AI-driven solutions for effective monitoring & diagnosis in the power

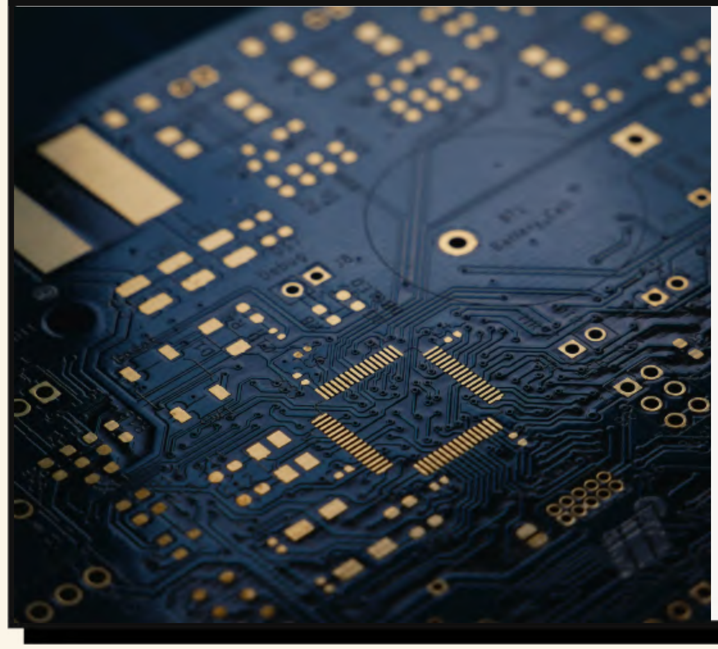
Agenda

- Business Problem
- Data understanding & preparation
- Our model
- Evaluation & Results
- Business Solution & Implementation

Business Problem

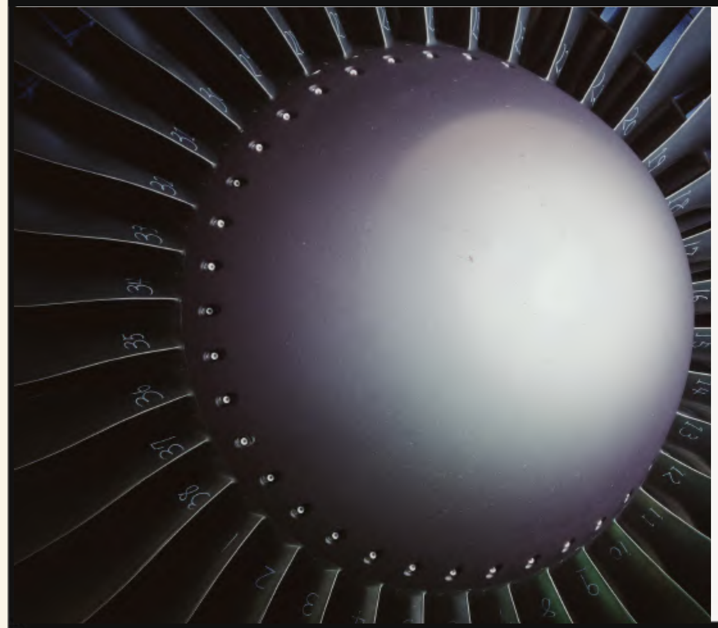
Challenges in Synchronous Generator Operation and Monitoring

An Overview



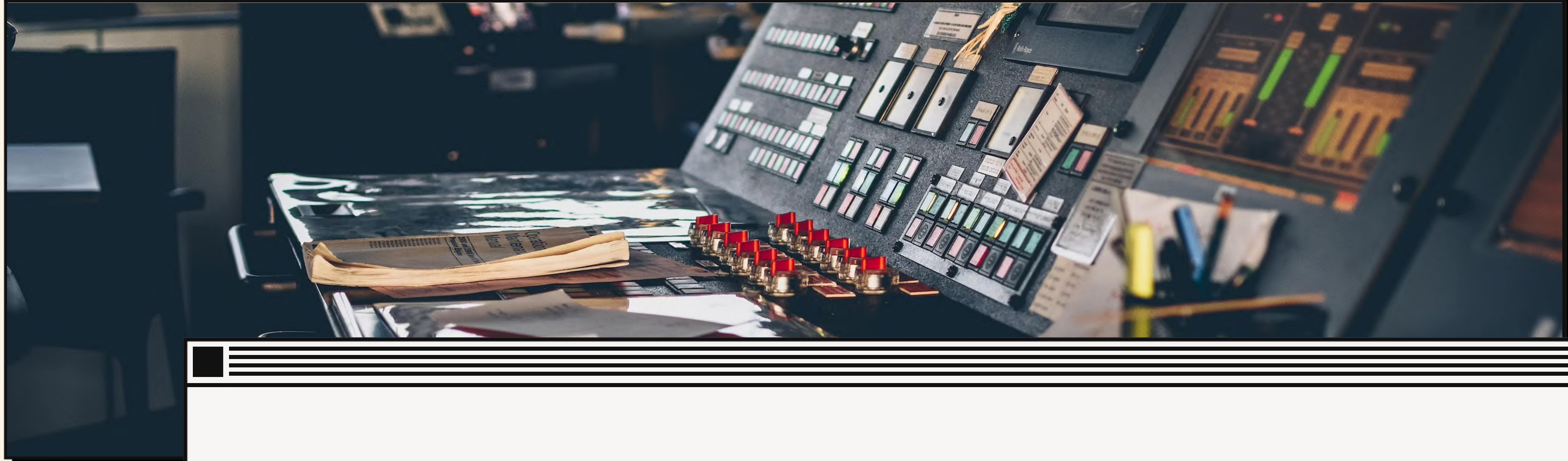
Short circuits between turns in rotor wings

Magnetic field asymmetry and vibrations



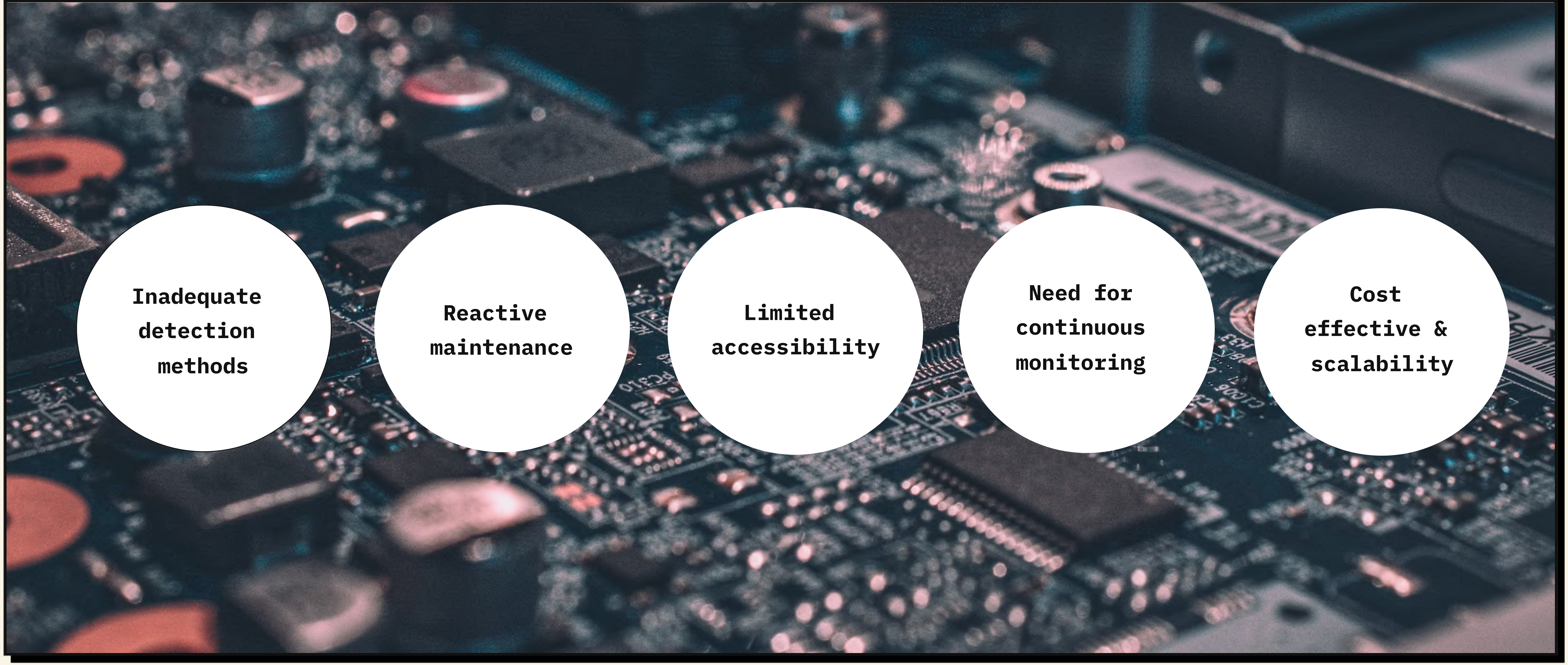
Increased excitation current and rotor thermal stress

Lack of early detection and monitoring systems



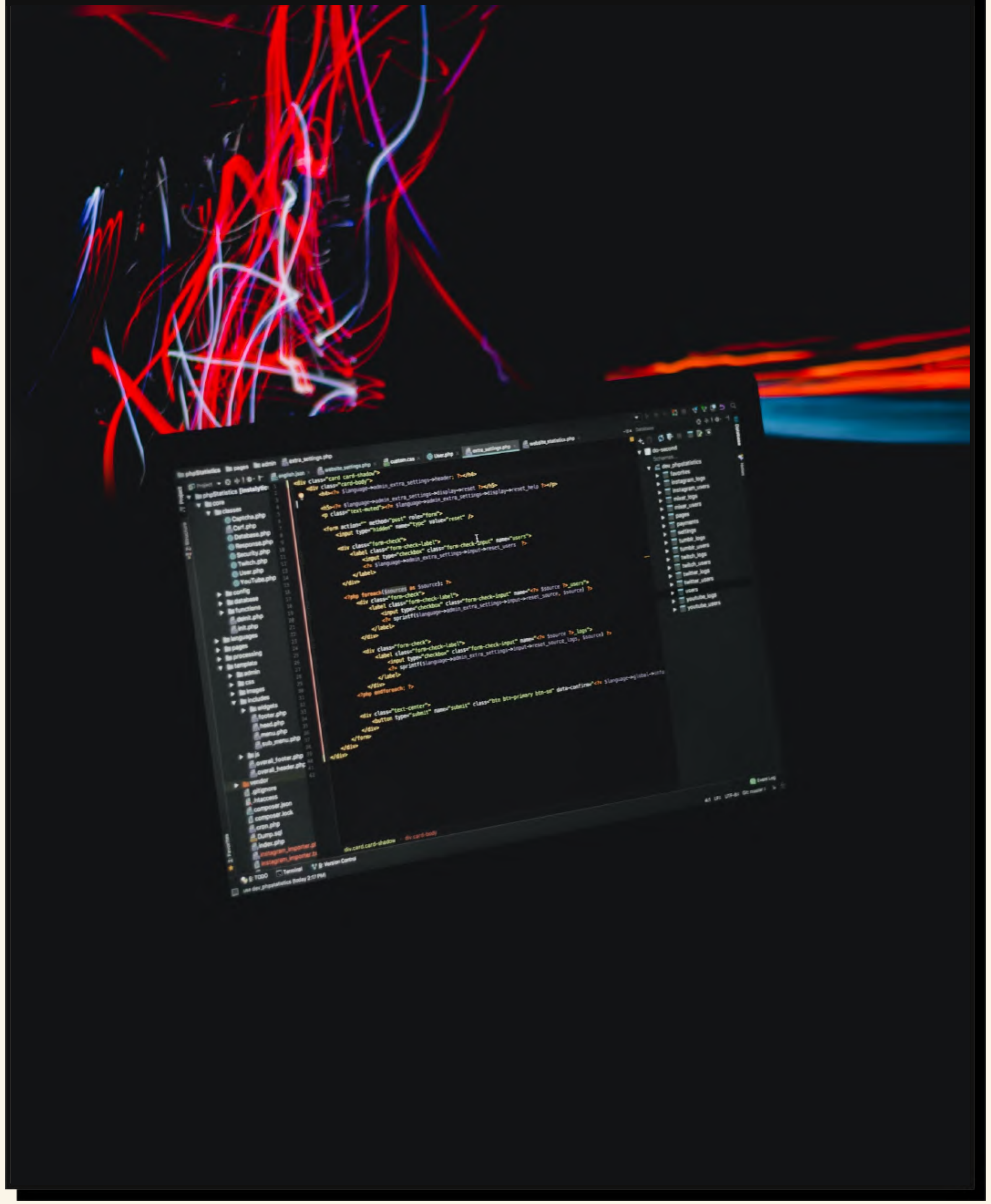
Lack of early detection and monitoring systems

Early detection of short circuits between rotor turns is crucial to prevent damage, but it can be challenging without specialized monitoring systems. Existing commercial solutions are expensive and designed for high-power generators, not suitable for low-power machines.


Inadequate detection methods
Reactive maintenance
Limited accessibility
Need for continuous monitoring
Cost effective & scalability

The need for AI-driven solutions

A monitoring and diagnosis system driven by AI can provide significant benefits. Utilizing machine learning algorithms and real-time data analysis, the system is able to continuously monitor generator performance, identify anomalies, and provide early warning signals for potential faults. This proactive strategy enables timely maintenance and reduces the possibility of unscheduled shutdowns.



Benefits of predictive maintenance

Cost saving

Increased equipment reliability

Improved safety

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Early detection of deviations can indicate mechanical problems, potentially preventing unexpected shutdowns, costly repairs, and extending machine life while ensuring efficient operation.

Data understanding & preparation

Data Sources

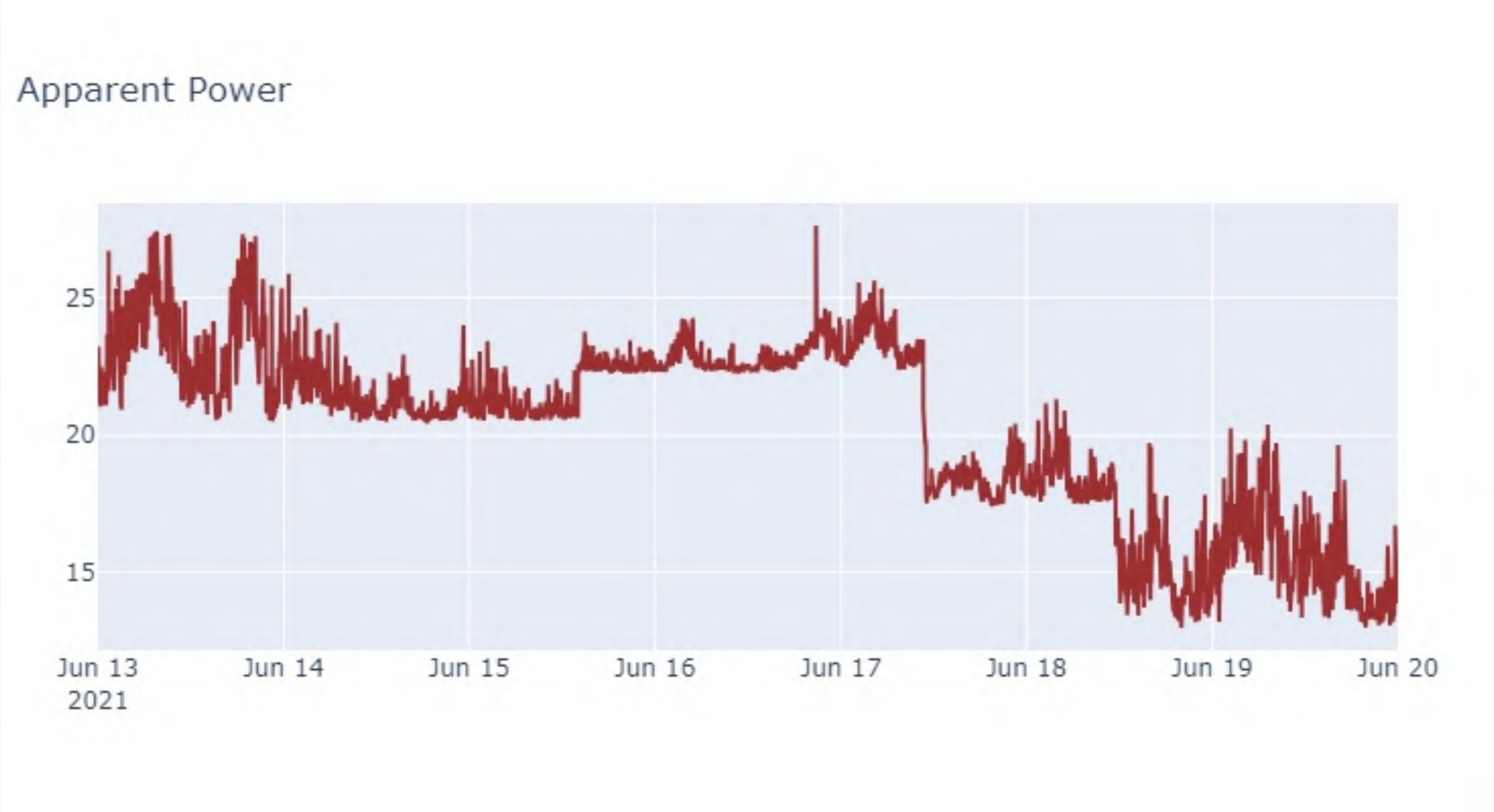
- Historical Data for 3 ESELEC machines
- Excel files
- Tabular Data mixed with unstructured data (text)
- Obtained by diagnostics on how the machines function based on Current, Voltage, Active Power, Reactive Power, Excitation Current, and Excitation Voltage.

We utilize advanced deep-learning techniques to predict the normal functionality of machines using the datasets provided.

E	F	G	H	I	J	K
Excitation Current	Excitation Voltage	Ua	Ub	Uc	Ia	Ib
Intensidad exc	Tensión exc	TENS GENER	TENS GENER	TENS GENER	CORRIENTE	CORRIENT
951,4179688	234,9040985	18,5485515	18,6986751	18,5965271	6,58083534	6,5277695
955,1901855	234,8660583	18,5485420	18,6992244	18,6023273	6,66840744	6,6053524
962,4663696	236,2702942	18,5398120	18,6829471	18,5873470	6,72225952	6,6858983
954,9241943	234,5890656	18,5454349	18,6952896	18,5950374	6,68414354	6,6745758
947,5934448	233,3480988	18,5474796	18,6730365	18,5926685	6,66368913	6,6575164
944,1710205	233,9493408	18,5307788	18,6752052	18,5817775	6,65065240	6,6383881
944,8619995	234,2433014	18,5382938	18,6931228	18,5687618	6,61648702	6,6107735
944,3134155	233,5362396	18,5521392	18,6764621	18,5782451	6,61045503	6,5993328
943,5946655	233,6966095	18,5282707	18,6702899	18,5817985	6,61405849	6,6125326
939,2054443	233,6299133	18,5342121	18,6632881	18,5610351	6,62169170	6,6256713
940,7849731	233,6776886	18,5267257	18,6672706	18,5769023	6,62201786	6,6104936
945,0574341	233,3090515	18,5510749	18,6790103	18,5657367	6,62011766	6,5985231
944,8793335	233,3274231	18,5385456	18,6750202	18,5624103	6,62015819	6,6093859
943,5834351	233,6175537	18,5475463	18,6867466	18,5935363	6,61523628	6,6265215
943,0353394	233,7891083	18,5739078	18,6717052	18,5753288	6,61671638	6,6221432
943,8800659	234,4943848	18,5730972	18,6697902	18,5921802	6,61390638	6,6025867
947,1552124	234,0451202	18,5769939	18,6693534	18,5712337	6,61411285	6,5995526
949,2115479	234,4207764	18,5712451	18,6600894	18,5443935	6,61525487	6,5986056
950,7527466	234,5762177	18,5496349	18,6623344	18,5738697	6,61233615	6,6300277
949,9127197	235,2830505	18,5542850	18,6726608	18,5677261	6,61773967	6,6195507
948,5859985	235,111557	18,5490284	18,6702480	18,5838699	6,62613678	6,5982618
947,0752563	234,2998199	18,5436706	18,6757373	18,5777015	6,61157512	6,5868973
951,6362915	234,4390869	18,5549774	18,6868763	18,5673866	6,60335493	6,5897665
952,4846802	234,7829132	18,5566463	18,6800136	18,5668830	6,60704612	6,6079387
950,3722534	234,3091125	18,5303268	18,6771888	18,5735168	6,61870288	6,6101598
947,4249268	234,2153778	18,5273704	18,6806526	18,5727767	6,61543464	6,6102333
949,9759521	234,2876434	18,5420074	18,6778583	18,5710735	6,60970783	6,6143040
948,3139648	233,980072	18,5620689	18,6423301	18,5797252	6,61514377	6,6172008
946,9251099	233,9694214	18,5405044	18,6551914	18,5895729	6,61450290	6,6169934
947,4974976	234,8421631	18,5334377	18,6717796	18,5862922	6,62469959	6,6189012
946,5908203	234,715332	18,5253562	18,6748962	18,5706825	6,62619686	6,6196193
945,9519043	234,4325867	18,5501022	18,6742267	18,5784187	6,62351894	6,6150665
948,7075195	234,7890015	18,5625743	18,6741352	18,5662879	6,62353801	6,6156048
950,9285278	235,6476135	18,5612373	18,6572895	18,5704803	6,63127851	6,6152958

Data Pre-processing

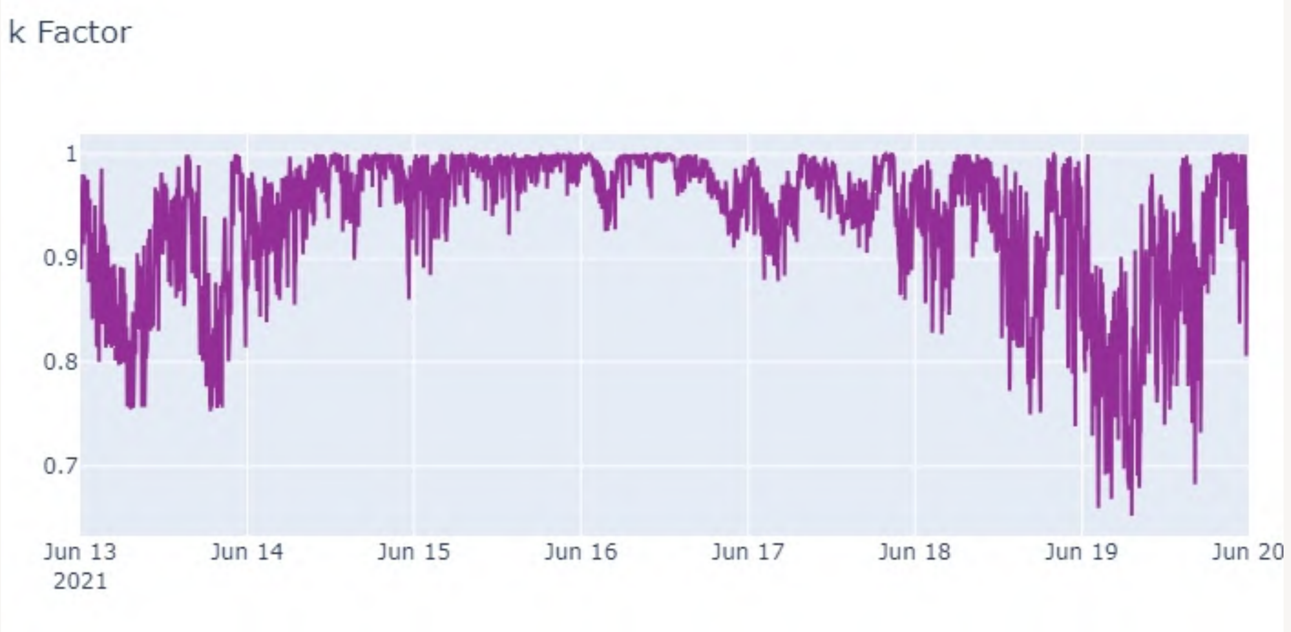
- Transformation and creation of new datasets
- Standardization of Variable Names and Measurement Units
- Features Creation for k factor and Apparent Power, etc
- Data Visualization for verification



Apparent Power is the combined effect of Active Power (capacity of the circuit for performing work during a certain period of time) & Reactive Power (power used to sustain the electromagnetic field in inductive and capacitive equipment).

If the apparent power significantly deviates from its normal range, it could indicate issues such as short-circuits within the generators. This can help identify future shutdown’s of the generators.

Data Preparation



k Factor

- Power Factor 'k' is the **ratio between Active Power and Apparent Power.** Active Power is the energy that the machine actually consumes, while Reactive Power is the energy lost during operation
- The value of 'k' is always less than or equal to 1 where a **low value indicates a higher degree of power loss**, often hinting at the machine's abnormal behavior

Outlier Detection & Removal

- Outliers were identified as **observations during abnormal machine operation**
- Two critical features were used for this identification: temporal data gaps and the power factor 'k'
- Set an initial **'k' threshold of 0.80** based on industry knowledge and eliminated everything below this threshold
- Utilized temporal data for enhanced outlier detection: **gaps indicate machine shutdowns or abnormal operation**
- Created a **'machine_fail' timestamp** series capturing these data gap instances and used it to cross-validate initially identified outliers

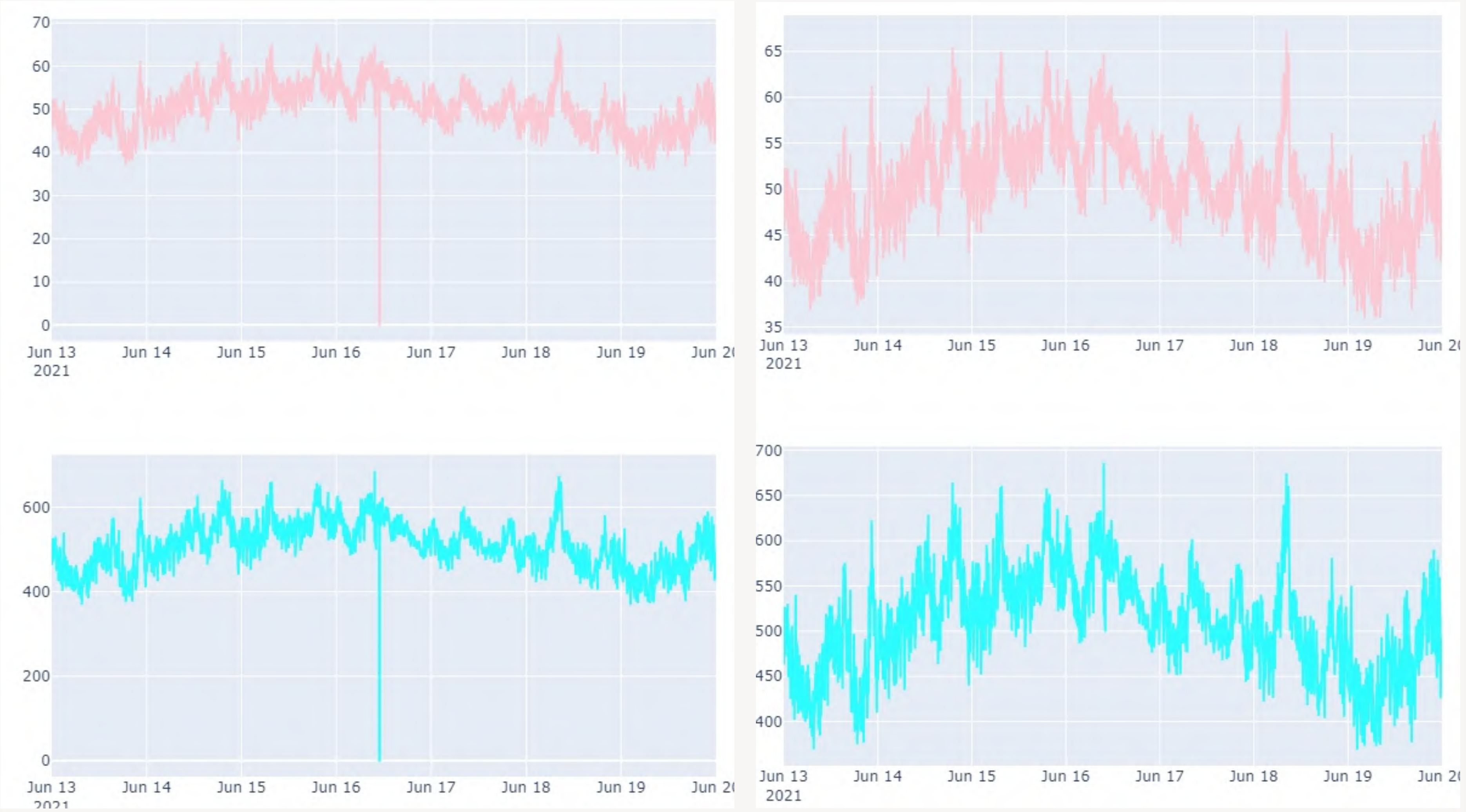


Figure 1: Excitation current before and after dropping textual data and null values

Elimination of missing and null values

- Removed uninterpretable or abnormal data points, including **textual entries** such as "bad," "shut-down," "N/A," and others to ensure high-quality training data. This approach catered to the specific aim of our project, which was to model normal machine operations.
- Performed a **systematic scan for zero values across all variables**, with special attention to those like Active Power that should not have zero values during normal machine operation.
- Zero values, indicative of machine downtime or measurement errors, were excluded to **maintain data quality and accuracy**.

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The thoroughly cleaned, transformed, and enriched data served as a dependable basis for detecting deviations from standard machine operations

Our model

Try Pitch

Why we chose LSTM Model?

01

Ideal for Time-Series Data

- LSTM can capture temporal dependencies

02

Memory Cells for Learning Patterns

- Memory cells allow the model to learn patterns over time

03

Handling Long Sequences

- Unlike traditional methods, LSTM is designed to overcome the vanishing gradient problem.

Methodology Overview

01

Data Preprocessing

- Scaling the data using MinMax Scaler.
- Reshaping the input data to a 3D array to fit the LSTM Model.
- Split the data into a train an test set.

02

Model Building

- Using keras to build a LSTM model.
- Hyperparameter tuning
- Activation Function: ReLU

03

Model Evaluation

- Calculating the Mean Squared Error to compare the difference between predicted and actual values.
- Plotting Actual vs Predicted values for Excitation Current.

Potential Solutions

Two potential alternative models to our LSTM model

Segmentation & Sequencing

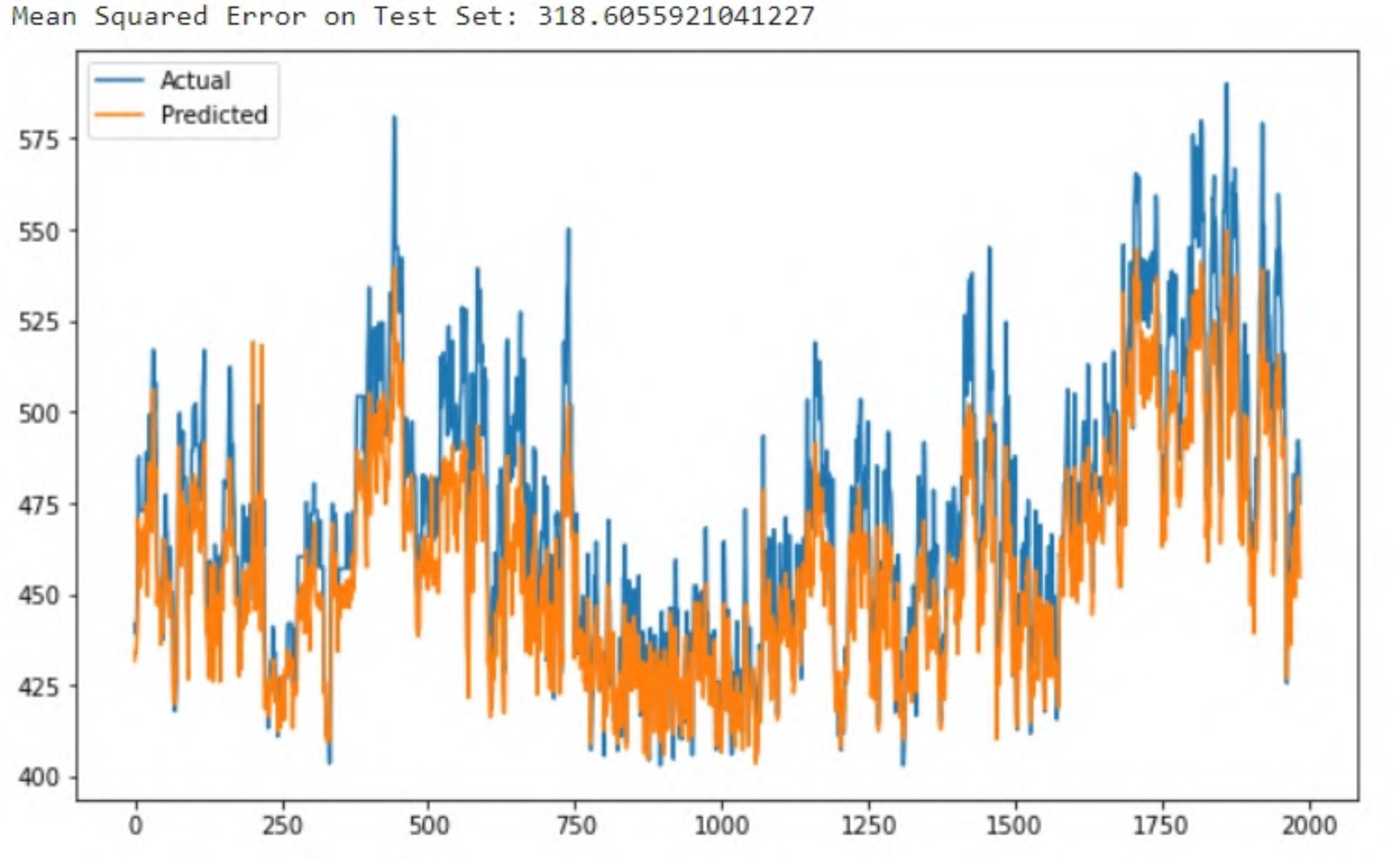
- Considers each period of normal operation as a distinct sequence
- Allows exclusion of periods of abnormal functioning from training data
- Focuses on learning patterns and dependencies associated with normal operation

Interpolation & Resampling

- Fills gaps in data by estimating missing values using surrounding data points
- Could alter normal functioning patterns with fabricated and synthetic data points
- This could lead to false conclusions from our model and compromise the reliability and accuracy of our model and overall analysis

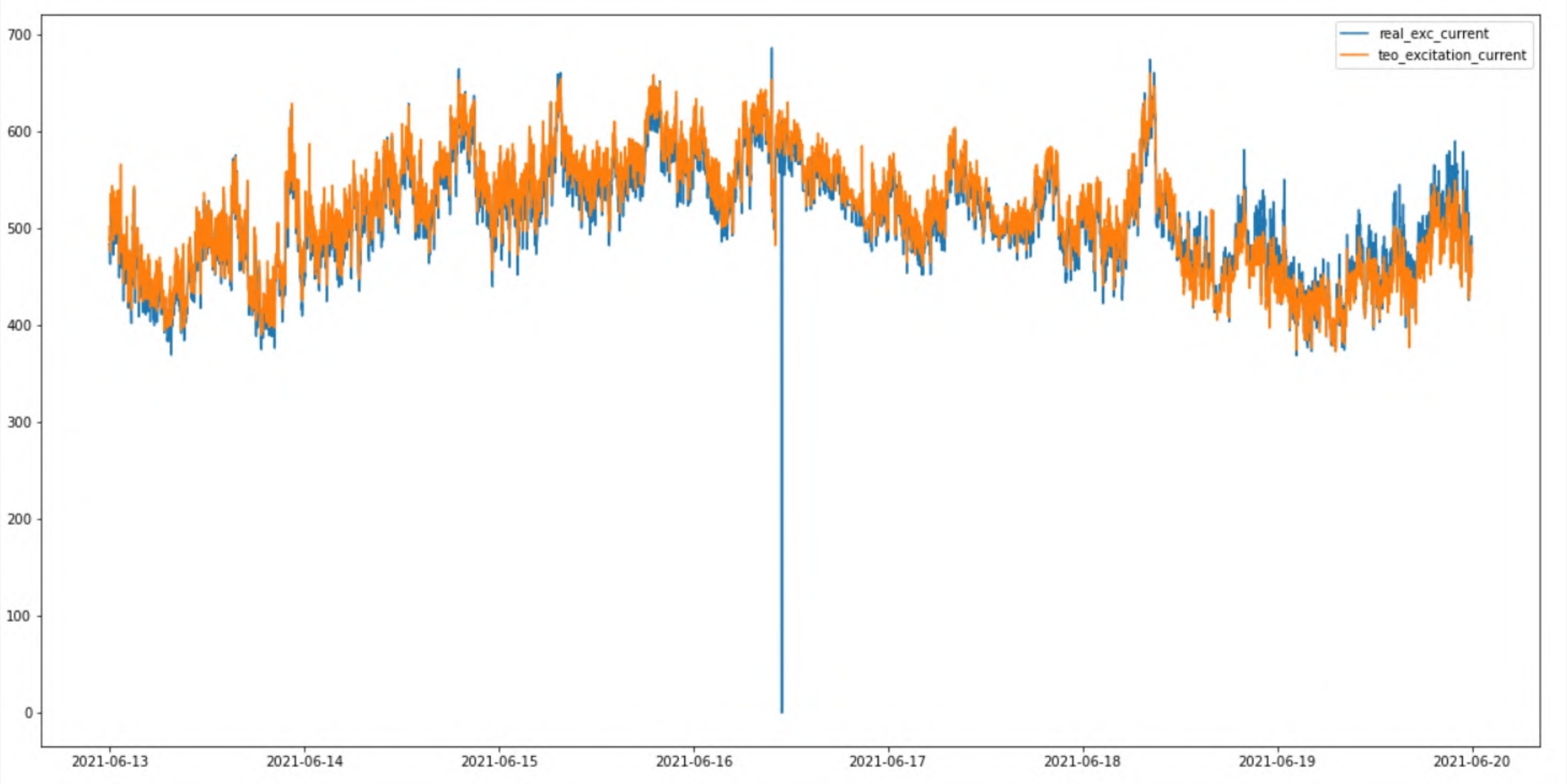
Evaluation & Results

Actual vs predicted values for Excitation Current



The **close alignment** of the orange line with the blue line indicates that the model's predictions are in good agreement with the actual values. This suggests that the model has **effectively learned the underlying patterns** in the training data and is able to generalize these patterns to unseen data in the test set.

Model's prediction (for Excitation Current) vs Excitation Current of CH1 generator



Orange: our model’s prediction for the theoretical excitation current
Blue: measured excitation current for CH1

Results

- Utilized evaluation metrics such as Root Mean Squared Error (RMSE) to assess the model's performance. The model achieved an **RMSE of approximately 23.69**, indicating a reasonable degree of accuracy in predictions compared to actual 'Excitation Current' values.
- The LSTM model has shown **promising results in predicting normal machine behaviour**, successfully modelling a stable and healthy 'Excitation Current' despite any potential machine malfunctions. This accomplishment directly addresses the initial problem presented by ELESEC, underscoring the model's utility in preventing generator shutdowns.
- Going forward, the model's performance could be enhanced further by tuning hyperparameters or exploring other model architectures to improve prediction accuracy.

Business Solution & Implementation

How is this beneficial for ESELEC?

Efficiency and Sustainability

- Excitation current anomalies indicate suboptimal energy usage in generator systems
- Addressing irregularities improves energy efficiency and reduces operational costs
- Environmental sustainability: Minimizing carbon emissions and promoting sustainable energy solutions

Predictive Maintenance

- Enhanced operational efficiency, cost savings, reduced downtime
- Preventing costly repairs and catastrophic failures, extending equipment lifespan
- Efficient resource allocation, maximized use of personnel and spare parts

Cost Savings from Maintenance

- Comparing costs of unplanned and scheduled downtime
- 35% reduction in unplanned downtime, calculated based on costs per hour
- Example: $70,000 annual savings from PM for 200 hours of unscheduled downtime at $3000 per hour

Future Work

Continuous Model Improvement

Collecting additional data:
- More data allows for better training and improves the accuracy and robustness of the models.

Utilizing Grid Search algorithms:
- Fully explore different model settings helps identify the best combination of choices, optimizing the model's performance.

Enhance Fault Localization

Incorporate Sensor Fusion techniques:
- Monitor additional aspects of the generators (temperature, sound, gas emissions)

Reduce downtime and improve operational efficiency:
- Efficient fault localization leads to quicker repairs

Incorporate Prognostics

Minimize unplanned downtime:
- Predict remaining lifetime to prevent unexpected failures

Optimize resource allocation:
- Efficiently allocate resources for maintenance tasks