as reported in Table 2.

Table 2. Association between production speed and product types.

Product type	Production speed (units/minute)
Type A	550
Type B	860
Type C	910
Type D	1010

To create the models, data starting from 1 January 2021, up to 31 August 2023 have been selected. It should be noted that some time intervals, even of entire months, were excluded through an ad hoc data control and cleaning procedure, as they were clearly affected by measurement errors and recording problems (from the initial dataset of 2915 records the training set was comprised of 1700 datapoints, each related to a working shift).

As expected, different product types are associated with different energy consumption levels, as shown by Figure 3. Thus, the first four inputs for each ANN model are four binary variables (type A, type B, type C, type D) to identify the type of product produced in the shift (Table 3).

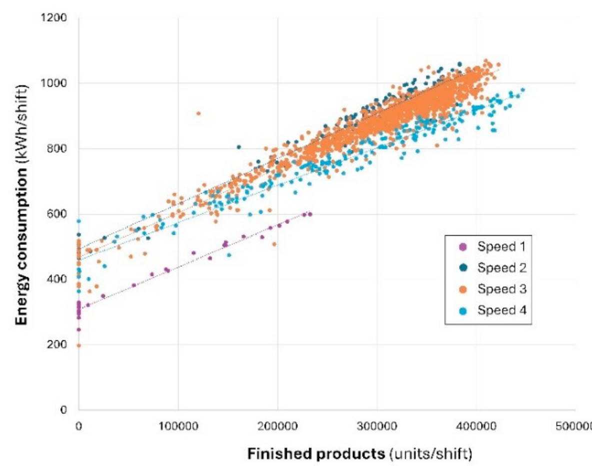

Figure 3. Relationship between energy consumption and finished products with different product types.

Table 3. Characteristics for the ANN models.

ANN model	Inputs	Output
ANN 1	Type A, Type B, Type C, Type D; Finished products	Energy consumption
ANN 2	Type A, Type B, Type C, Type D; Total processed products	Energy consumption
ANN 3	Type A, Type B, Type C, Type D; Operating time	Energy consumption
ANN 4	Type A, Type B, Type C, Type D; Adjusted operating time	Energy consumption
ANN 5	Type A, Type B, Type C, Type D; Net operating time	Energy consumption

The ANN models were implemented in MATLAB. The dataset was split 70-15-15 for training, validation, and testing. The Levenberg-Marquardt algorithm was chosen for training because of its high convergence speed and greater stability. An iterative approach determined the optimal number of neurons in the hidden layer by gradually increasing them from 1 to 20 and evaluating the best architecture based on the minimum MSE.

Compared to traditional methods based on statistical regressions, the proposed ANN models offer the advantage of capturing complex nonlinear relationships between operational variables and energy consumption, providing greater flexibility and adaptability to diverse production contexts. This capability enables the identification of energy anomalies that might remain undetected by traditional linear methods. For instance, ANN 1 achieved a Mean Absolute Error (MAE) of 22.59 kWh and a Mean Absolute Percentage Error (MAPE) of 2.77%, both lower than those obtained with a traditional linear regression model (MAE: 23.68 kWh, MAPE: 2.88%), highlighting the improved predictive accuracy of the ANN-based approach.

4.3 Results

The application of the described control system successfully identified various energy performance anomalies automatically during the period from September 2023 to March 2024.

Figure 4 highlights the detection of instances where significant energy consumption occurred despite zero production.

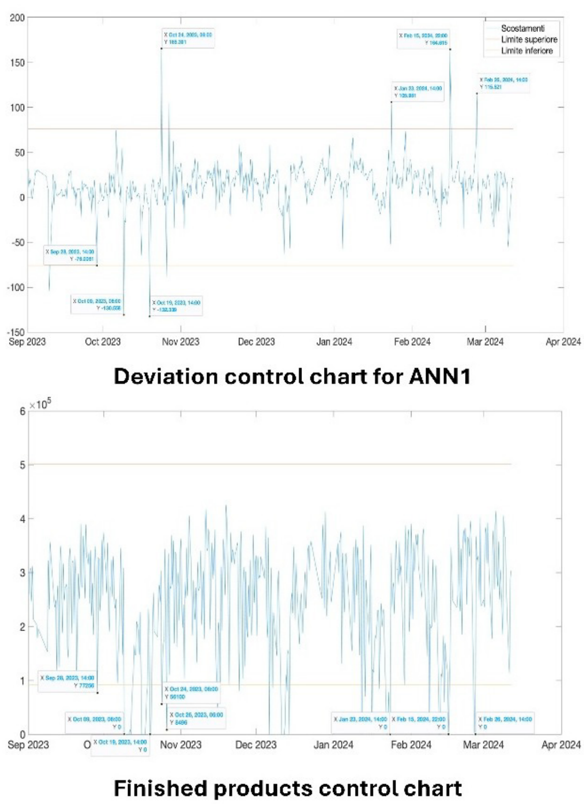

Figure 4. Comparison between the deviation control chart of ANN 1 and the control chart for finished products to identify moments with zero production but relevant energy consumption.

Figure 5 shows how it is possible to identify stops with unusual energy consumption.

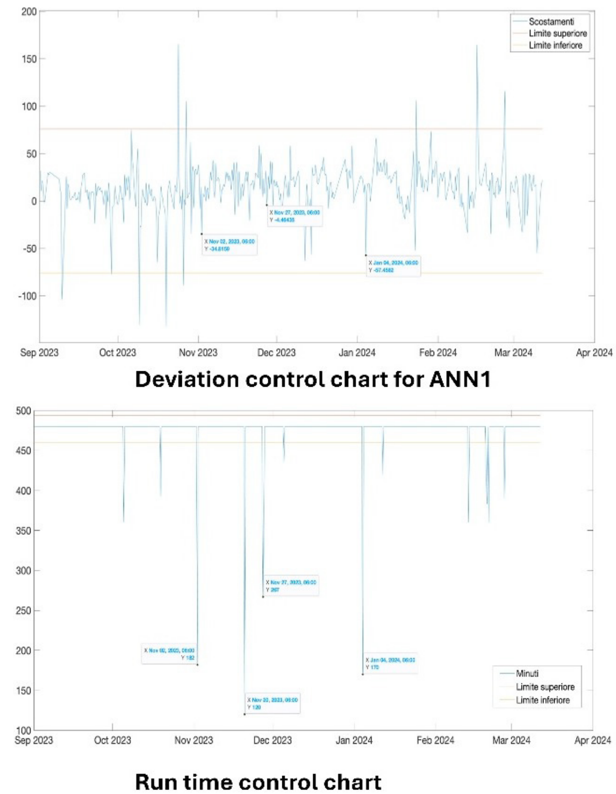

Figure 5. Comparison between the deviation control chart of ANN 1 and the control chart for run time to identify moments with with relevant energy consumption during planned stops.

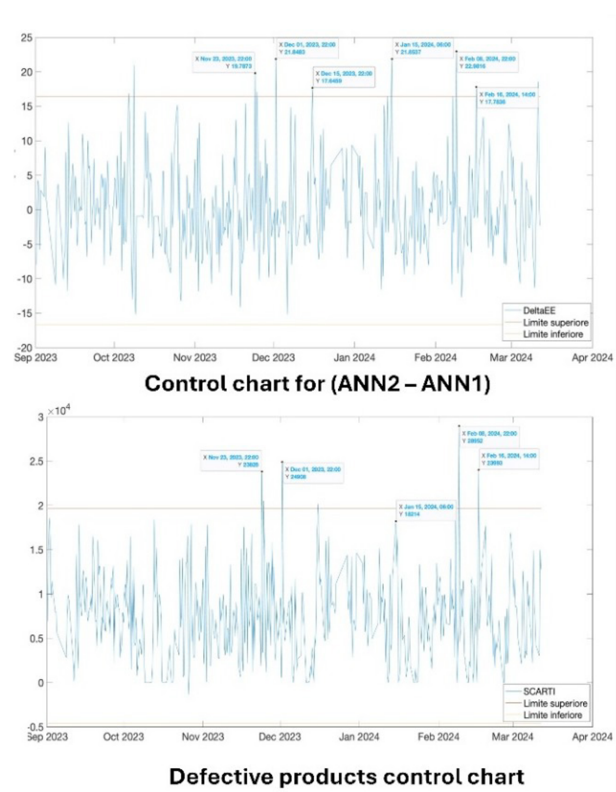

Figure 6. Comparison between the control chart of the difference between ANN 1 and ANN 2 and the control chart for defective products to identify energy consumption due to high defects rate.

Figure 6 shows how the control chart of the difference between ANN 1 and ANN 2 can be used to identify energy consumption anomalies due to high defects rates.

Finally, the last anomalous behavior has been identified and analyzed. Figure 7 shows an interval of time with an energy performance more efficient than expected. After some investigation it was confirmed that a change in operation set points had been implemented.

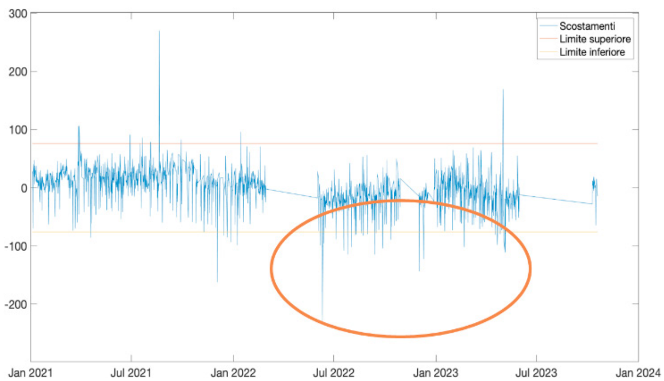

Figure 7. Deviation chart for ANN 1, with highlighted moments with an energy performance higher than predicted.

6. CONCLUSIONS

This study introduces a decision support tool based on Artificial Neural Networks for identifying the operational causes of energy consumption anomalies in production lines. The proposed methodology involves systematic data collection, preprocessing, and the development of a decision tree to diagnose inefficiencies and provide actionable insights.

By integrating ANN models with control charts, the tool not only detects deviations in energy performance but also correlates these anomalies with key operational factors, such as downtime, production speed, and defect rates.

The results from a real case study confirm the system's effectiveness in identifying various types of energy inefficiencies, such as energy waste during downtime, excessive consumption linked to defective products, and even unexpected improvements due to operational adjustments.

It should be noted that by shining a light on inefficiencies tied to managerial decisions, such as planned stoppages that still consume significant energy during setup or maintenance, the tool helps understand how strategic choices directly influence energy efficiency. This insight can foster more conscious and deliberate management practices, helping companies achieve better energy performance.

Future developments will aim to adapt the methodology to more complex production environments and enhance the tool's real-time diagnostic capabilities.

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