Automated statistical anomaly detection in an integrity monitoring application for a furnace

James Yelland | Hatch Digital

HATCH

Furnace integrity monitoring – a critical process

Furnaces are key assets

- Furnaces are a critical and capital-intensive asset in a metals value chain
- Failures can cause significant production losses and safety hazards
- Prolonging campaign life saves capital

Integrity monitoring

- Ensuring furnace integrity by monitoring data from manual and instrument measurements
- Aiming to identify any anomalies that may signal an integrity risk
- **This particular client had hundreds of integrity monitoring instruments being manually reported on bi-weekly**

HATCH

What's wrong with manual anomaly detection?

The pain points

It's time consuming
Reviewing data from 500+ sensors takes days

It's hard to consistently spot anomalies
Graphs are cluttered and extensive experience is required

It's hard to know if they're significant
This looks out of place now, but have we seen it before?

A BETTER WAY

Automatically detect anomalies

Using well-defined rules

That reference historical data

HATCH

Using algorithms to replicate human analysis

Types of integrity instruments

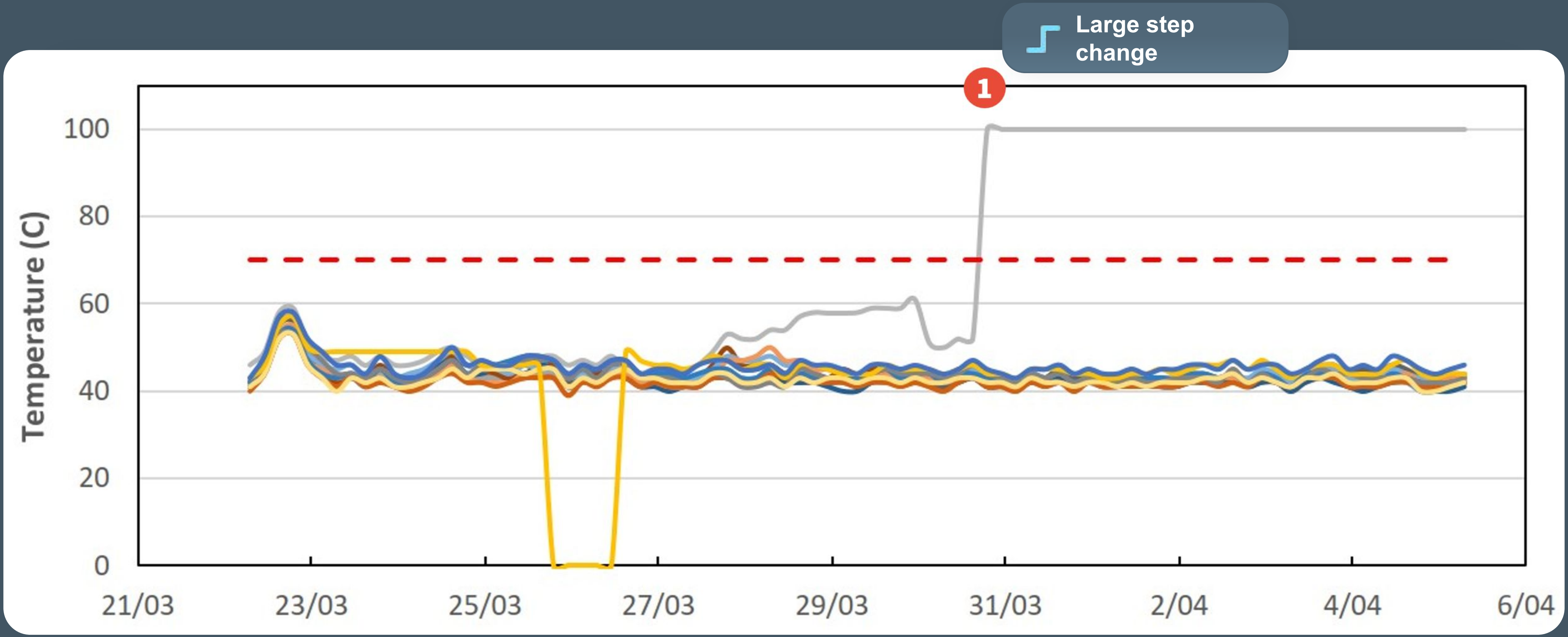
- Cooling water flow rates
- Refractory temperatures
- Tapblock temperatures
- Binding system movement
- Feed and fuel rates
- Electrode powers

The 6 common behaviours detected by humans

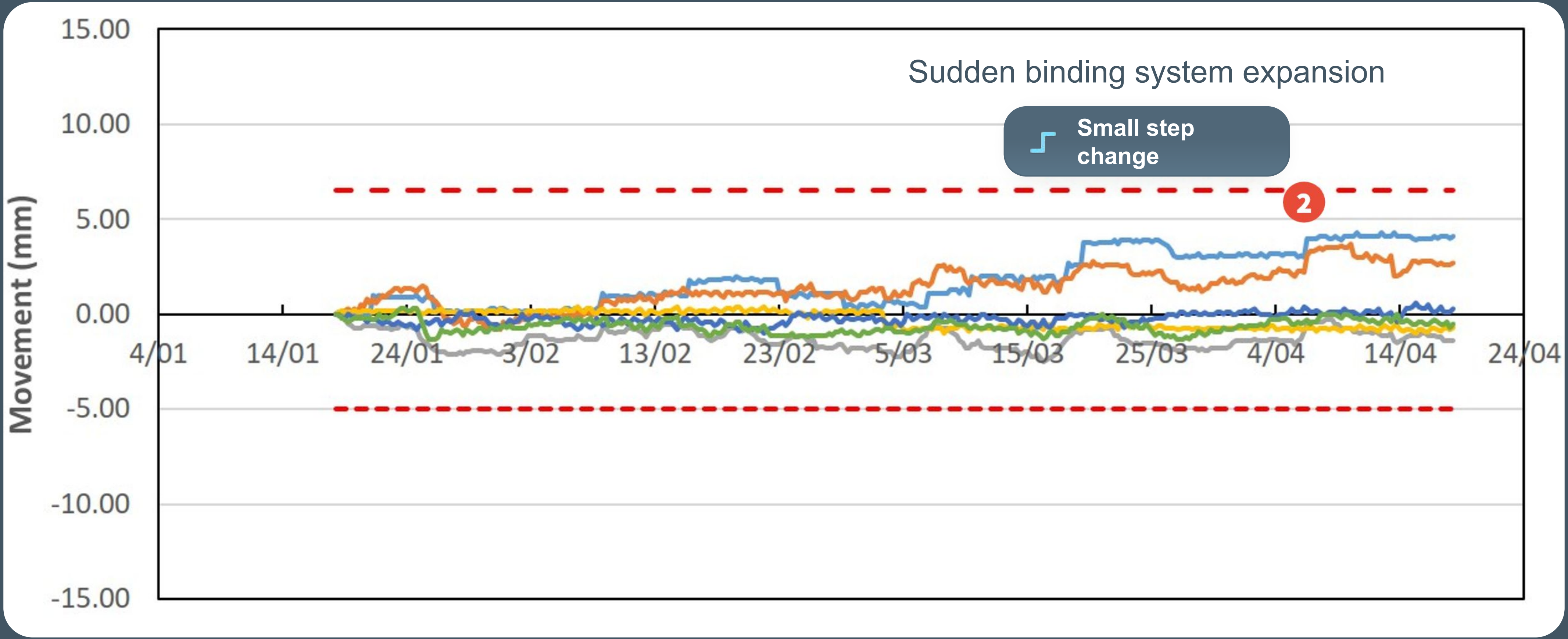
#	Behaviour	Possible implications
1	Large step change	Instrument failure Instrument calibration
2	Small step change	*Instantaneous* change in furnace conditions
3	Short-term gradient (hourly trend)	*Rapid* change in furnace conditions
4	Long-term gradient (daily – monthly trend)	*Slow* change in furnace conditions Instrument drift
5	Spike	Short event or instrument malfunction
6	Change in relationship to proximate instruments	Complex furnace condition change Complex instrument issue

Examples from the manual reports

Calibration event in a refractory thermocouple



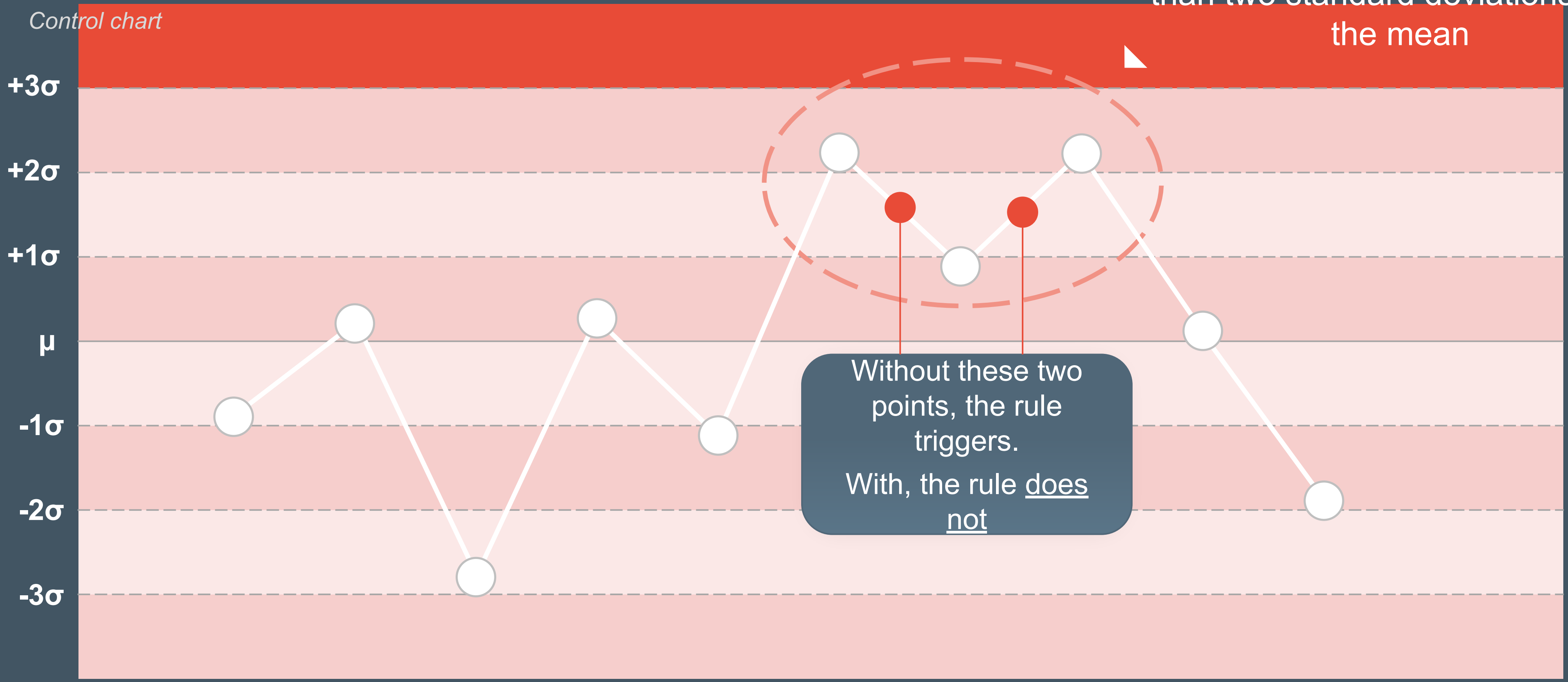
Examples from the manual reports



HATCH

The Nelson rules – an option?

Nelson Rule #5
Two of three consecutive points on the same side of the mean, more than two standard deviations from the mean

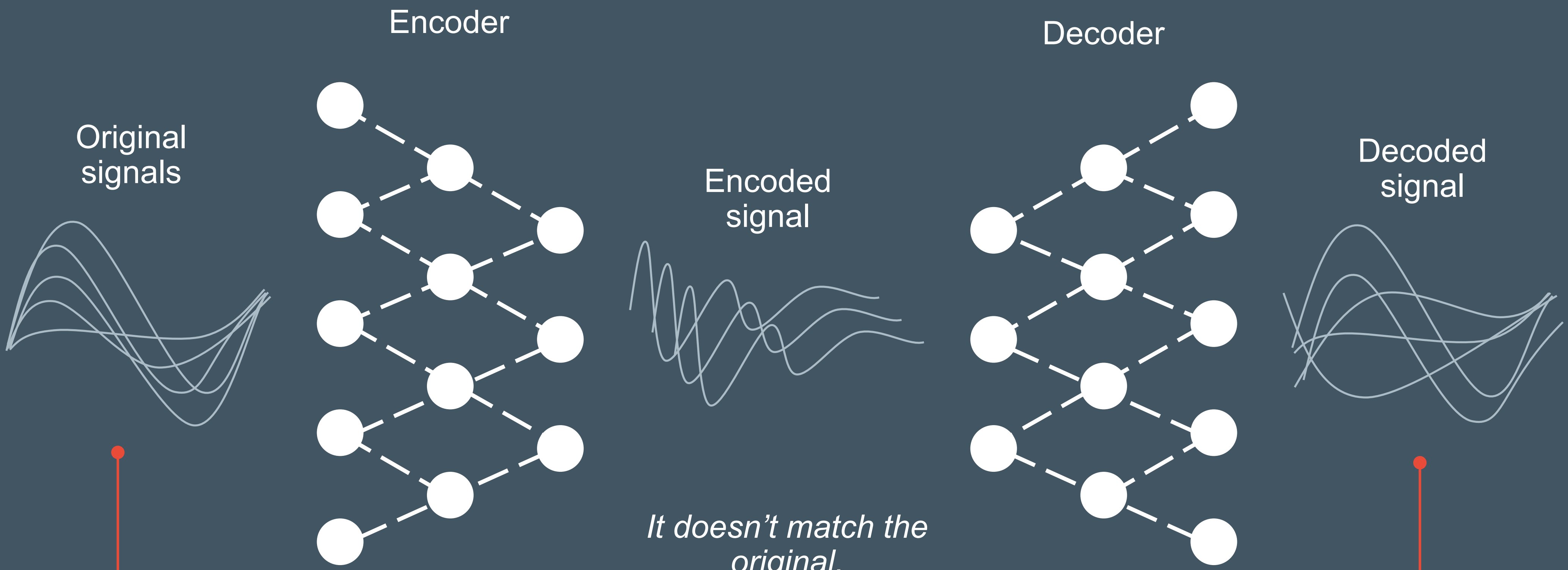


+ Simple to understand

- Too sensitive to sample frequency

(Nelson, 1984)

Advanced machine learning – an option?



It doesn't match the original.

→ The networks don't understand this new data = Anomaly

But why?

(Neloy and Turgeon, 2024)

HATCH

Behaviour-specific statistical rules

The four requirements for rule design

1. A rule should be calibrated against a period of historical data
2. A rule can be tuned in sensitivity according to the nature of each sensor
3. A rule should be specific to each type of anomalous timeseries behaviour
4. A rule should be able to quantify the statistical significance of an anomaly

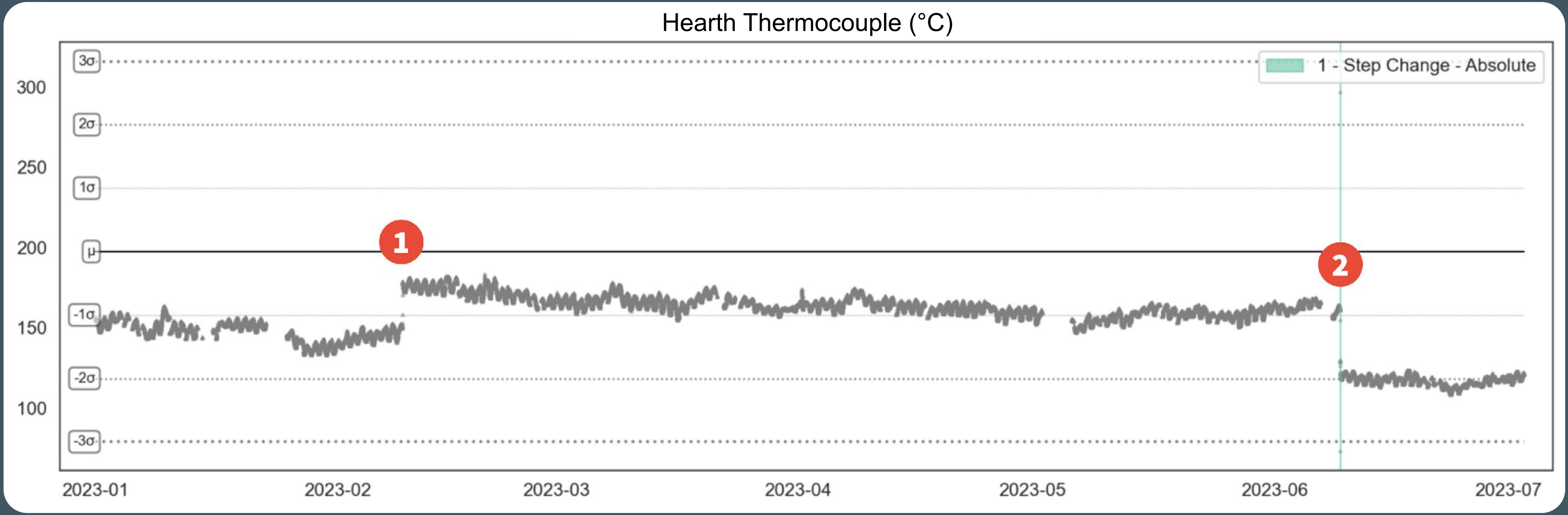
HATCH

Absolute step change | Rule 1

Large step change

Parameters

- Step change threshold (in standard deviations) - α



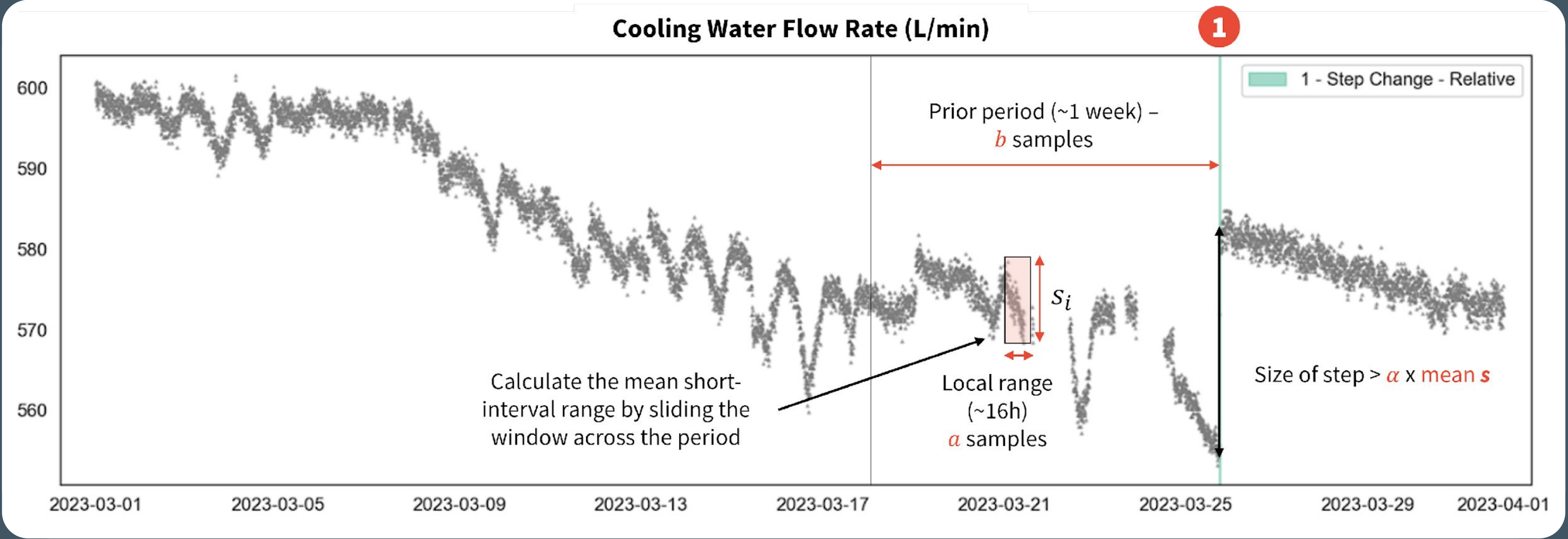
HATCH

Relative step change | Rule 2

Small step change

Parameters

- Local range window size – a samples
- Prior period size - b samples
- Magnitude threshold - α



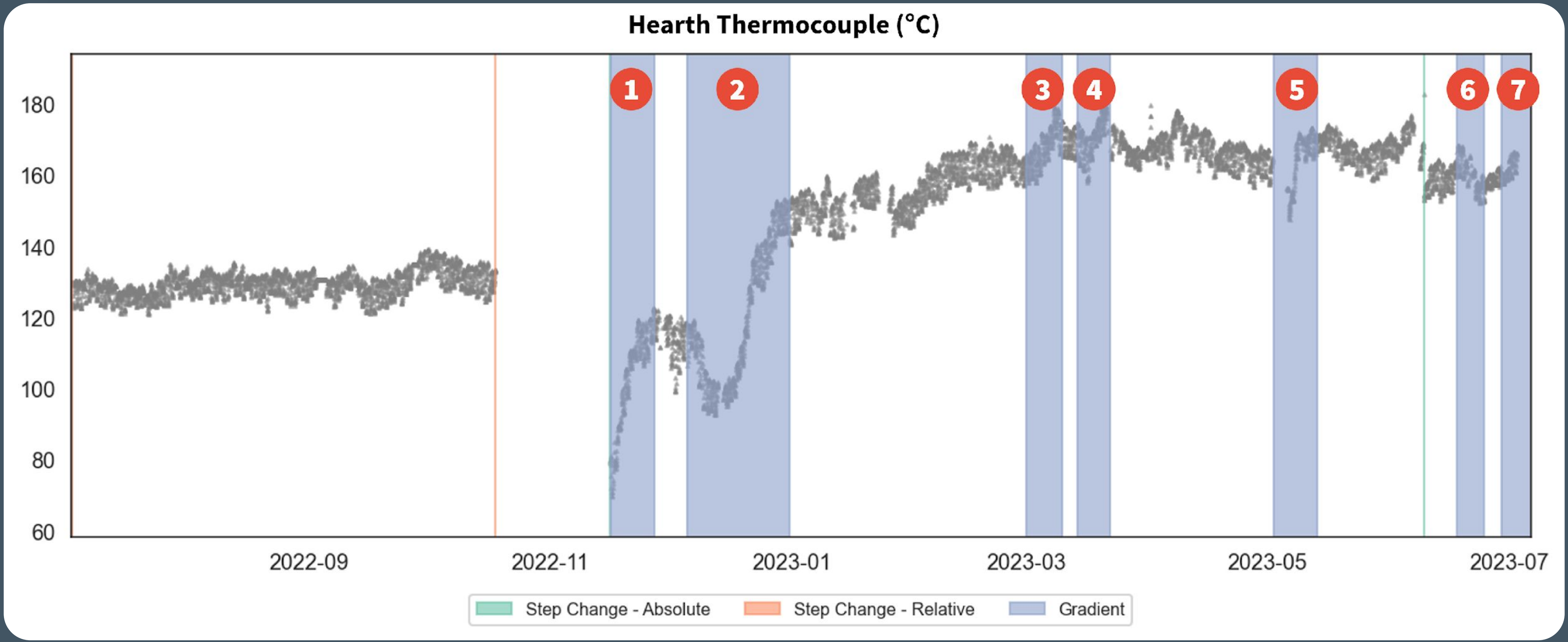
Gradient | Rule 3

Short-term gradient

Long-term gradient

Parameters

- Window size - n samples
- Threshold (in standard deviations away from the historical mean) - α

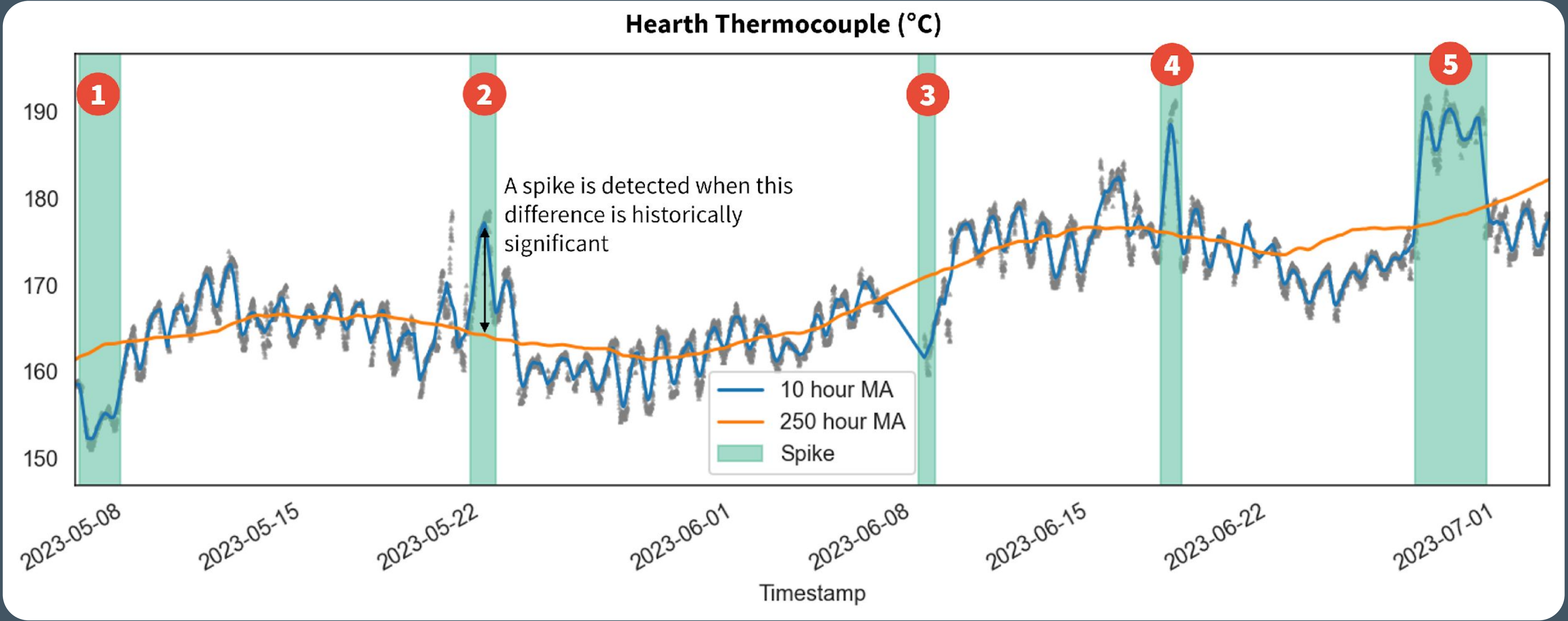


Spike | Rule 4

Spike

Parameters

- Local window size - a samples
- Larger window size - b samples
- Threshold (in standard deviations of historical difference) - α



HATCH

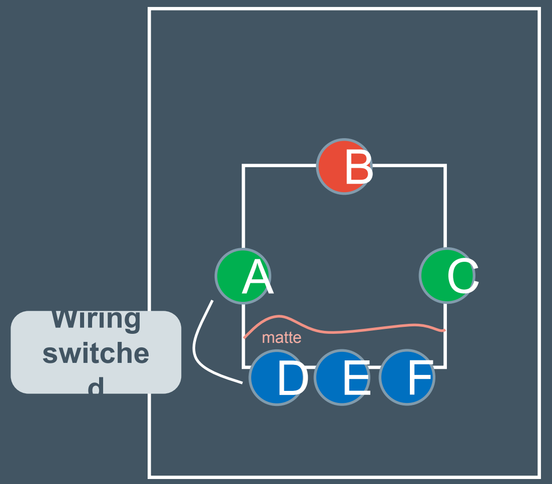
Cosine similarity | Rule 5

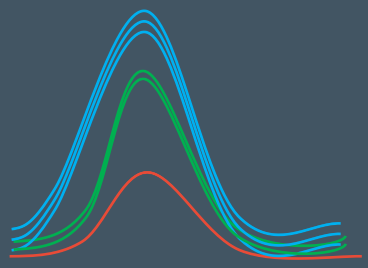
Change in relationship

Parameters

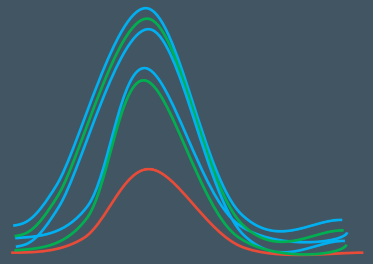
– Threshold for considering a data point an outlier

Matte taphole – thermocouple locations

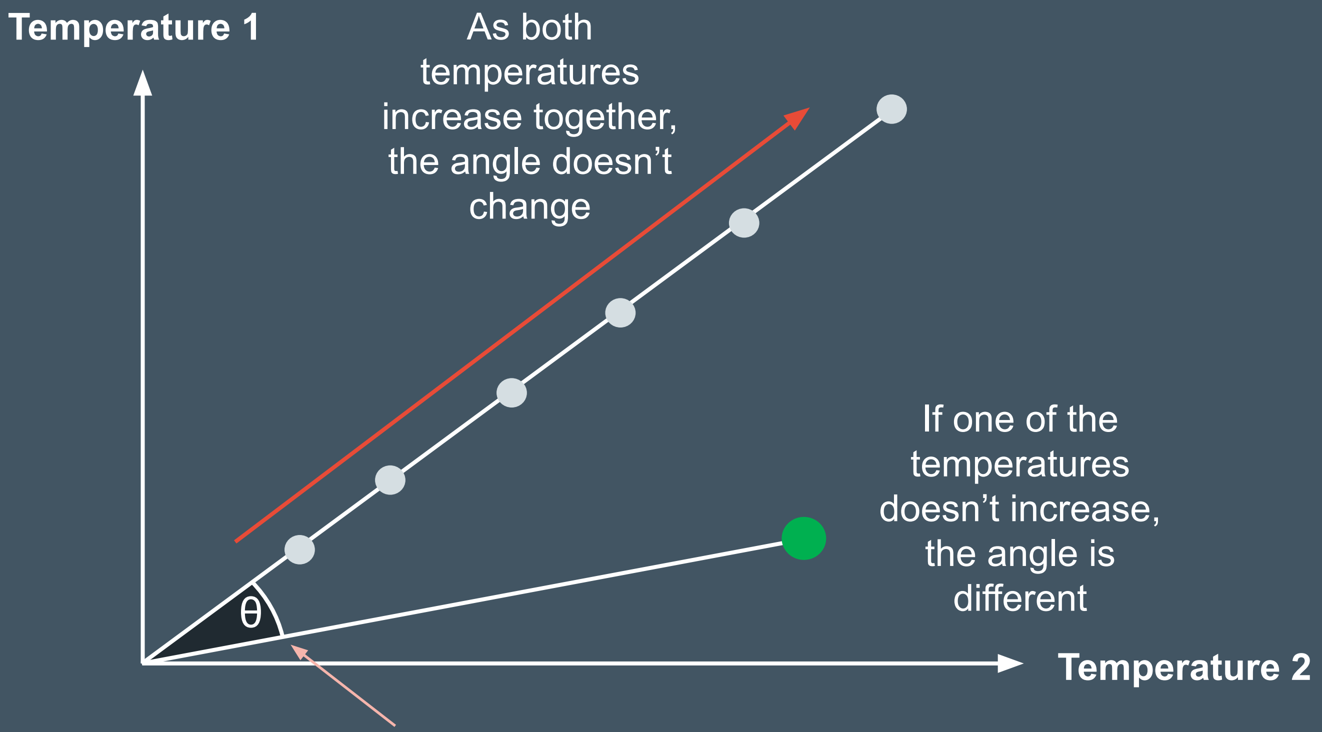




Correct wiring during tapping



Incorrect wiring

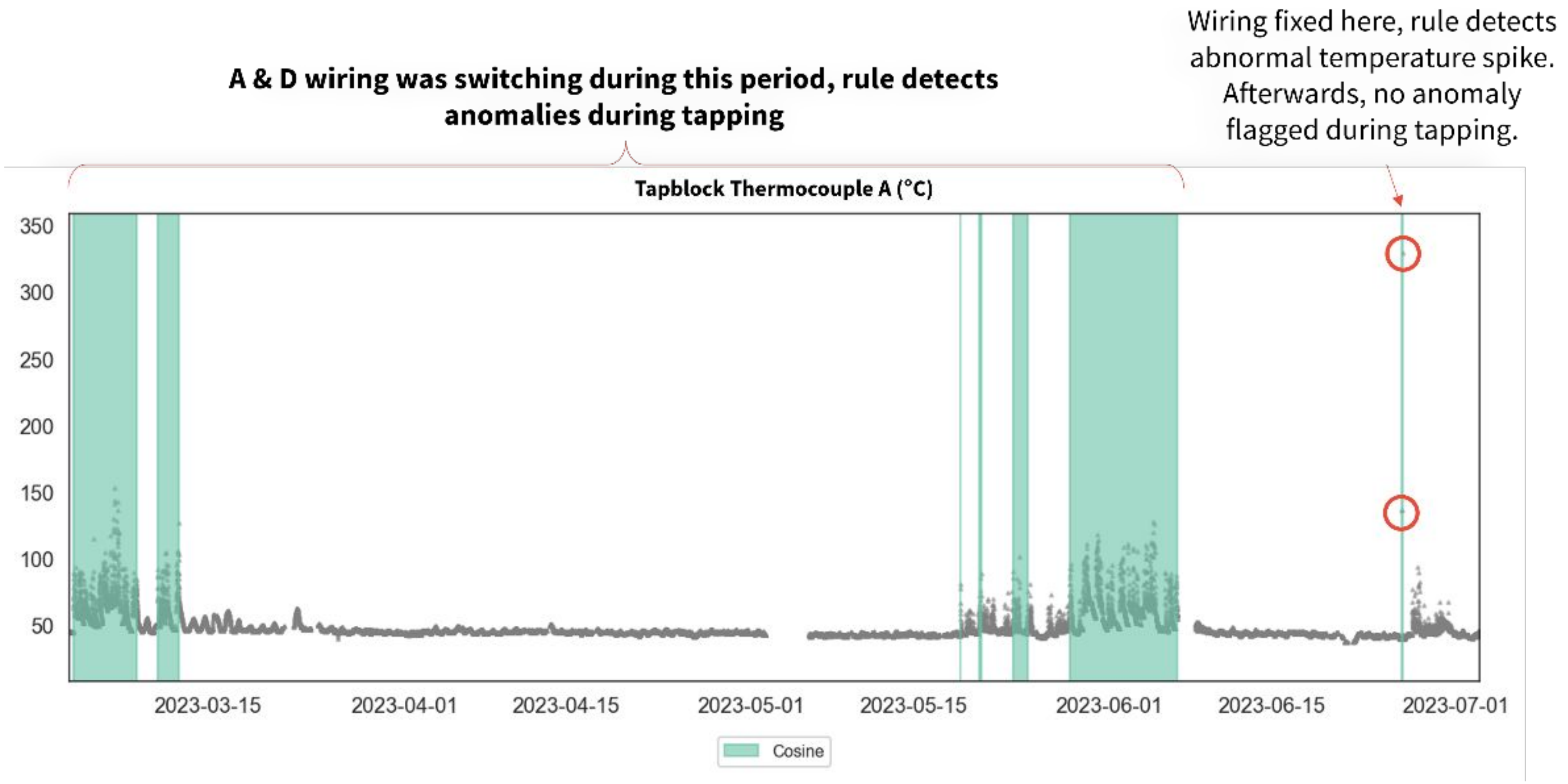


A point with a high θ away from the closest point is considered abnormal

Cosine similarity | Rule 5

Parameters

– Threshold for considering a data point an outlier



HATCH

Algorithm vs. manual

5/6 remaining were determined not to be significant

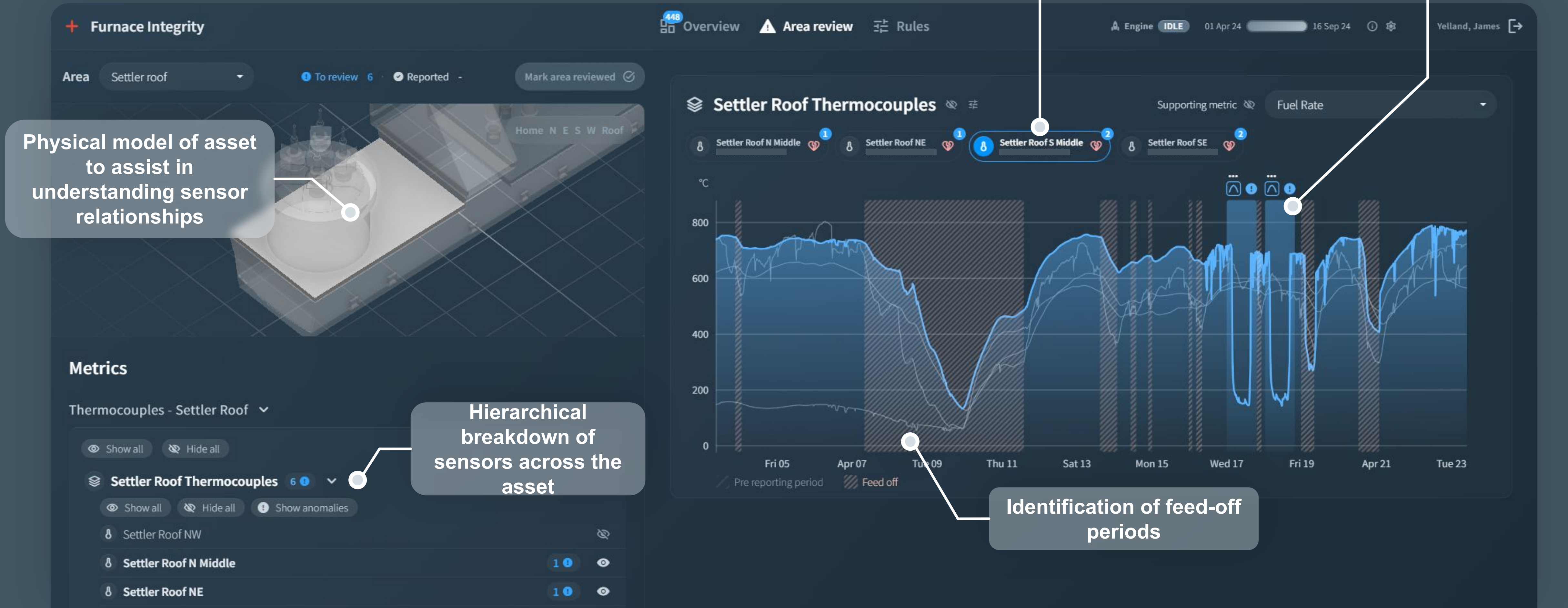
= 96% detection

Sensor Group	Rules Used	Manual Anomalies	Manual Anomalies Detected Automatically	Anomalies not Detected Manually
Hearth temperature	Absolute step change Relative step change Gradient Spike	10	4	6
Binding movement	Absolute step change Relative step change Gradient	6	6	9
Cooling water flow rate	Absolute step change Relative step change Gradient Spike	1	1	5
Cooling water temperature	Spike	0	-	6
Sidewall temperature	Absolute step change Relative step change Gradient	2	2	10
Tapblock temperature	Cosine similarity	6	6	1
Total	-	25	19 (**76%**)	37

HATCH

Building the rules into an application prototype

Data from site is automatically ingested into the tool daily, and the detection rules run thereafter



Where to next?

What's limiting this?	**Rule parameters must be manually tuned per sensor per rule**	**Simple statistical rules lack the ability to detect complex anomalies**
How could it be fixed?	Explore options for automated parameter tuning, e.g. by learning from engineer accept/reject decisions	Link signal pattern deviations to real-world events or other process behaviour

HATCH

Thank you

james.yelland@hatch.com

Connect with me on LinkedIn