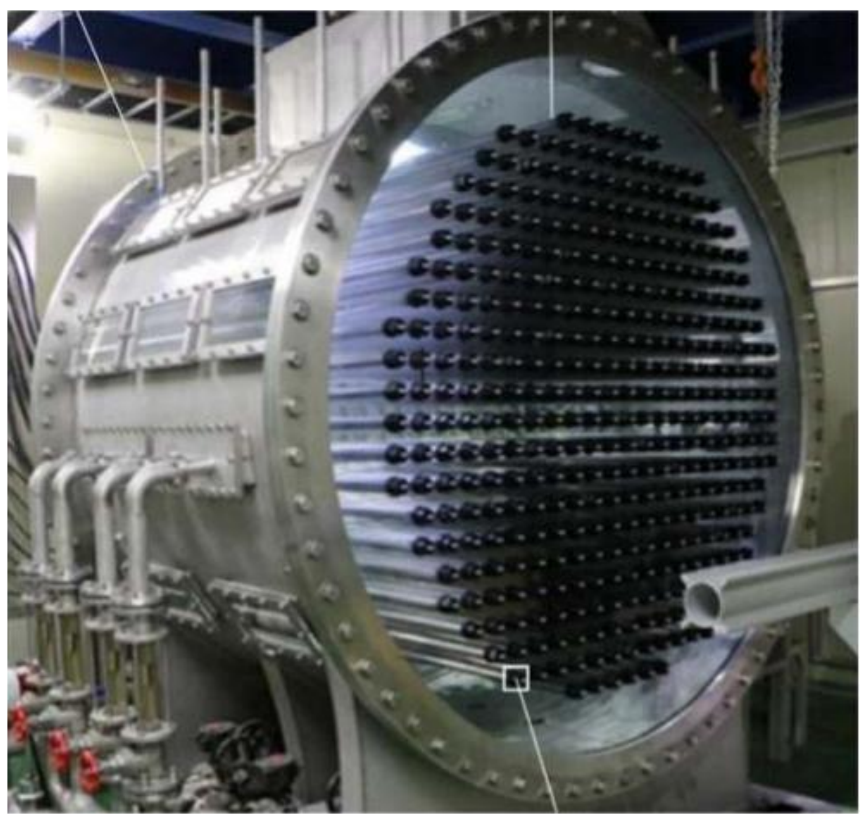
Enhancing Remaining Useful Life Predictions for Nuclear Reactor Filters using Knowledge Models

Callum Paul Manning, Andrew Young, Graeme West, Stephen McArthur

University of Strathclyde, Glasgow, UK
Email : callum.manning.2017@uni.strath.ac.uk

University of Strathclyde Engineering

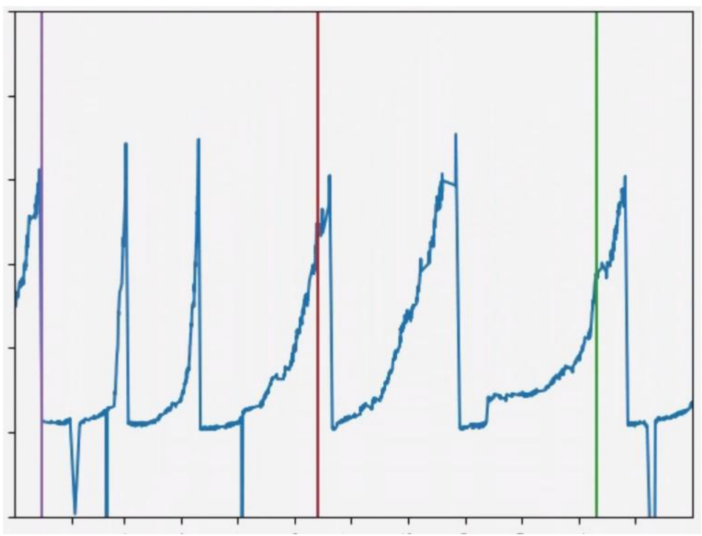
Introduction



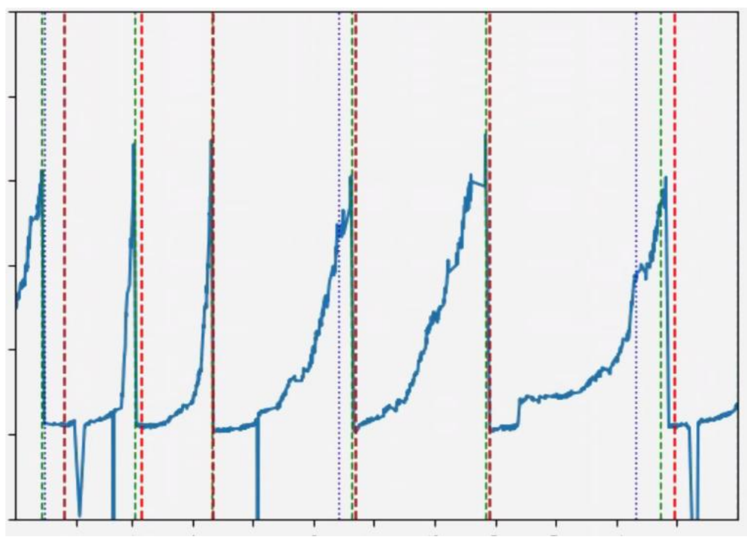
- This work aims to find the **remaining useful life** of Heavy Water Filters in CANDU Reactors
- **Differential Pressure** across the filters, builds as the **filter degrades**
- While a wealth of **historical data** is available, there are **many hidden variables** other than just differential pressure.
- The **filters** are **not uniform in degradation**.
- The aim of this project is to see if **Knowledge models** can be used to keep track of those variables and therefore improve prediction

Current Methodology

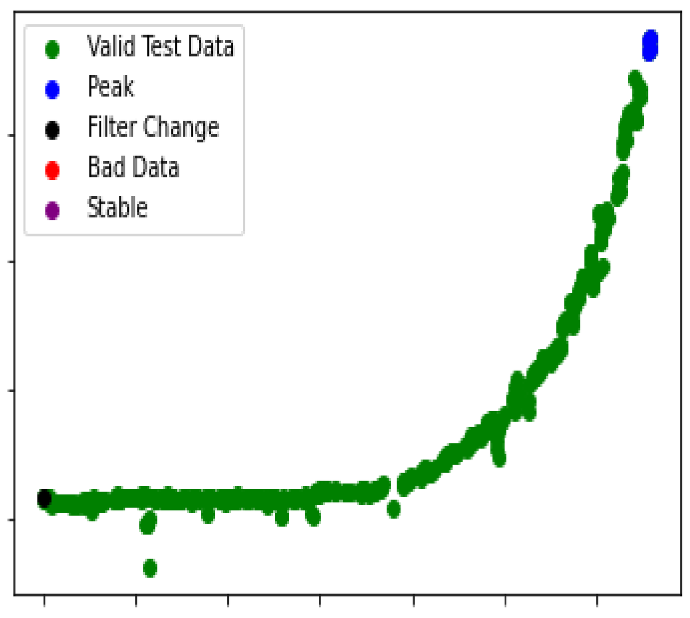
- The **current methodology** extracts **differential pressure** across these filters using data contained in **maintenance logs**
- It uses a **sliding window** to search across this **Time series data**, and automatically split the **pressure data into curves**, each of which correlates to **a filter's lifespan**
- The data points across the lifespan are then filtered and categorized
- **Curve fitting** is then applied to **predict** the remaining useful life of the filter.
- The **bounds** for this **curve fitting** is adjusted based on the 7 known examples of '**full degradation curves**' which **span** from **filter change date to alarm value**



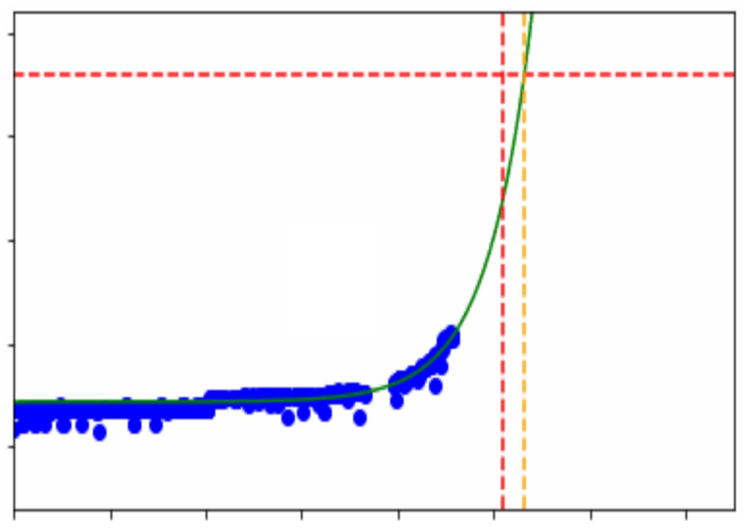
Differential Pressure Data across a single quadrant of Channels



Automated Splitting of filter lifespans



Identification of Key Data Points



Curve Fitting and remaining useful life prediction

Enhancing this Prediction

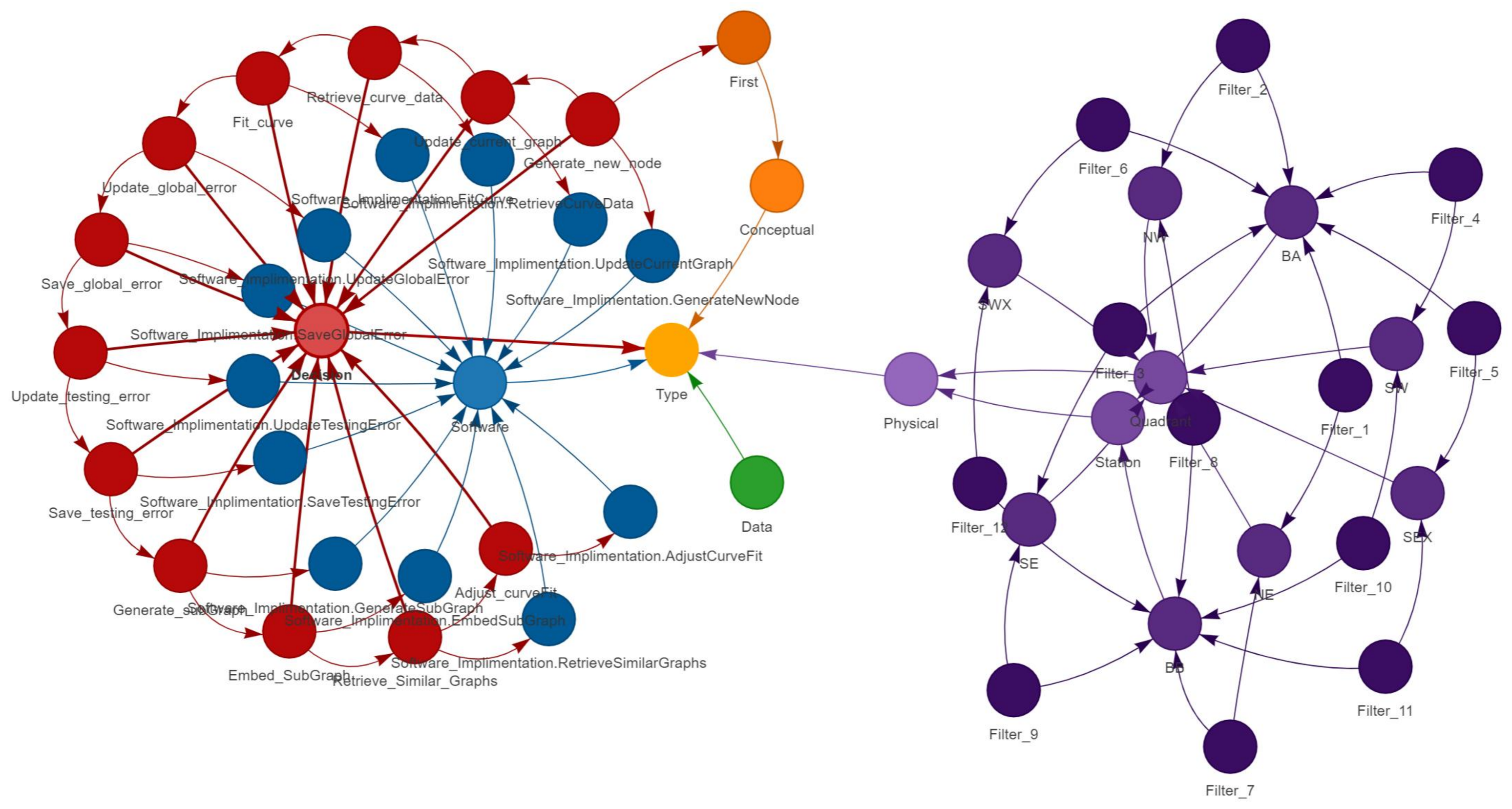
- Not all filters degrade at equal rates
- The different quadrants, in different stations, different filter sizes, different times of year -> all effect the degradation rate
- But the **current mechanism does not take into account any of these factors**
- A key component here is the decision-making process must be both **transparent and explainable**.

Graph Retrieval

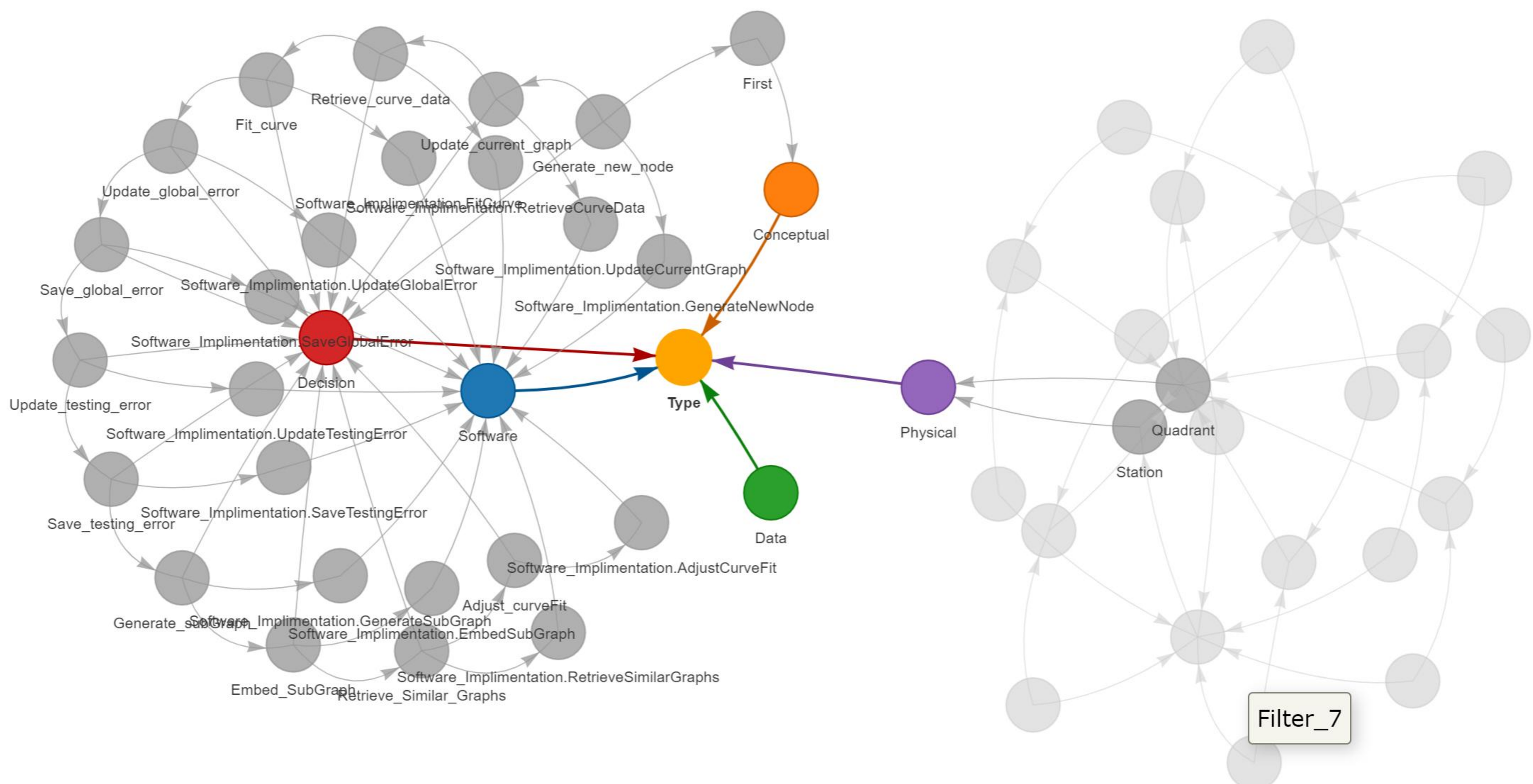
- The **current** methodology **improves curve fitting** by using bounding based on the **handful of completed curves**
- The next step here is to **map all data regardless of completion** to the **knowledge model.**
- The **model** will then use the most **similar previous examples** in terms of filter variables to improve the **predictive curve fitting**

Knowledge Models

- A **Knowledge Model** is a **NeuroSymbolic Knowledge Graph** used to model a decision-making process.
- The model relates the **physical** asset, to the **decision-making** process, to any **software** that impacts that decision process, **data** used across that decision and any **conceptual** elements that exist in that process.



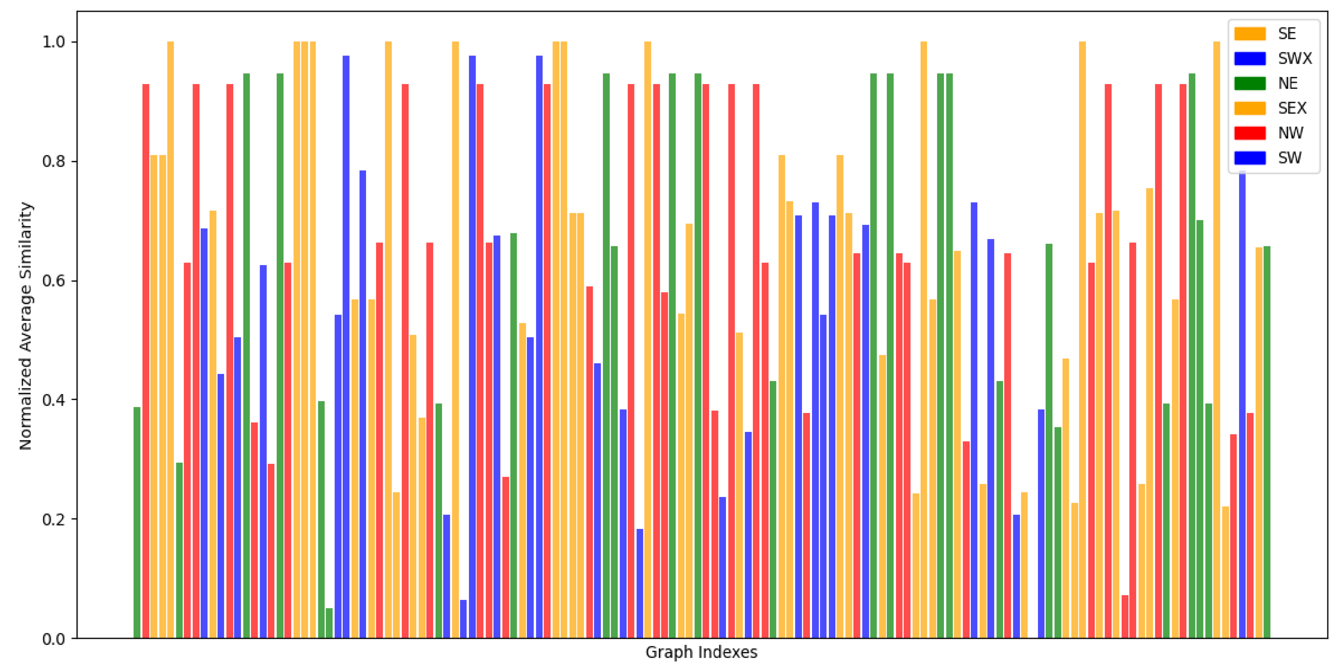
Knowledge Model before Data is passed through Decision Process



Key Node types in graph, Decision, Software, Data, Physical, Conceptual

Similarity

- Using the **knowledge model**, each new data point can be **examined** based on it's **relationships** with all other data points.
- This **Similarity analysis** helps identify **outliers** and assess the potential accuracy of predictions
- Similarity scores can also serve as a **proxy** for the **expected reliability** and consistency of predictions



Comparative Similarity of Data Points based on Knowledge Model Relationships

Future Work and Next Steps

- This is the **first step** in a **larger attempt** to make use of **Knowledge Models**
- **Next Steps** involve using **Graph Embeddings** to in place of current relationship based **similarity**
- Using these **similarity** values to help more **accurately bound curves**
- Following that **showcasing** the **reusability** of **Decision-Making elements**

BrucePower™ Innovation at work

UNIVERSITY of STRATHCLYDE ADVANCED NUCLEAR RESEARCH CENTRE