# MANDALA

# Multivariate ANomaly Detection& expLorAtion



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## **MOTIVATION & GOALS**

- The increase in large and complex data sets across various industries has led to a growing need for data analytics tools that provide practical insights to facilitate decision-making
- MANDALA is a comprehensive platform for seamless identification, analysis, and comprehensive understanding of anomalies in complex multivariate time series data
- The platform subsequently facilitates the exploration and comparative assessment of anomaly candidates, their related dimensions, and temporal aspects
- Through its user-friendly interface and a range of features, MANDALA offers a toolset to effortlessly tackle the complexity of large and high dimensional sensor data.

## **Project FactBox**

Project Name SERAM
Project ID StratP II 3.4.1
Duration 21 Months

Area 3

Cognitive Decision Making

**Project Lead**Dr. Belgin Mutlu

# **APPROACH**

- Semi-supervised learning method using kernel density estimation (KDE) to detect anomalies
- Scatterplot matrices (SPLOMs), hexagonal binning plots and line plots as visualization and exploration aids
- These techniques allow versatile comparisons between individual dimensions, pairs of dimensions and the whole dataset, while also facilitating temporal analysis of anomalies.

# CONTRIBUTION

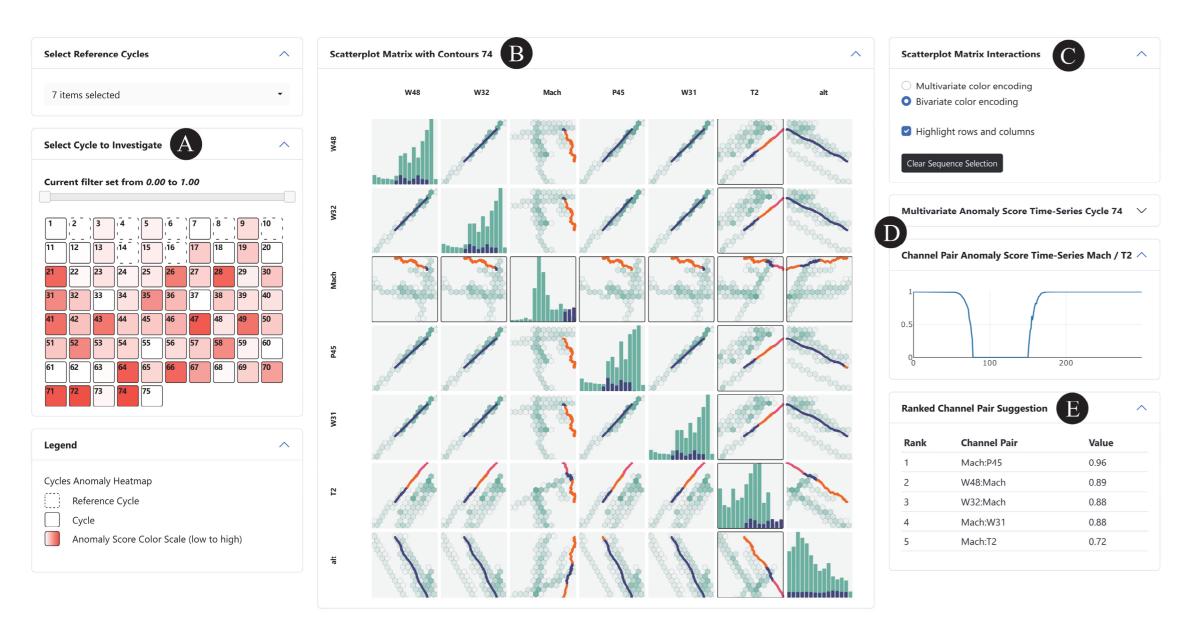
#### **Scientific contribution**

- User guidance in identifying, assessing, and exploring anomalies in multivariate time series data
- Novel methods for detecting anomalies within a temporal range in a multidimensional space
- Helping users in pinpointing contributing parameters to anomaly scores in multivariate time series data

#### **Economic contribution**

- Minimize downtime, reduce operational disruptions, and optimize resource allocation
- Ensure product quality, reducing defects and minimizing costly recalls
- Timely maintenance, prolonging equipment life and preventing expensive breakdowns

### **FRAMEWORK**



(A) The semi-supervised approach involves users in selecting reference data. Anomaly candidate cycles, distinct from the reference data, are highlighted using a red color scheme.

- (B) The scatterplot matrix offers semantic zooming and presents bivariate data of the analyzed anomaly candidate cycles through scatterplots. The distribution of bivariate data in the reference set is depicted as hexagonal binning plots. Along the diagonal, separate histograms compare the univariate distribution of each reference data dimension with the anomaly candidate cycle.
- (C) The color of scatterplot points can be customized for multivariate or bivariate color-encoding, allowing flexibility in the analysis scope.
- (D) The temporal scope of anomalies can be investigated via line plot views, which also interactively impact the scatterplot matrix through linking and brushing functionalities.
- (E) Bivariate anomalies are ranked by their anomaly score, and this ranking is presented in the ranked channel pair suggestion view.

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