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Prioritized Anomaly Management in Steel Production Using Self-Supervised AI

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ABSTRACT

Due to the unavailability of highly curated data, manufacturers are increasingly adopting anomaly detection to analyze large volumes of operational data in real-time. It is very difficult to review every anomaly manually because of limits on available manpower. This paper, therefore, presents a novel approach to automatically prioritize anomalies to direct human attention to where it is most needed. Using anomaly severity, anomaly persistence, signal importance, anomaly spread, and contextual information, the automated anomaly detection AI enables prioritization of attention to review the critical anomalies for timely diagnosis and corrective actions. We present practical cases of deploying this approach in line-scale steelmaking operations.

Keywords: Generative AI, Time Series AI, Deep Learning, Time Series Analytics, Hot Mill Productivity, Anomaly Detection, Anomaly management, Condition-Based Maintenance

INTRODUCTION

Due to the relative infrequency of specific causes of downtime and complex process issues that cause downtime, it is not feasible to create supervised early warning systems for reducing downtime. Anomaly detection is, therefore, increasingly important for smart manufacturing to prevent unplanned equipment failures, reduce downtimes, and improve the safety and productivity of operations. The primary application of anomaly detection is to perform condition monitoring of the plant assets to identify significant changes in critical parameters that can be early indicators of potential sub-system faults or process failures. Prevalent methods for anomaly detection in steel manufacturing can be roughly classified into two broad categories: model-based methods and data-based methods. In the model-based approach, numerical models are built to represent the physical characteristics of the assets. This requires accurate knowledge of the physical system and the faults, which are often challenging to obtain.

Additionally, the model-based methods apply to limited 'known' problems that have occurred in the past, rendering the approach ineffective for novel or unknown problems when they occur. Empirical or data-based anomaly detection, on the other hand, does not require prior knowledge of faults and failures and utilizes the data from supervisory control and data acquisition (SCADA) and programmable logic controller (PLC) systems for generating an early warning when the data deviates from the expected normal behavior.

However, many data-based approaches require a lot of manual effort in defining and evaluating normal behavior versus anomalous behavior of the signals. Some such approaches may require a steel mill to manage several thousands of such definitions and rules to classify an anomaly. While rules-based condition monitoring is a low-hanging fruit, setting up complex rules spanning multiple signals, each with its own threshold values, is also not a scalable approach. Once built, maintaining such rules for perpetuity is difficult and requires specialized skill. Over time, the state of the equipment/asset changes due to (1) reconfiguration, (2) wear and tear, and (3) maintenance done on it. Such changes would sometimes shift the baseline performance under different load conditions.

Furthermore, once an anomaly is detected and flagged for human attention, the analysis and review of the anomaly takes considerable effort before deciding an action that is beneficial for production. An automated and self-learning system, on the other hand, alleviates the challenges faced in setting up, maintaining, and scaling the classic anomaly detection system.

This paper describes a practical application of such an anomaly detection system that enables automated identification and prioritization of anomalies for beneficial actions by the plant team. The following sections will elaborate on the approach and how it speeds up the resolution of operational anomalies.

MOTIVATION FOR AUTOMATED ANOMALY DETECTION

In the context of automated production systems, anomalies are often indicators of impending failures. However, this perception oversimplifies a complex reality. An anomaly, while noteworthy, does not invariably indicate a problem that necessitates immediate action. The following expands on the nuanced understanding of anomalies in automated systems. It discusses the limitations of manual approaches, emphasizes the significance of distinguishing between 'knowns' and 'unknowns', and advocates for dynamic, context-aware automated solutions.

Anomalies in system behavior or data patterns often trigger alarms, but it’s crucial to understand that not all anomalies are precursors to failure. In complex systems, anomalies may represent outliers that are inconsequential or even expected variations in data. Action on every anomalous signal can lead to unnecessary interventions, wasting resources and potentially causing more disruption.

Effective anomaly detection hinges on distinguishing between 'knowns' and 'unknowns'. 'Knowns' refer to anomalies that are understood and expected within the system’s operational parameters. These are manageable and often do not require intervention. 'Unknowns', however, are anomalies that fall outside of expected patterns and may signify deeper issues. Discerning between these two is vital for efficient system management.

Relying on manual analysis of each anomaly is impractical, especially in large-scale systems. Manual monitoring can also lead to mistrust in the alerts that point to critical issues, as analysts struggle to filter out insignificant alerts from crucial ones.

Normal behavior in automated systems is not static; it evolves over time. What is considered normal today might be an anomaly tomorrow, and vice versa. This fluidity necessitates an automated system capable of understanding and adapting to the changing context. A static rule-based approach is inadequate for this dynamic environment. To address the dynamic nature of normal behavior and the impracticality of manual anomaly analysis, there is a pressing need for automated anomaly detection that is context-aware. Such a solution should possess the intelligence to learn from historical trends, adjust to new patterns, and discern between benign and critical anomalies. This level of sophistication ensures that the system remains effective and trustworthy, reducing the likelihood of alert fatigue and enhancing overall operational efficiency.

Our previous paper has presented this automated and scalable AI-based anomaly detection system using the convolutional variational autoencoder (CVAE) architecture. The paper titled *“Hands-Free, Fully Autonomous, Plant-Scale, Anomaly Detection AI”*, presents the design of such an automated anomaly detection AI that enables manufacturers to address some of the common challenges in adopting and scaling the AI. Some of the advantages previously discussed are listed below as a recap:

- No-setup approach utilizing existing mill data for smart analytics, eliminating the need for costly IoT investments and time-consuming data set-up efforts.
- Detection of known and unknown asset behaviors, alerting the operations team to novel critical operating conditions that could potentially lead to productivity losses.
- Detailed view of anomalies, their severity, and causal factors for proactive diagnosis and intervention across the plant.
- Rapid and automated learning of baseline operating behavior for robust anomaly monitoring as equipment and conditions change, without the need for data science and model tuning efforts.
- Well-suited for diverse applications in steel manufacturing processes with varying time series data complexities
- Plant-scale deployment without specialized operational or data science requirements.

In this paper, we focus on a practical application of such an anomaly detection system that enables automated prioritization of AI-detected anomalies to provide a stream of actionable alerts. The following sections will elaborate on the approach and how it enables faster time to resolution of operational anomalies by the plant production and maintenance organizations.

ANOMALIES IN TIME SERIES DATA

To demonstrate the benefits of the automated anomaly management system, we deployed the anomaly detection AI application, called Falkonry Insights, across the melt shop, casting lines, hot mill, and cold mill of a leading US-based steel manufacturer. The primary objective of the AI deployment was to automatically identify indications of equipment conditions that precede delays (i.e. slowdowns or stoppages) without the need for upfront effort on analytics setup and continued effort on maintenance.

The SCADA data for these lines were streamed to Falkonry on a 1 Hz to 10 Hz rate via a data acquisition system. As Falkonry Insights learned the baseline behavior of the data in a few days, the detection of anomalies started to surface. These anomalies can be categorized into 3 different categories based on the duration of their detection and the severity of the anomaly. In the figures below, the time series signal trends are displayed along with the anomaly scores in the form of heatmaps. The heatmap view paints the color gradient from deep blue to bright yellow as increasing anomaly severity with shades of orange-yellow being the highest. Heatmap allows users to see an overall picture that may get lost in discrete anomalies and also identify cause-effect relations from the lead/lag behavior of anomalies.

1. **Spike anomaly** - These are anomalies the AI detects when there are short-lived spikes seen in the data, say, for less than 120 seconds. Such spikes in the data may represent any of the following operating conditions:

    a. **Equipment Start/ Stop:** For example, a motor is powered up to go from idle (~0 rpm) to running (say 4,000 rpm). In such a case, the electric current drawn by the motor, torque, speed, etc. will all see a step increase (see Figure 1 below) compared to the behavior observed during the idle state. Similarly, a step decrease (see Figure 2 below) is observed during the motor shutdown

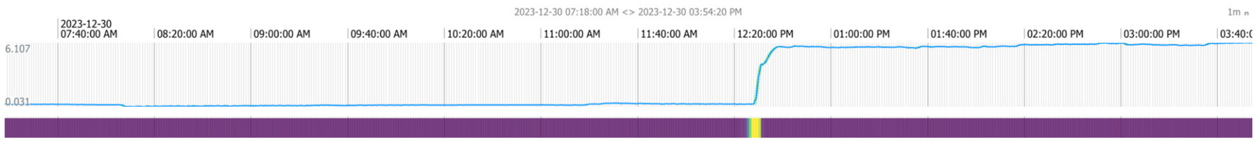

Fig 1. Signal trend and anomaly heatmap during the equipment start

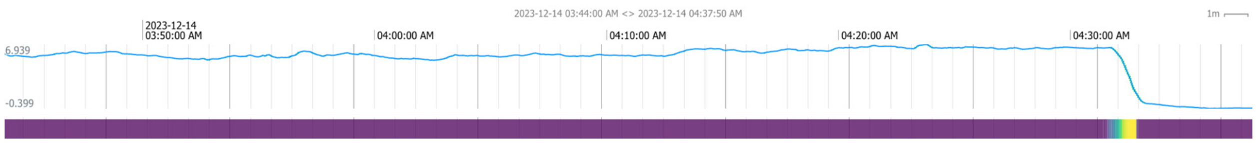

Fig 2. Signal trend and anomaly heatmap during the equipment shutdown

Spikes seen in the signal charts above are generally considered "expected" spikes. If such spikes occur frequently, say, multiple times a week, the AI will initially detect and identify them as an anomaly but with sufficient examples from the data, it later self-learns the behavior as normal.

    b. **Unexpected spike anomaly**: This refers to unexpected spikes that are not associated with known normal behaviors. For example, when data indicates that the motor has received an unexpected spike in current levels, the motor is understood to be running normally before and after the spike (see Figure 3 below).

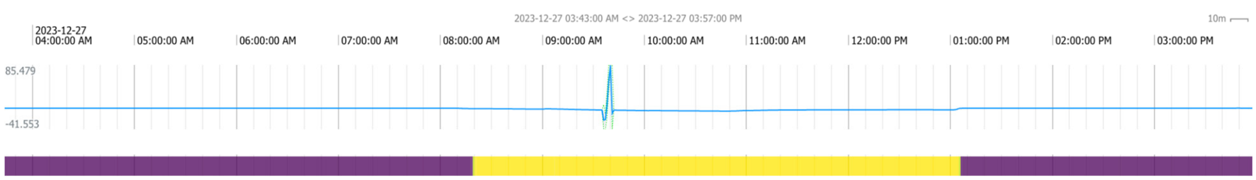

Fig 3. Signal spike with early onset of anomaly

However, the AI notices an anomaly way before the spike is observed, requiring the subject matter expert's (SME) attention to understand the spike's impact on the health of the asset. The SMEs may also use information like this to aid the root cause analysis process.

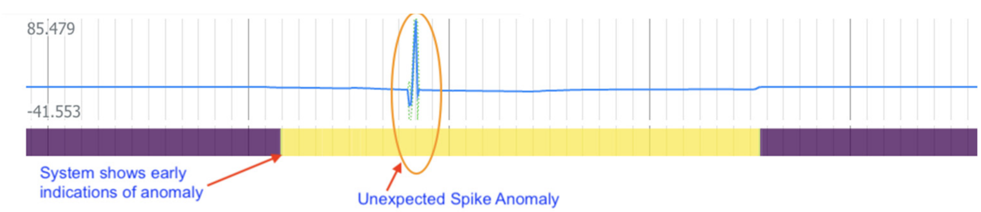

Fig 4. Zoom in on signal spike with early onset of anomaly

It is seen from this example (see Figure 4 above) that the automated anomaly detection AI is capable of detecting the early signs of signal deviations that are otherwise not evident to the naked eye during manual data analysis. The zoomed-in view in Figure 5 shows the signal deviations picked up by the AI detection. The onset of such an anomaly would be missed by the traditional alarms as the signal values do not breach the set threshold. In this example, the anomaly continues to last for about 5 hours with a visible spike in between. The normalcy in the signal is attained with a small growth in the signal values to the right end.

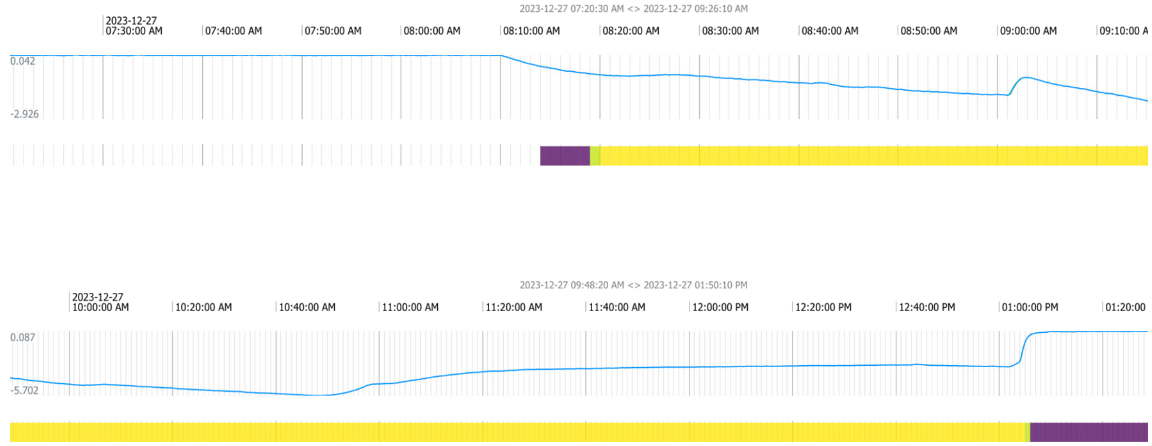

Fig 5. Extra Zoom in on signal spike with early onset of anomaly;

Chart above: the anomaly before the spike; Chart below: anomaly after the spike

2. **Short burst anomaly:** Another variant of the spike anomalies are the short burst anomalies where the signals would fluctuate between two values during within a few hours. See the illustration in Figure 6 below where the motor current abruptly drops to zero and then there are a couple of false starts before it stabilizes to the normal ranges. The anomaly detection AI is capable of detecting such behaviors in the data as anomalies.

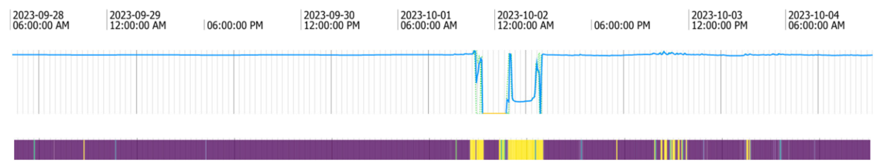

Fig 6. Signal and anomaly heatmap for short burst anomaly

Such behaviors may be considered normal by the manufacturer but such fluctuation can negatively impact the health of the assets they control or the quality of the steel produced during this period.

3. **Long-running anomaly** could also arise when a sensor is either dead or stops communicating due to a variety of reasons such as a disabled communication network or production system on a complete shutdown for maintenance or an upgrade. The anomaly detection AI is capable of detecting such unusual behaviors (1) slow-changing wear and tear on the asset, which is illustrated in figure 7.1, or (2) where the data stopped arriving in the AI system, as seen Figure 7.2. below, indicating that there may be a problem with the communication network.

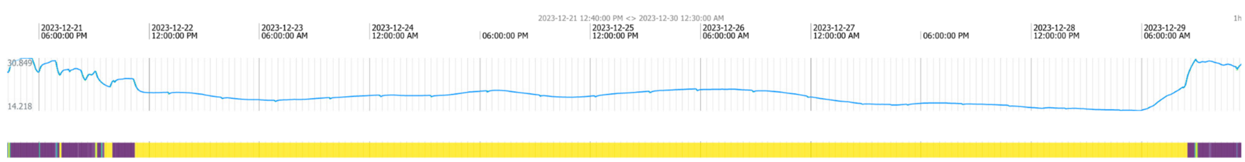

Fig 7.1. Example of a long-running anomaly because of slow-changing degradation

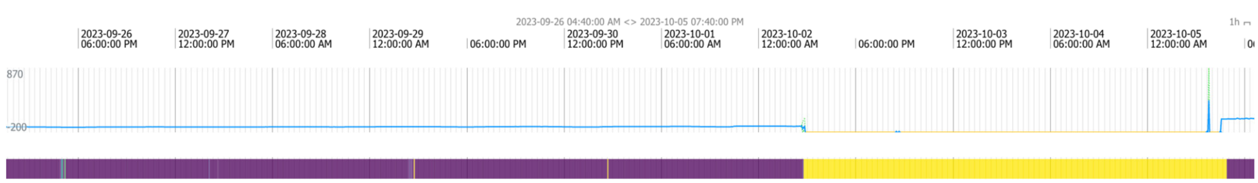

Fig 7.2. Example of a long-running anomaly because of malfunctioning sensor

4. **Systemic anomalies:** In addition to detecting anomalies discussed above on individual signals, an anomalous trend over a group of signals from a sub-system may point to a systemic issue. Such anomalies usually occur when there is a change in the operating condition of an asset or the entire line. For instance, the changes in signal behavior seen in Figure 8 below could be due to a variety of reasons, not limiting to -

    i. The operating conditions changed e.g. winter set in causing the ambient temperature to drop
    ii. The production load changed because the secondary systems kicked in/out to share the load
    iii. The product mix changed and therefore the signals capture new and unique characteristics or specifications
    iv. Load carrying capacity on a part of the system was negatively impacted thereby adding to the load for the upstream (or downstream) systems to a point where the entire system starts to exhibit anomalies as it comes to a halt.

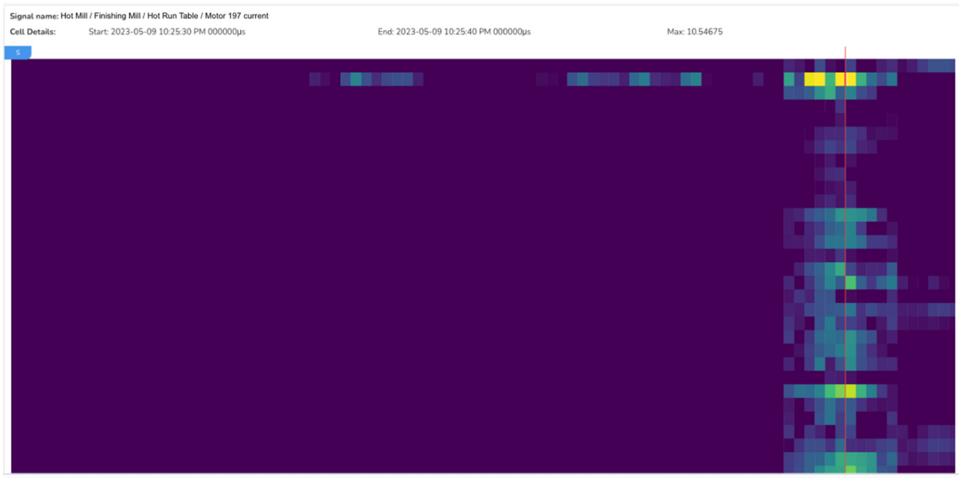

Fig 8. Example of a long-running anomaly resulting in a systemic failure

To improve maintenance and production in these and other lines, it is necessary to produce actionable alerts from the AI detections on the data and deliver them to plant teams in charge of maintenance and production.

ANOMALY PRIORITIZATION METHODOLOGY

As AI learns the normal behavior of operations, it is necessary to introduce a prioritization framework to efficiently relay alerts to the plant team for targeted intervention. The post-AI filtering of anomalies minimizes any noise in the alert system and focuses attention only on actionable events for beneficial production impact. This prioritization framework uses the following parameters to decide whether to trigger an alert:

1. **Criticality of the asset or equipment:** This involves user input to identify the importance of each asset in the production line. The focus is on understanding how crucial each piece of equipment is to the overall operation. A failure in a critical asset could lead to significant downtime or loss of production. Therefore, the prioritization approach targets alerts to anomalies in these high-value assets.

2. **Conditionality of other production indicator signal:** Conditionality of other production indicator signals: This refers to the interdependence of various signals and indicators in a production environment. AI systems analyze the state of 'conditional signals' defined by the user and prioritize the anomaly if the set conditions are met. End-users may configure the AI detection based on the value or state of these conditional signals. Conditional signals could be numerical (eg: speed, temperature, torque, etc) or categorical (operational state, steel grade, etc). For example, an anomaly in the blast furnace charging system is prioritized if the natural wind signal meets a certain threshold.

3. **Severity of anomalies:** The AI system evaluates the extent of deviation from normal operational parameters. Severe anomalies are those that represent a significant departure from the normal and could potentially lead to critical failures or safety hazards. Anomaly scores are positive real-valued numbers where a higher score indicates greater deviation from normal.

4. **Persistence of anomalies:** This aspect focuses on the duration and consistency of an anomaly. Transient anomalies might be less concerning than those that persist over time. Persistent anomalies are likely indicative of a more significant underlying issue that requires immediate investigation and action. While a long-running anomaly will be picked up in alerts, depending on the persistent duration of the short-bust anomalies may also lead to an alert.

a. Further, anomaly drop tolerance is an important factor when understanding the persistence of anomalies it is important to know that there will be breaks in the consistency of the anomaly pattern. Anomaly drop tolerance takes into account such breaks and groups distinct chunks of anomalous behavior as a single alert.

5. **Anomalies across different signals:** This involves analyzing if an anomaly is isolated to a single signal or if it's impacting multiple aspects of the production process. These are classified as univariate and multivariate anomalies. Traditionally, anomalies on one signal are considered to be data issues such as bad sensor reads, whereas multivariate anomalies are more correlated to condition issues.

6. **Contextual information such as production plan and maintenance schedule:** Incorporating contextual information allows the AI system to make more nuanced decisions. For example, if a production line is scheduled for maintenance, anomalies detected shortly before this period might be deprioritized. Similarly, understanding the current and upcoming production plans can help determine the impact of an anomaly on overall operations.

By integrating these factors, the post-AI environment becomes a robust process that not only identifies anomalies but also prioritizes them based on a comprehensive understanding of the production environment. This approach ensures that responses are not just reactive but are strategically aligned with the operational objectives and constraints of the organization.

NOTIFICATION SENSITIVITIES AND END-USER ACTIONS

We define notification sensitivity, which is the desired level of responsiveness with which the alert system notifies users about detected events or anomalies. A low notification sensitivity is more tolerant for deviations and triggers alerts 'less often', whereas a high notification sensitivity ensures no anomalies are missed by the users. The notification sensitivity is defined based on the anomaly duration and the nature of the anomaly (spike, short-burst, or long-running) in order to provide robust and reliable alerts:

1. **High sensitivity** - Notify AI detections that persist for a short duration say up to 2-15 mins. This will generate a greater number of alerts and likely overwhelm the end-user who will have to investigate and dispose of each one of them. This level of sensitivity will typically include the spike anomalies as explained earlier.
2. **Medium sensitivity** - Notify AI detections that persist for a longer duration, say 15-50 mins. This will generate fewer alerts and will be manageable for the end-users to investigate and dispose. This level of sensitivity says that the manufacturer is not keen on receiving alerts when spike anomalies are detected by the AI.
3. **Low sensitivity** - Notify AI detections that persist for a longer duration, say 50+ mins. This will generate very few alerts and might miss a lot of potential delay-inducing anomalies like the spike anomaly. This level of sensitivity will typically capture systemic issues that cause component degradation over a long period of time.

The default criteria are set for ***medium sensitivity*** and therefore the system will not notify the user about short-duration or transient anomalies. The sensitivity can be fine-tuned towards a higher or lower side or a combination of sensitivity on different subsystems depending on the user requirement. The table below summarizes the type of anomalies captured by different sensitivity levels and when an alert would be generated for the end-users in the default setting.

Sensitivity for detected anomaly	Spike Anomaly	Short-Burst Anomaly	Long-Running Anomaly
High	Event notification generated	Event notification generated	Event notification generated
Medium	NO event notification generated	Event notification generated	Event notification generated
Low	NO event notification generated	NO event notification generated	Event notification generated

Table A. Anomaly types captured by different sensitivity levels

QUANTIFICATION OF EFFICACY

The key to assessing the performance of anomaly prioritization is understanding its performance in terms of Beneficial Detections – detections that offer a high likelihood of operational benefits. A typical line or mill teeming with assets generates hundreds of data streams from production schedules, maintenance plans, plant events, and so on. This amalgamation forms the "total addressable space" as highlighted in the Figure 9. Within this vast data landscape, some events hold the key to improving operations. Using AI, a subset of this data undergoes analysis to transform into actionable alerts. These actionable alerts constitute the Beneficial Detection Rate (BDR), which is the ratio of beneficial detections to the total count of pertinent events that happen in the plant, making it an actionable metric for evaluating the performance of the anomaly detector. A high number of beneficial detections creates trust in the anomaly detection system, meaning the operations teams can act on the findings, whether through urgent action or through planned intervention.

From the human action perspective, beneficial detections comprise of the following scenarios:

- Alert Action: True detection that led to a corrective action taken or scheduled by the asset operators or maintenance engineers. These are beneficial detection and such actions when taken would prevent a delay or stoppage on the production line. It is therefore made part of the BDR calculation. Multiple types of actions can be taken or scheduled based on the review of AI detection:
    - Intervention: It is determined that there has to be an immediate unscheduled intervention to avoid an escalation. The escalation of the issue may lead to a safety or environmental violation or simply higher repair costs or downtime duration.
    - Wait to completion: It is determined that it is best to let the process come to its logical end before any maintenance work is done. The operations team schedules an action during the next scheduled downtime. For example: The failure of a circulation fan in a reheat furnace does not require immediate action if the backup fans are activated. The redundancy allows for delaying the action till the current production run is complete, avoiding the 6-8 hour start-stop cycle for unplanned furnace maintenance.
- Root Cause Analysis: True detection that helped the asset operators to perform root cause analysis of impending as well as any unexpected issues and schedule a future intervention. The timely root cause analysis allows for better planning (such as the availability of spare inventory) of actions and enables tight turnaround times for getting the production back online.
- No Action: True detections that help asset operators analyze and conclude the problem but there is not enough time to take preventive action, such as in the case of electrical failures that happen instantly without any precursor conditions, or in the case of detections that are very close to imminent asset failure. In such cases, preventive actions are not possible, but the operations team is equipped with the knowledge of the system and executes the appropriate procedure to get the production started. Additionally, there are opportunities for future actions that contribute to the improvement of the early warning system:
    - Data collection: Some anomalies can lead to inconclusive diagnosis results due to missing data or signals in the AI analysis. Such a situation justifies bringing the missing data to the AI analysis to improve the efficacy of AI detection
    - Precursor Labeling: Certain anomalies can be associated with the earliest signs of failure, while the production largely remains within specification for a considerable amount of time before the show signs of failure/degradation become apparent. This enables the users to create the knowledge base and create a label for the precursor condition. Such a label could be used to create an early warning system in the future.

All the above-listed scenarios constitute beneficial detection, however, alert action is the only scenario that immediately addresses the production issues through corrective actions. Overall, beneficial detection doesn't only encompass acted-upon problems; it also includes detections that enhance future AI detection and problem avoidance.

The typical workflow for triggering a notification for an actionable anomaly would be -

- A Delay (stoppage or slowdown) occurs at the production facility which could potentially lead to a production loss
- The AI detects the anomalous signal behavior that is responsible for the onset of this delay. The anomaly prioritization parameters are evaluated.
- When the prioritization and notification criteria are met, an alert is sent to the production team, warranting root cause analysis and action on the equipment/production line
- AI Detection Report (ADR) is created. The report includes information for understanding the anomaly
- The production team analyzes the AI detection to determine whether and which action to take.

We now introduce the metric, Beneficial Detection Rate, which indicates the performance of this anomaly detection system as an aggregate KPI. **Beneficial Detection Rate (BDR)** is a ratio of the number of beneficial detections to the sum of the number of reported delays and the number of actions taken by the production and/or maintenance teams in a given time period.

$$\mathbf{BDR} = \frac{\text{\# of Beneficial Detections}}{\text{\# recorded scoped delays + \# of alert-action}}$$

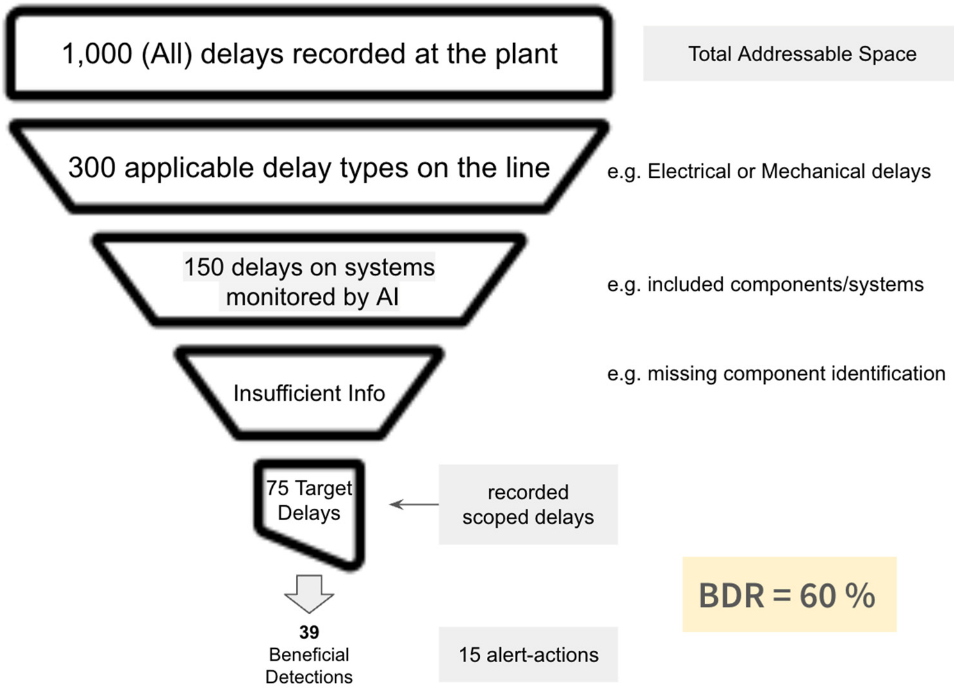

Fig 9. Example of Beneficial Detection Rate Calculation

A typical steel plant may pause/stop production for a variety of reasons, such as waiting for a production plan, material swap, scheduled maintenance, etc. Not all of these stoppages that cause delay in production can be possibly monitored by anomaly detection. A percentage of the delay causes are detected by the AI monitoring system, subject to the availability of the automation and sensor data for monitoring. Typically, these are electrical and mechanical excursions that occur as the components or the equipment wear out. These anomalies are presented to the production team through alerts. A subset of these alerts may be inconclusive due to the lack of information required to triage the anomalies. Finally, we are left with a set of recorded delays, a percentage of which will lead to alert actions that prevent the delay or stoppage of the production. This funneled approach to anomalies is presented in Figure 9 above. The review of early detection of anomalies is restricted to these narrowly scoped delays called target delays.

APPLICATION CASES

Case 1: Ball Screw Failure in the Reheat Furnace

The reheat furnace, consisting of several components such as an oven, circulation system, conveyor system, cooling table, and so on, is monitored by the anomaly detection AI. As evident in Figure 10, the earliest onset of an anomaly was detected on 2023-09-02 at 02:00 PM, followed by the persistence of the anomaly along with an increasing severity as highlighted in Zone A. After an hour, the anomaly spreads to other torque signals as highlighted in Zone B. This triggers a higher priority alert for investigation. A detection report containing the snapshot of contributing signals is generated and sent as an email alert to the operations team. It is worth noting that the legacy monitoring system does not trigger any alarm for such an anomaly as all the signal values are well within the set threshold. Around 4 hours after the spike in Zone B, there is abnormally high variability in the min and max values as highlighted in Zone C and D. This lasts for almost 4 hours, followed by a stoppage in production for the corrective actions. The root cause analysis revealed a malfunctioning ball screw as the cause of the unusual system behavior.

Fig 10. Anomaly progression before ball screw failure

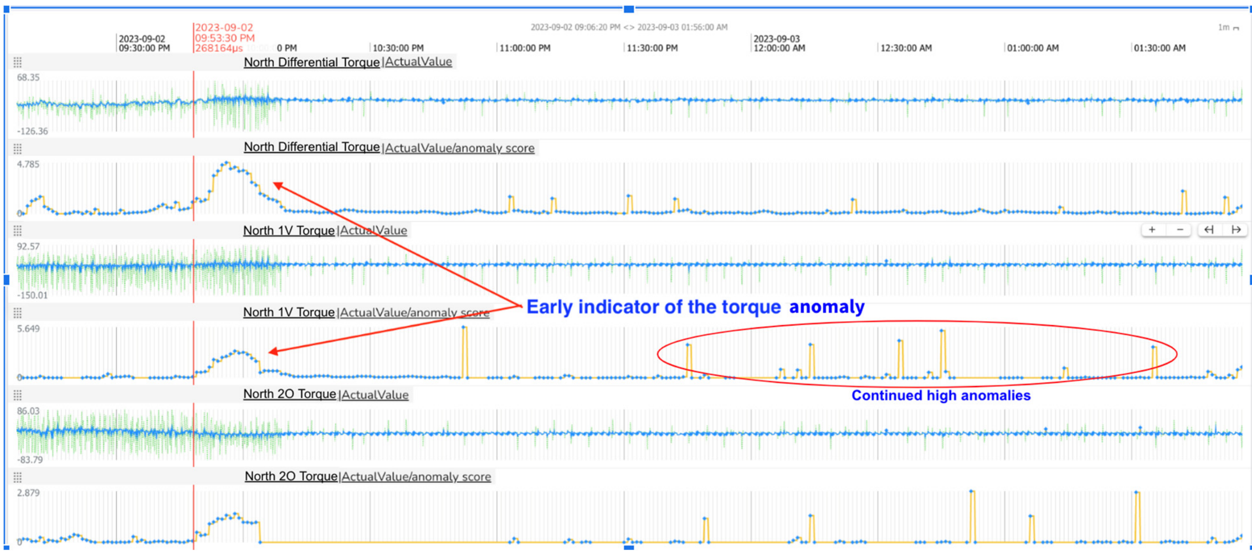

Fig 11. Signal trend and anomaly scores before ball screw failure

Case 2: Increased Vibration in Circulation Fans

The circulation fans in the reheat oven witnessed higher vibrations than normal, which were detected by the AI about 100 minutes before the beginning of the load condition. The higher vibration levels had an effect on the fan speed and the current trends, enabling the higher prioritization of the anomaly due to the spread across different signals. The alert was triggered to the operations team, and preliminary root cause analysis concluded the fault in the bearing of the fan. Attempts to restart the fan did not help in this case as evident in the figure. Production continued in this case as backup fans were started. A work order is created to fix the bearings of the fan during the next scheduled maintenance window.

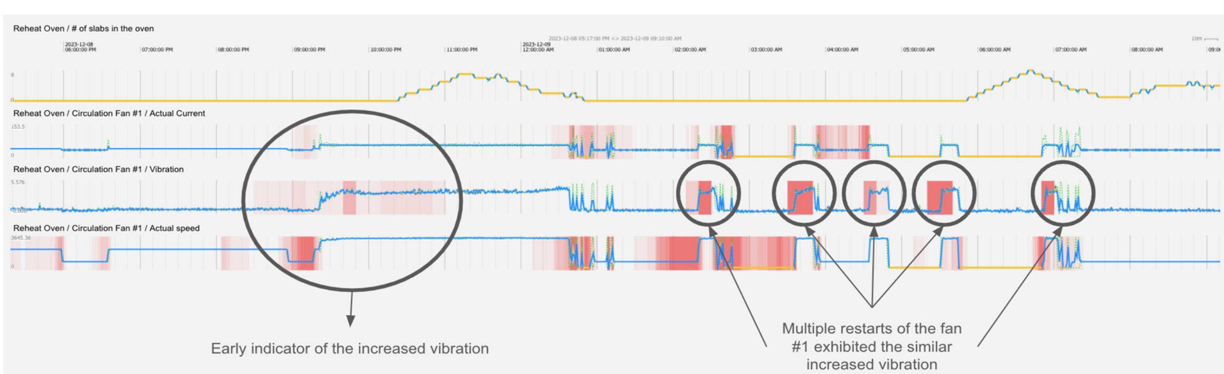

Fig 12. Signal trend with anomaly score overlay for increased vibration on circulation fans

RESULTS

The presented cases in the previous section illustrate the benefit of the anomaly prioritization method, enabling the operations and maintenance team to focus on the alerts that potentially have a beneficial action that positively impacts the plant operations. We have aggregated the performance of this anomaly detector across the mills - Melt Shop and Cold Mill - over a 3-month duration. To evaluate the efficacy, we calculate the Beneficial Detection Rate across the lines as summarized in the table below.

Assessment Duration: 2024-10-06 to 2024-12-31			
	Cold Mill	**Melt Shop**	**Aggregated**
# Beneficial Detections	**51**	**6**	**57**
# Scoped Delays + Actions	53	12	65
Beneficial Detection Rate	96.22%	50.00%	**87.69%**

Table B. Aggregated beneficial detection rate across the lines under AI monitoring

Melt Shop Analysis:
The AI detected early anomalies that eventually resulted in delays on the production line. Out of a total of 4,524 minutes of delays experienced on the Melt Shop only 860 minutes of delays that the AI were detected. With a 50% BDR, the plant potentially avoided 409 minutes of delay with timely corrective actions for each of the alerts highlighted. The methodology to compute the beneficial detection rate is evident from the illustration in Figure 13 below.

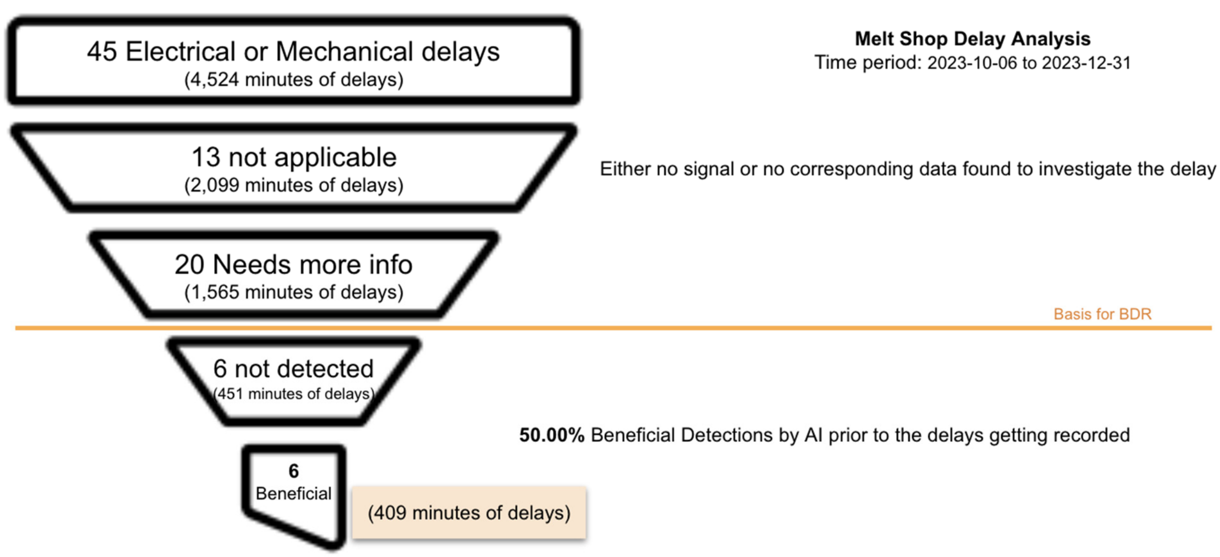

Fig 13. Melt shop beneficial detection analysis

Cold Mill Delay Analysis:
The Cold Mill recorded a beneficial detection rate of 96% with total delays of 585 minutes, all of which were detected at the onset of the anomaly. There was at least 1 beneficial detection that was used to create a maintenance work order because the detection also helped in identifying the root cause of the imminent delay. In figure 14 below, notice this beneficial detection is outside the funnel because a timely action avoided any delay in the production line.

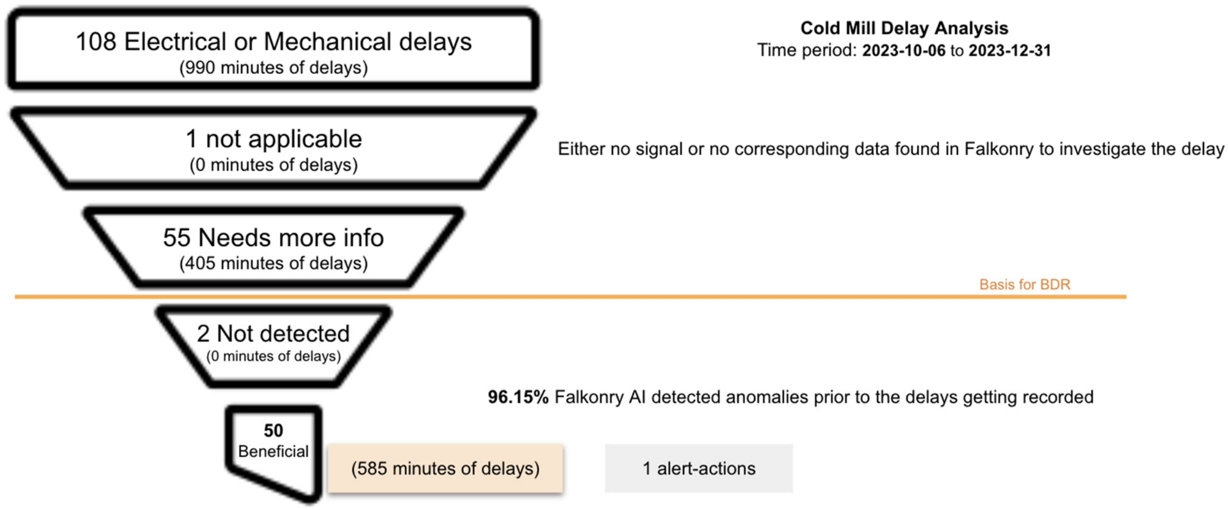

Fig 14. Cold Mill Beneficial Detection Analysis

It is important to note that while the maintenance management systems capture all the production delays, some of them are avoidable by making better production plans and having the material ready to process. Such delay causes are not intended for AI monitoring and therefore, it may not be possible to achieve a 100% beneficial detection rate.

CONCLUSION

In this paper, we discussed a robust anomaly prioritization framework and presented the results from the field with a high real-world efficacy of 87% beneficial detections as an aggregate across multiple lines of the steel plant. Automated anomaly detection is key to achieving smart plant operations, but anomalies themselves may be too many to manually review by the operations team. With the presented anomaly prioritization framework, we focus human attention on the critical anomalies that require timely corrective actions. We also established Beneficial Detection Rate (BDR) as a reliable indicator of the AI's contribution to operational improvement.

We have also demonstrated that the beneficial detections are not just limited to acted-upon problems that immediately improve productivity, but also include scenarios that enhance the efficacy of AI for future detection and problem avoidance. With every beneficial detection having a direct impact on operational improvement, a high number of beneficial detections reduces the payback period for the adoption of AI.

The presented approach works with existing data and technology infrastructure prevalent in steel manufacturing and eliminates the upfront setup and training efforts required to set up an actionable alert notification system at the required scale. The automated anomaly detection combined with a robust anomaly prioritization method enables measurable impact of AI in overall productivity improvement.

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