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Improving the interpretability of causality maps for fault identification

- ❖ Results
- ❖ Conclusions & recommendations

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2 September 2020

Aim:

To improve the interpretability of causality maps for fault identification.

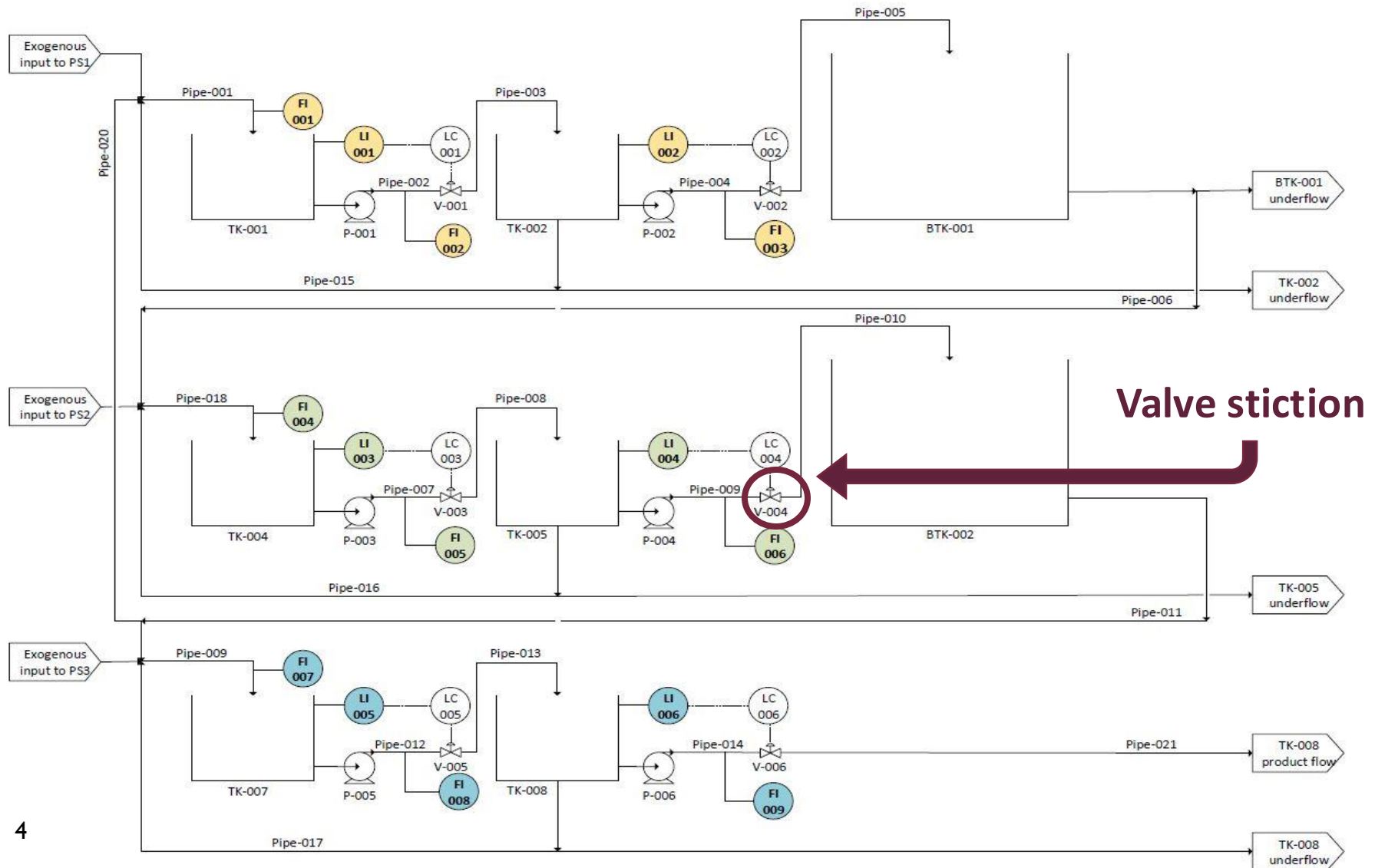
Objectives:

1. Identify and assess ways to incorporate **process knowledge** in causality maps.
2. Identify, propose, and assess **tools and visualisation techniques** to aid in interpretation of **plant-wide causality maps**.
3. Perform a **usability study** to gain insights on whether causality maps with the proposed tools and visualisation techniques can be **practically applied in industry**.

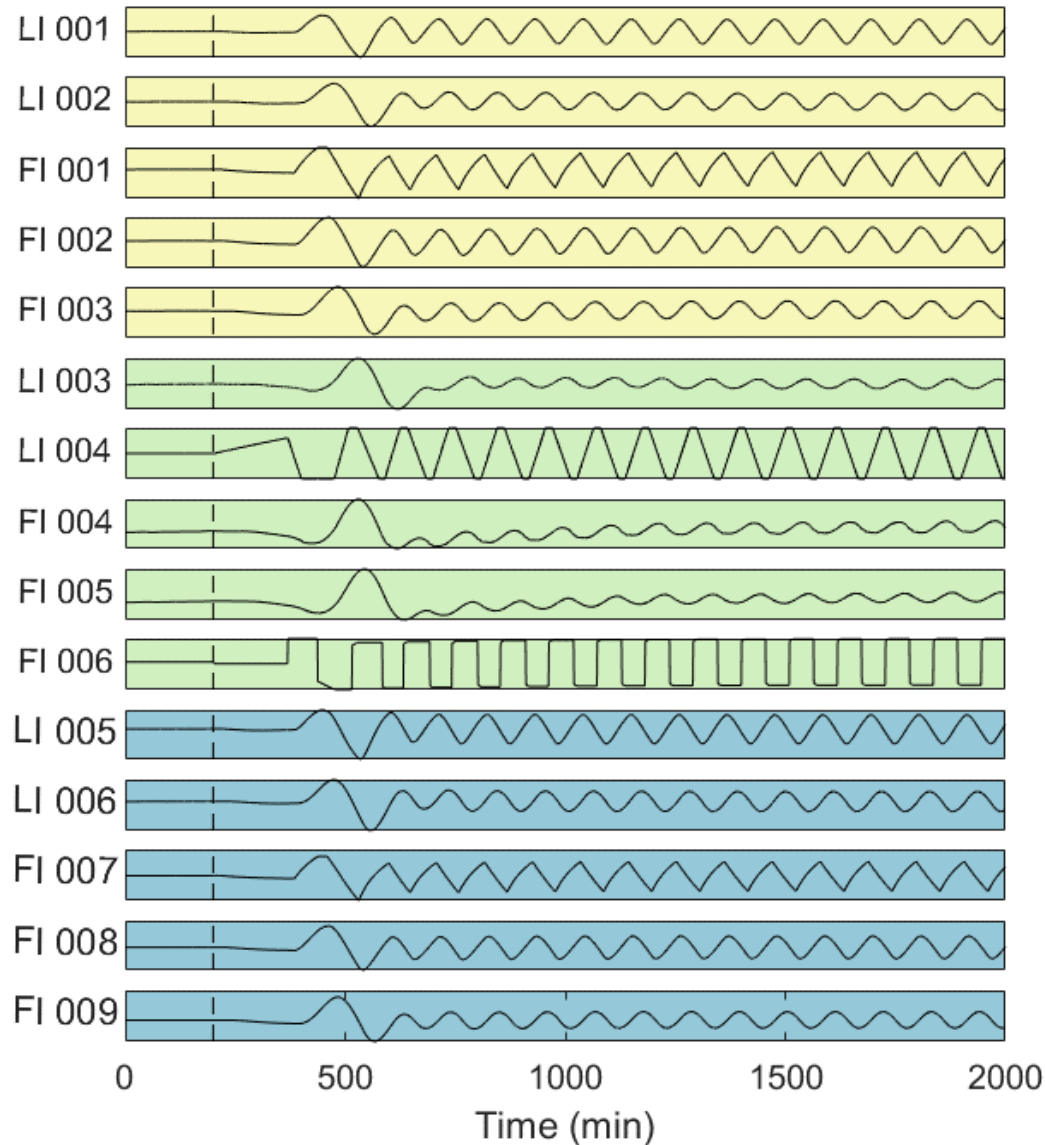
Causality analysis workflow

1. Variable selection
2. Data selection
3. Causality analysis calculation
4. Incorporate process knowledge & tools to aid in interpretation
5. Causality map construction
6. Causality map interpretation

Case study: Tank network simulation



Case study: Tank network simulation



Causality analysis workflow

1. Variable selection
2. Data selection – Sampling period (SP) & Time window (TW)
 - ❖ Heuristic approach for selecting SP and TW
3. Causality analysis calculation – Conditional Granger causality (GC)
4. Incorporate process knowledge & tools to aid in interpretation
 - ❖ (Definition of the ideal causality map)
 - ❖ Using process knowledge to constrain connections
 - ❖ Using process knowledge to constrain potential root causes

4. Incorporate process knowledge & tools to aid in interpretation
 - ❖ Visually displaying node rankings
 - ❖ Connections-slider
 - ❖ Variables-slider
 - ❖ **Hierarchical approach for causality analysis**
5. Causality map construction
6. Causality map interpretation
 - ❖ Usability study - survey

Heuristic approach for selecting SP & TW

- Identified as gap in literature.
- Proposed methodology:
 1. Using process knowledge, identify and select a **known causal connection** between two variables showing an effect of the fault.
 2. Select a **range of SPs** to investigate.
 3. Select a **range of TWs** to investigate.
 4. Calculate the **causal strength for the known causal connection** using each combination of the SPs and TWs selected to investigate.
 5. Identify and select the combination of SP and TW that results in the **largest connection strength of the known connection**.

Heuristic approach for selecting SP & TW

- Application to case study:

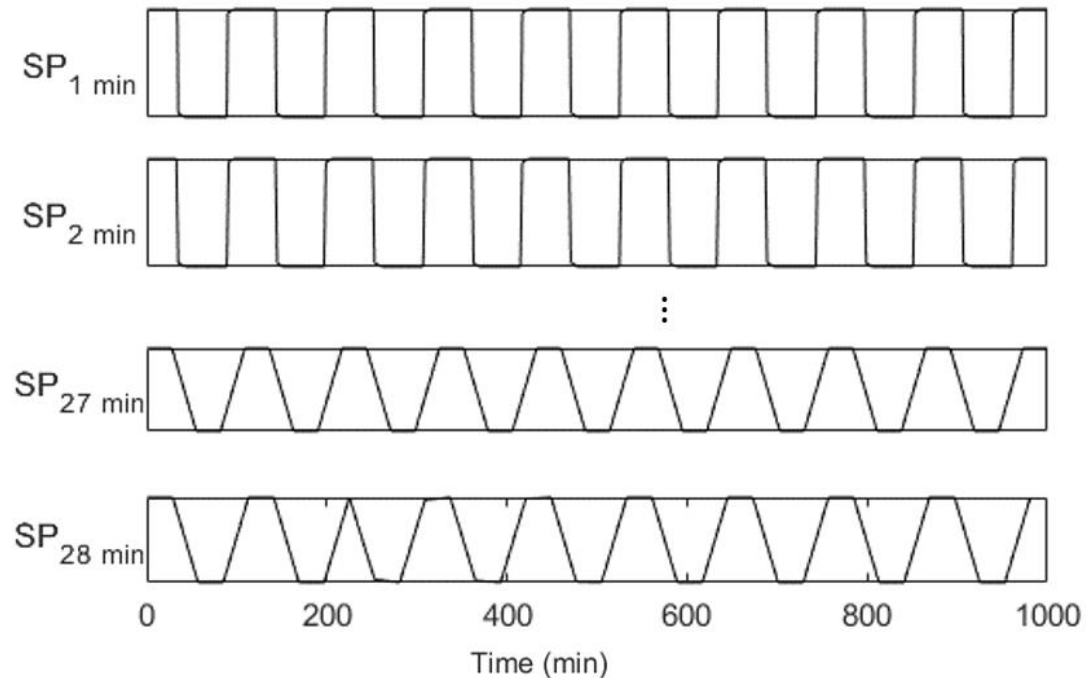
1. *Known causal connection:*

- ❖ *FI 006 → LI 004 (control loop)*

2. Range of SPs:

- ❖ Smallest SP: SP provided by the sensor (1 min)

- ❖ Largest SP: Largest SP where acceptable resolution of data is maintained (27 min)



Heuristic approach for selecting SP & TW

3. Range of TWs:

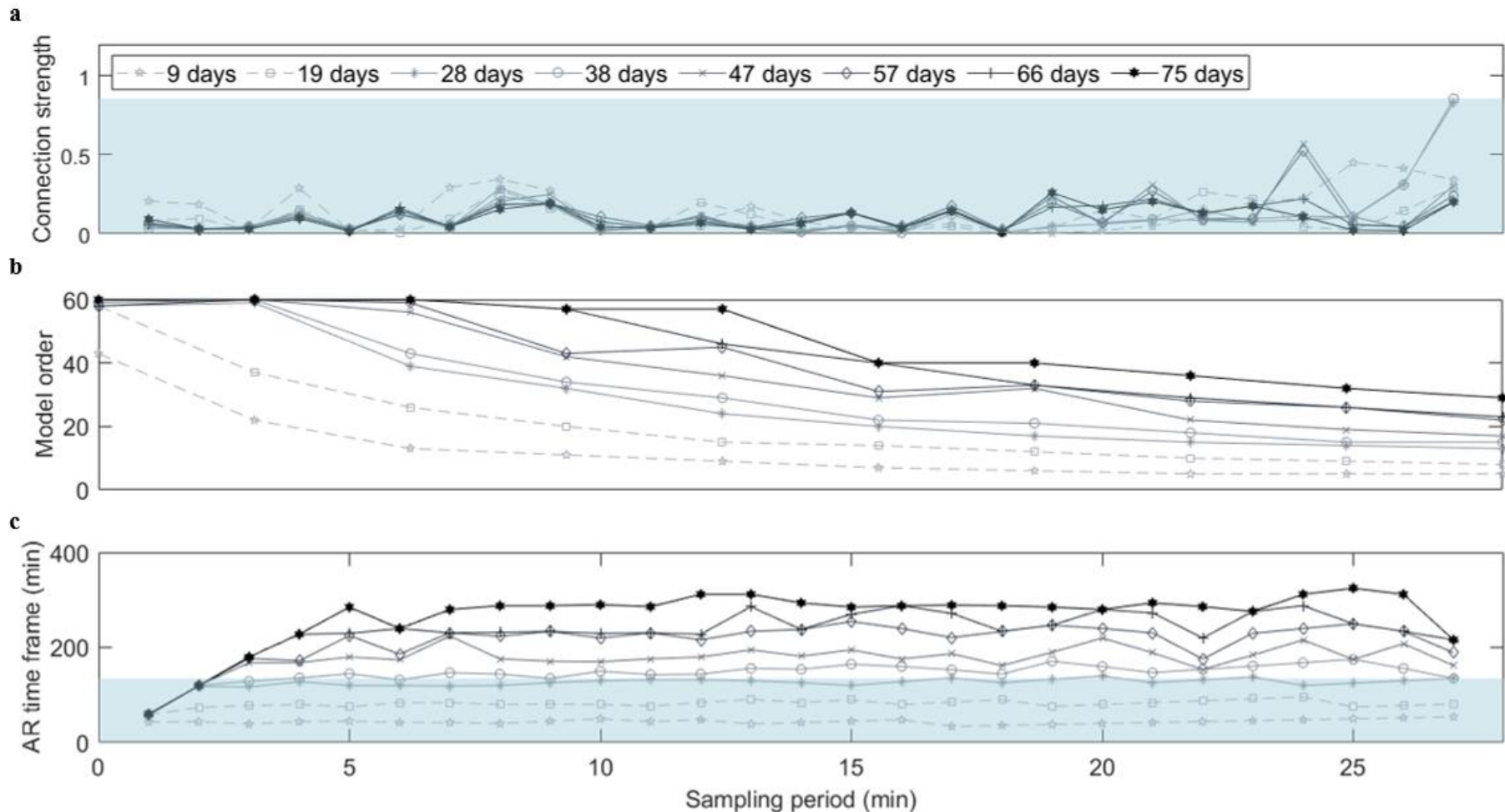
- ❖ Selected to provide sufficient samples for a unique OLS solution for the full model with max model order of 60 in conditional GC for each SP:

13 562 samples → TW in order of weeks/months

SP (min)	1	2	3	4	5	6	7	8	9
TW (min)	13562	27124	40686	54248	67810	81372	94934	108496	122058
TW (days)	9	19	28	38	47	57	66	75	85
SP (min)	10	11	12	13	14	15	16	17	18
TW (min)	135620	149182	162744	176306	189868	203430	216992	230554	244116
TW (days)	94	104	113	122	132	141	151	160	170
SP (min)	19	20	21	22	23	24	25	26	27
TW (min)	257678	271240	284802	298364	311926	325488	339050	352612	366174
TW (days)	179	188	198	207	217	226	235	245	254

Heuristic approach for selecting SP & TW

4. Strength for the known causal connection.

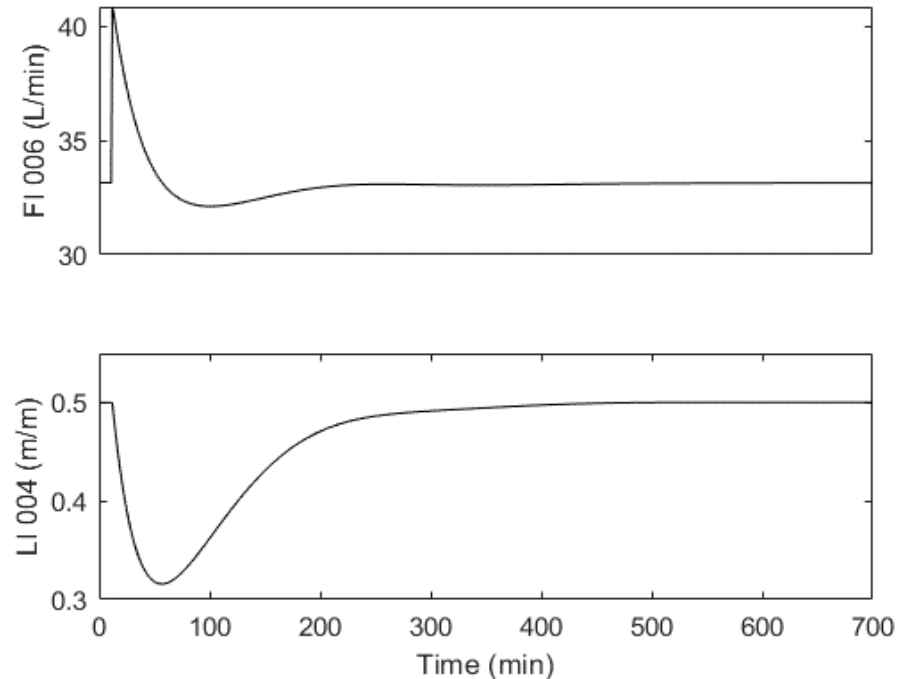


5. Select SP = 27 min, TW = 38 days → AR time frame = 135 min

Heuristic approach for selecting SP & TW

- Main findings:

- ❖ No singular trend of connection strength as $f(\text{SP}, \text{TW})$.
 - Corresponds to ‘black’ & ‘sweet’ spots as SP & TW interact with process dynamics.
 - Time frame of 135 min captures majority of dynamic response of *LI 004* to a step change in *FI 006*.



- ❖ Time frame keeps increasing with TW, past the ‘sweet spot’ that corresponds to process dynamics.
 - AIC does not penalise the number of parameters heavily, leading to incorrectly large model orders when large TWs are available.

Definition of the ideal causality map

- Developed using a top-down approach:

Level 1:

The ideal causality map is easily interpretable to successfully trace the propagation path of a fault back to its root cause.

Level 2:

The ideal causality map:

- Is relevant to the current fault.
- Provides confidence in its connections.
- Is visually interpretable.

Definition of the ideal causality map

Level 3:

Relevance to current fault:

- The true root cause variable is included in the causality map.
- All variables included in the causality map show an effect of the fault.

Confidence in connections:

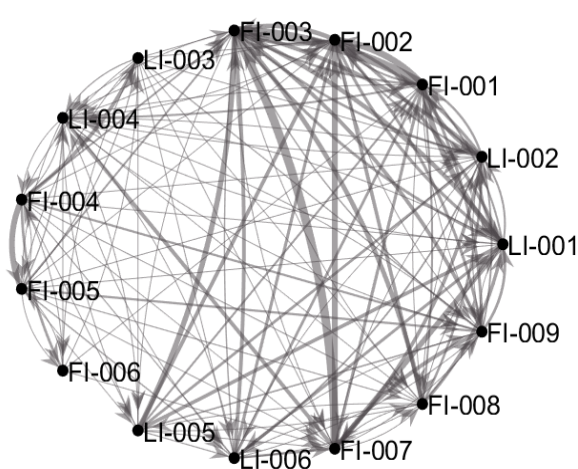
- No spurious connections are displayed in the causality map.
- All true fault propagation paths are displayed in the causality map.

Visual interpretability:

- The causality map is not too dense (i.e. does not have too many edges).
 - The causality map does not have too many nodes.
 - The causality map clearly points to the root cause, preferably by being acyclic.
-

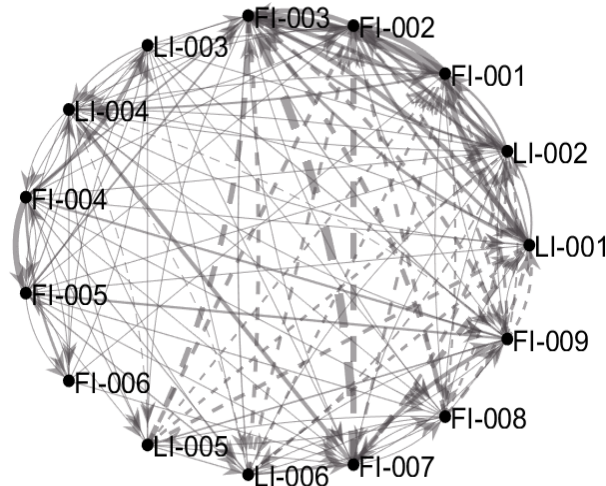
Incorporating process knowledge

- Constrain connections
 1. Perform data-based causality analysis
 2. Validate connections with connectivity matrix from P&ID



Standard map:

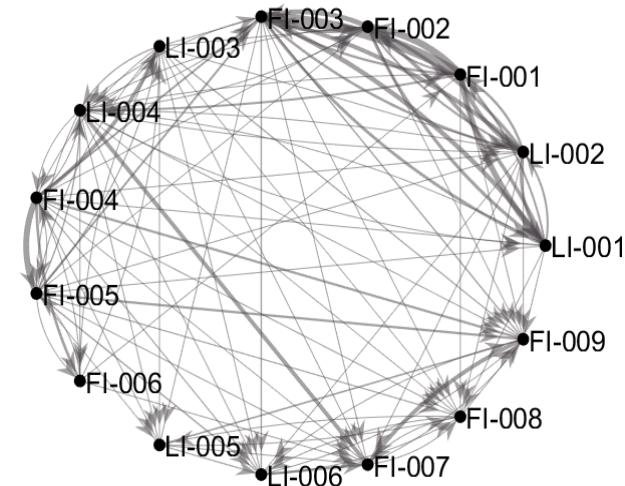
- 28/139 (20 %) of connections are spurious
- Graph density = 0.66



Solid lines = Validated

Dashed lines = Non-validated

- All spurious connections dashed lines (P&ID-dependent)
- Graph density = 0.66

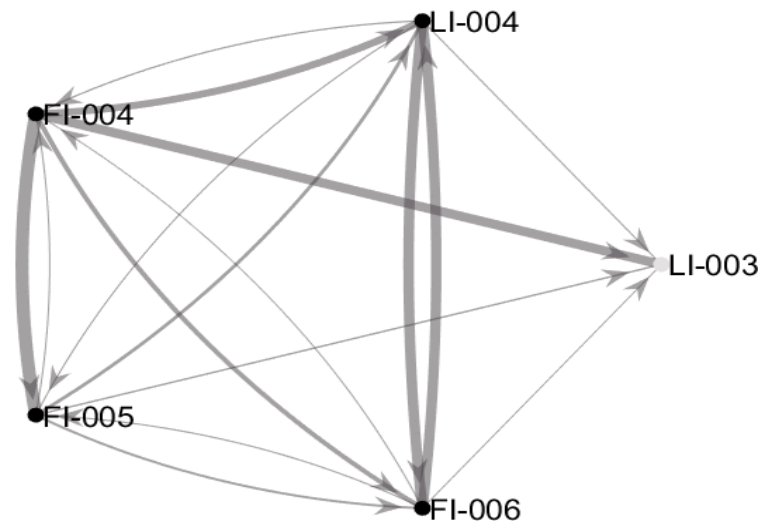


Validated map:

- No spurious connections (P&ID-dependent)
- Graph density = 0.3

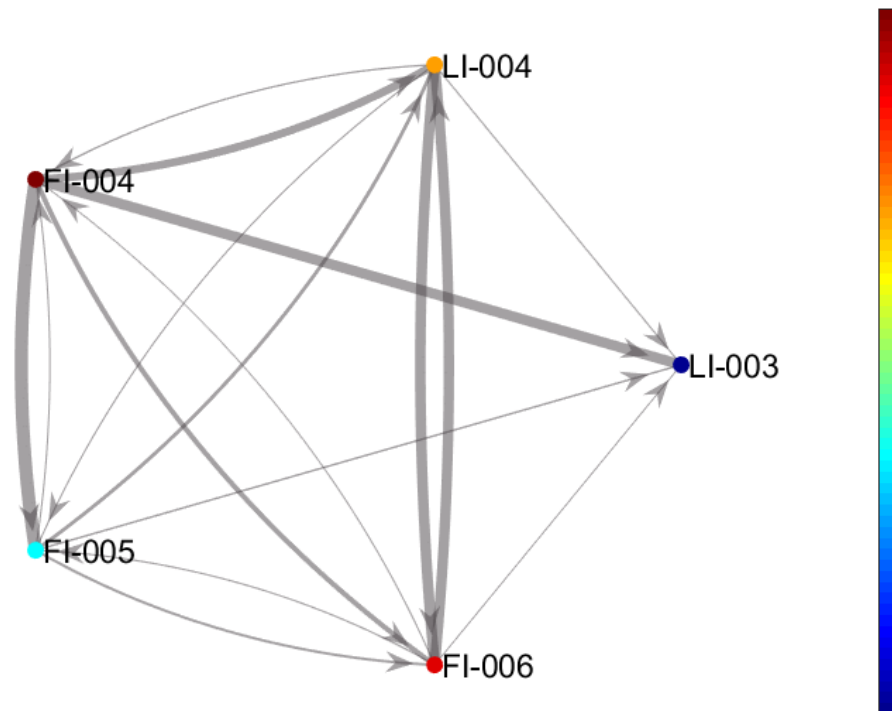
Incorporating process knowledge

- Constrain potential root causes
 - ❖ Based on assumption that all variables in causality map show an effect of the fault.
 - ❖ According to smearing effect, the root cause must be able to reach all other variables showing an effect of the fault.
 - ❖ Therefore, nodes that cannot reach all other nodes in the causality map cannot be the root cause – so they are faded:



Tools for interpretation

- Display node rankings
 - ❖ Node rankings determined using page rank algorithm

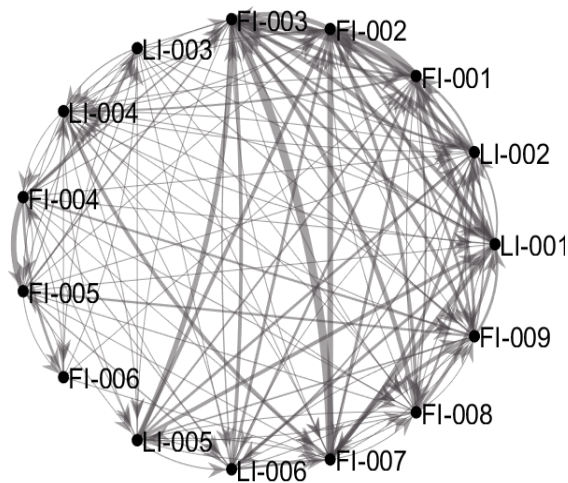


- ❖ Very useful for cyclic maps

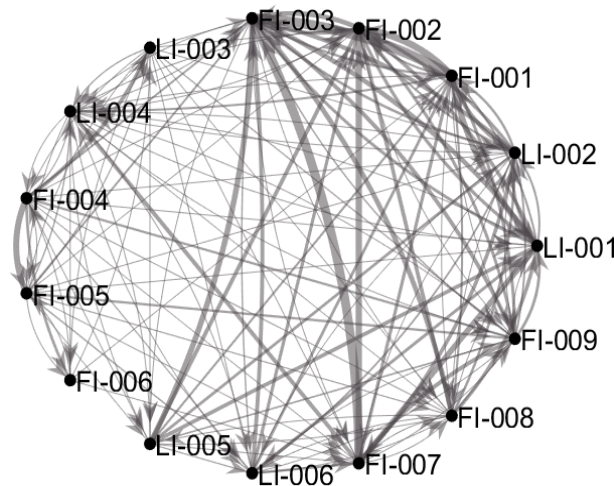
Tools for interpretation

- Connections-slider

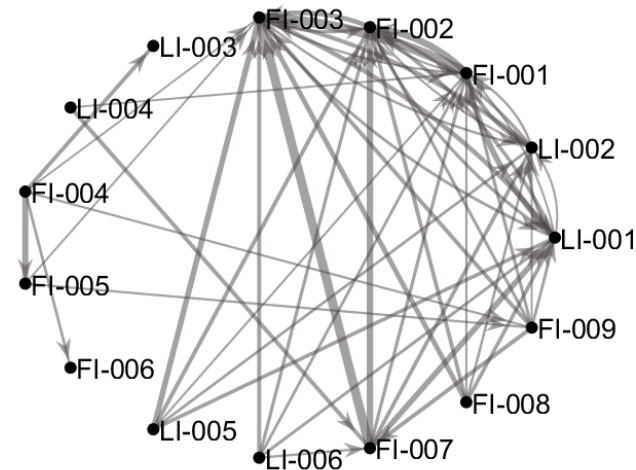
- ❖ Display map for different significance levels (α) in F-test.
- ❖ Smaller α decreases graph density, but important connections may be lost.



$\alpha = 0.05$



$\alpha = 0.01$ (default)

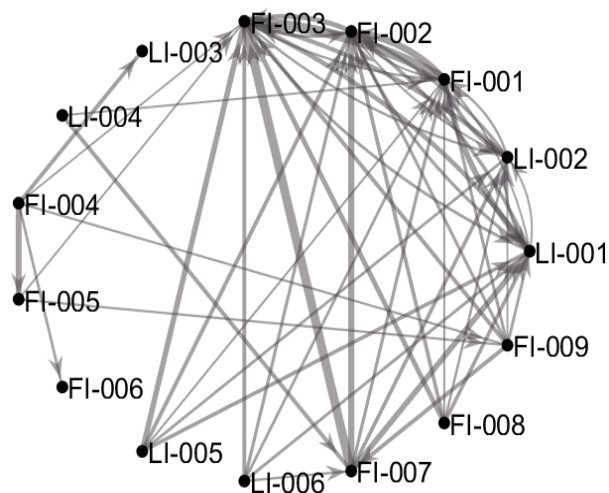


$\alpha = 1 \times 10^{-16}$

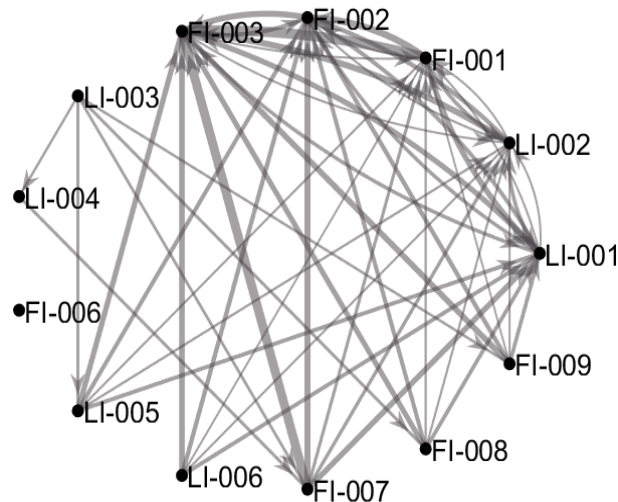
Tools for interpretation

- Variables-slider

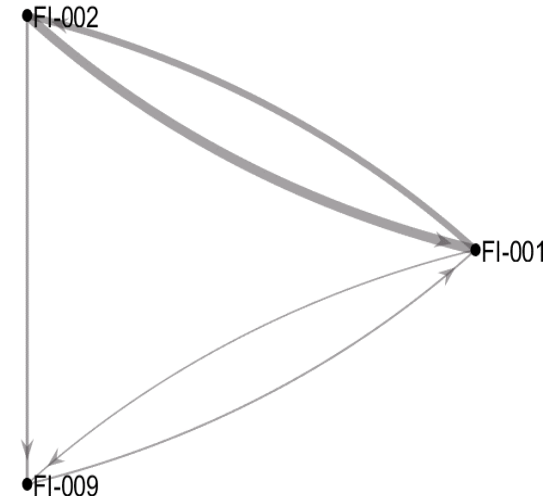
- ❖ Display map for variables with different oscillation contributions (OC).
- ❖ OC determined using the spectral envelope method.



$OC > 0$ (default)



$OC > 0.6$



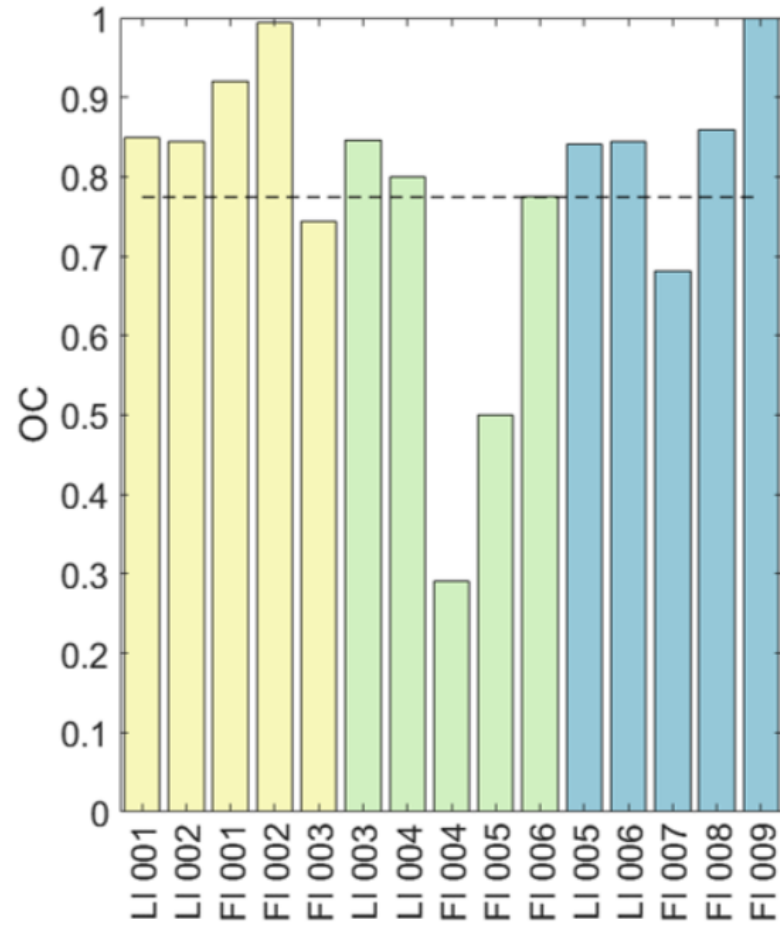
$OC > 0.9$

- ❖ **Problem:** Root cause variable (FI 006) is not present in all the maps.

Tools for interpretation

- Variables-slider

- ❖ **Problem:** Root cause variable (*FI 006*) is not present in all the maps.
- ❖ **Reason:** Root cause variable does not have the largest OC.
- ❖ **Solution:** Perform once-off variable selection using the spectral envelope method.
- ❖ Survey finding: Variables-slider is confusing.



Two causality maps

1. Map 1: Less detailed, plant-wide map

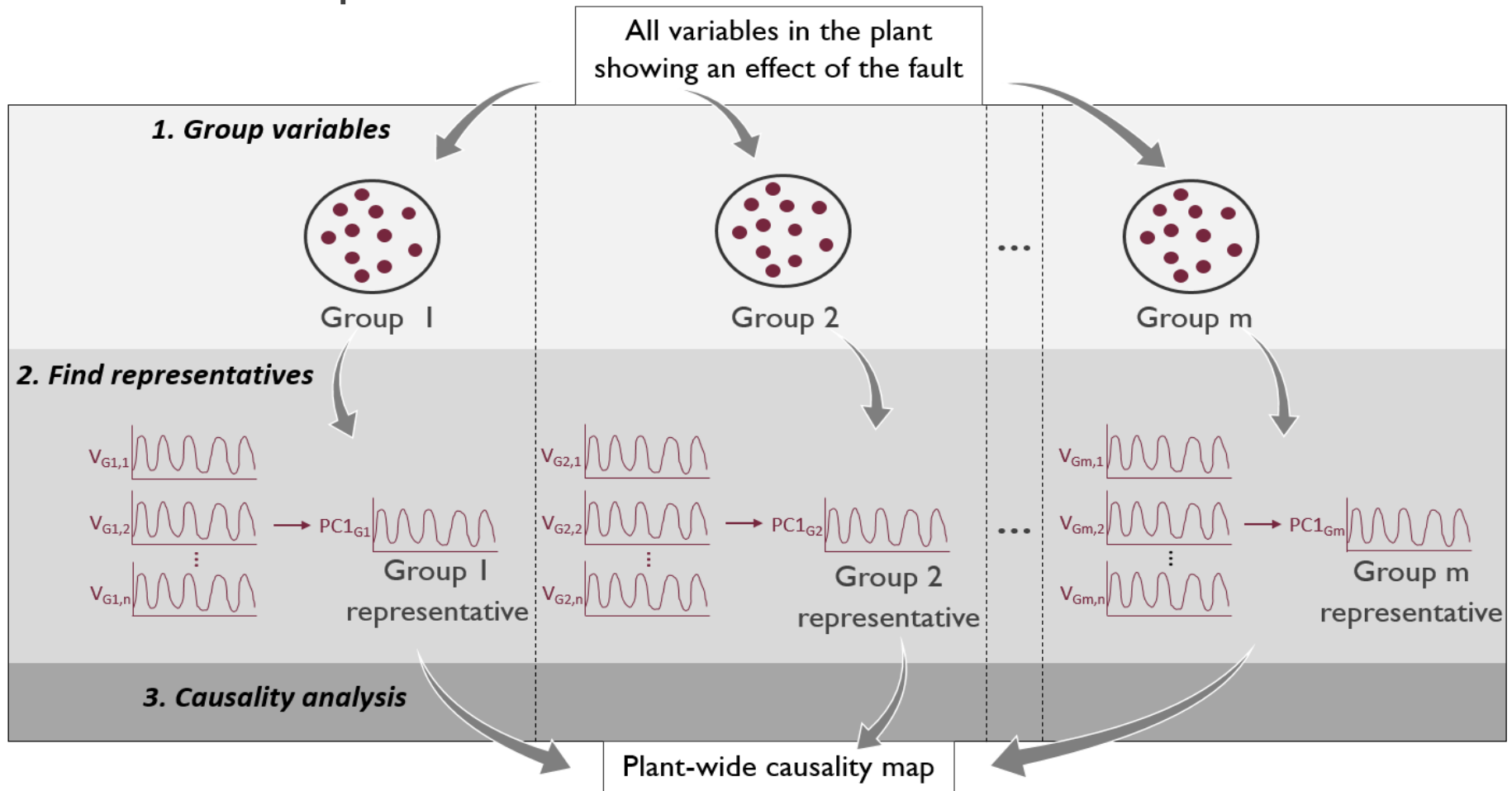
- Localise fault to smaller section

2. Map 2: Detailed map of smaller section

- Localise root cause to specific variable/control loop/process unit

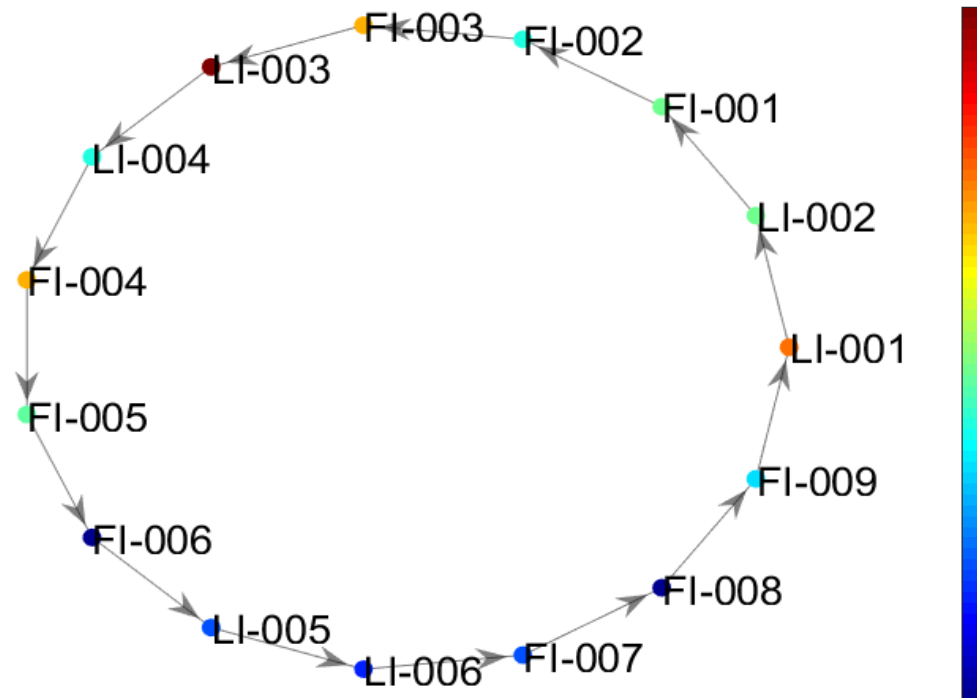
Hierarchical approach

Plant-wide map:



Hierarchical approach

Current approach: Transitive reduction (TR)

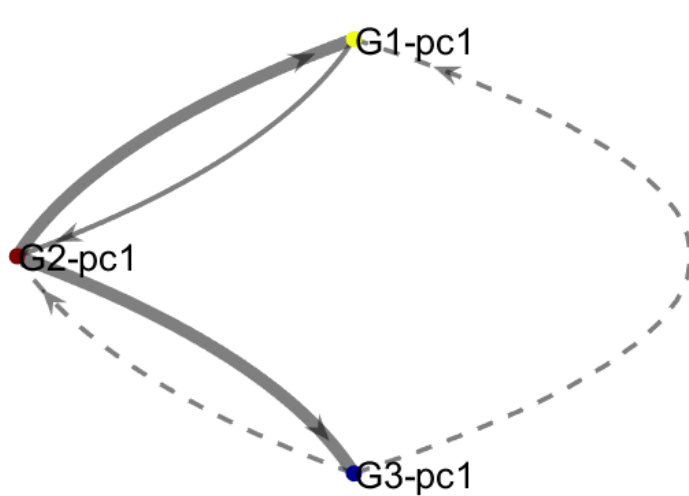


- Many variables
- No clear root cause

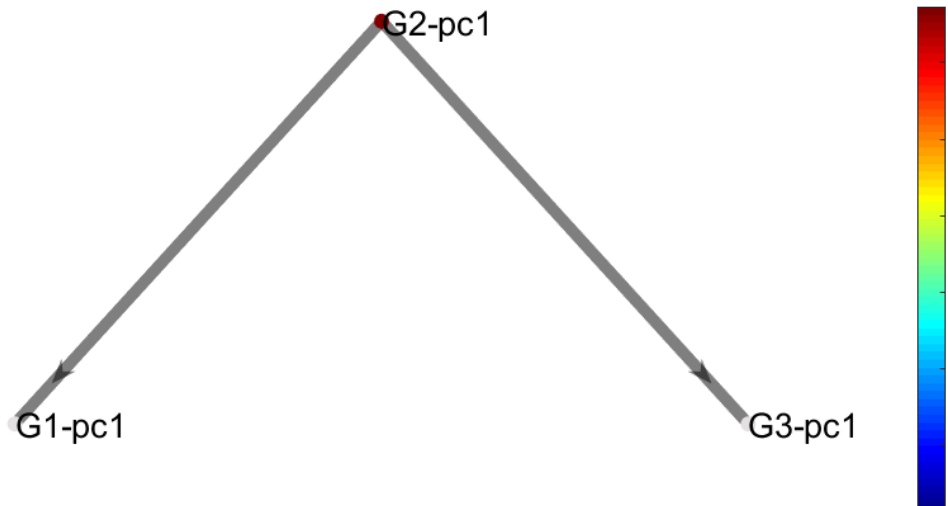
Hierarchical approach

PS-PCI:

- Variables grouped according to plant sections
- 1st principal component represents each group of variables



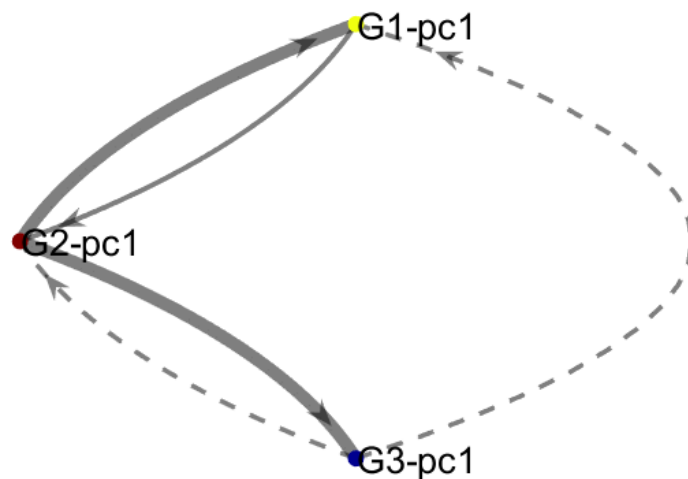
$\alpha = 0.05$



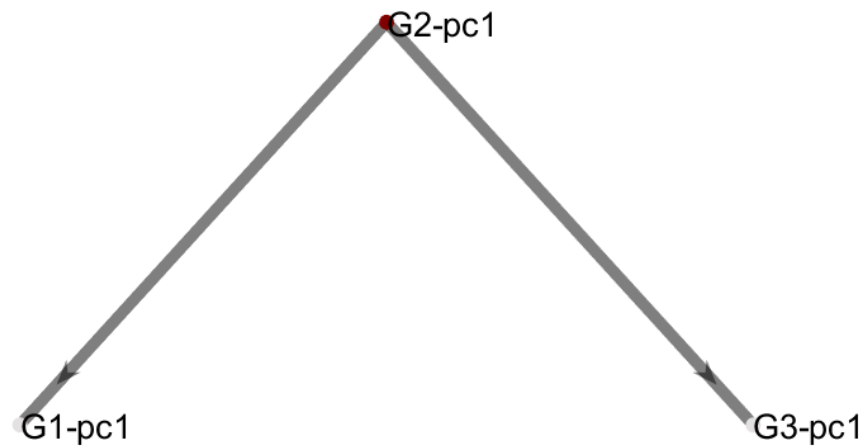
$\alpha = 0.01$

PS-PCI advantages:

- Clearly identifies true root cause location: G1-pc1 (PS2)
- Fewer nodes improves interpretability
- Requires significantly fewer samples: 602 vs. 13 562 for standard map/TR
- Tools for interpretation can be adapted for application to PS-PCI



$\alpha = 0.05$



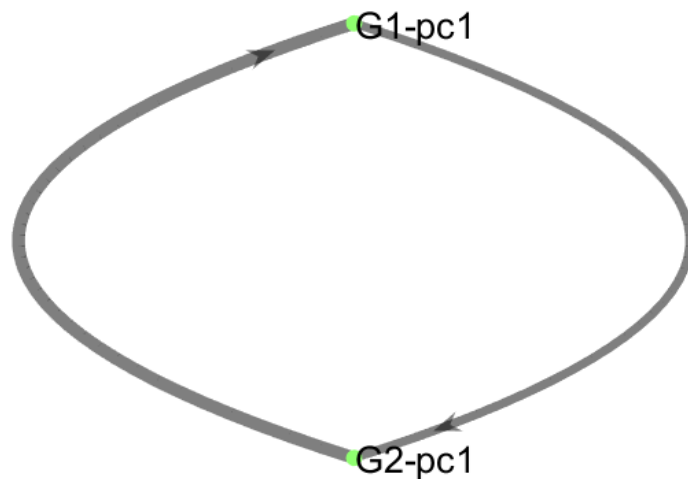
$\alpha = 0.01$



Hierarchical approach

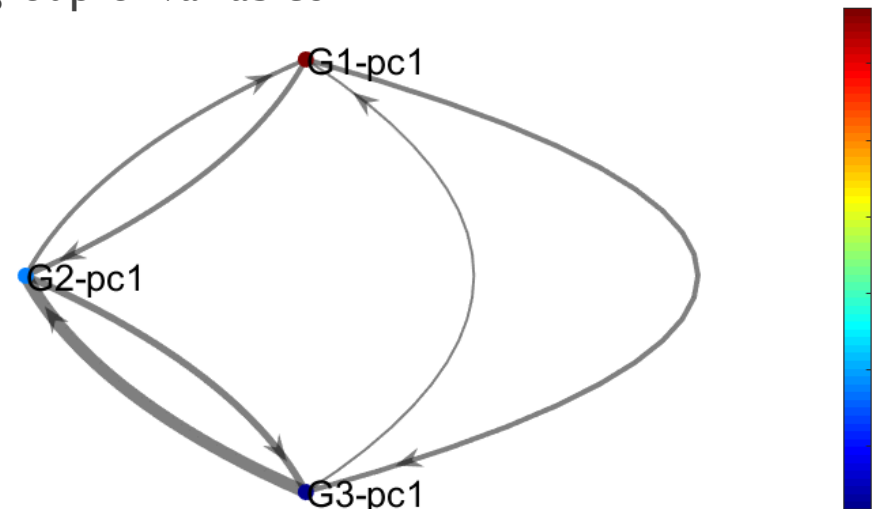
Mod-PCI:

- Variables grouped according to modules identified in the data
- 1st principal component represents each group of variables



$\alpha = 0.05$ or $\alpha = 0.01$ (in standard map)

G1		G2
LI 003	LI 005	LI 001
LI 004	LI 006	LI 002
FI 004	FI 007	FI 001
FI 005	FI 008	FI 002
FI 006	FI 009	FI 003



$\alpha = 1 \times 10^{-16}$ (in standard map)

G1		G2	G3
LI 001	LI 005	LI 004	LI 003
LI 002	FI 008	LI 006	FI 004
FI 001		FI 007	FI 005
FI 002			FI 006
FI 003			FI 009

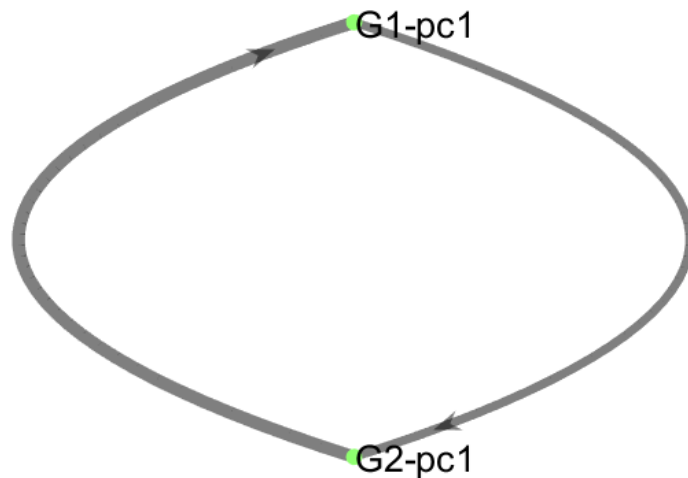
Hierarchical approach

Mod-PCI advantages:

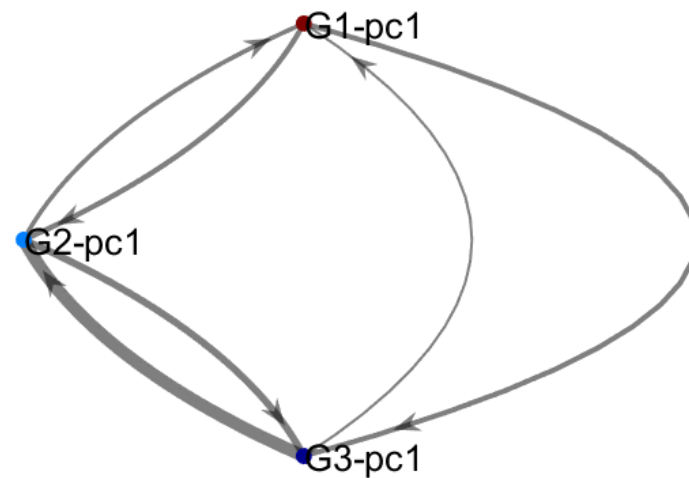
- Fewer nodes improves interpretability

Mod-PCI disadvantages:

- Does not identify true root cause location
- Does not require fewer samples than standard map (because modularisation is performed from standard map)
- Does not support connections validation with P&ID



27 $\alpha = 0.05$ or $\alpha = 0.01$ (in standard map)
G1 = true root cause location

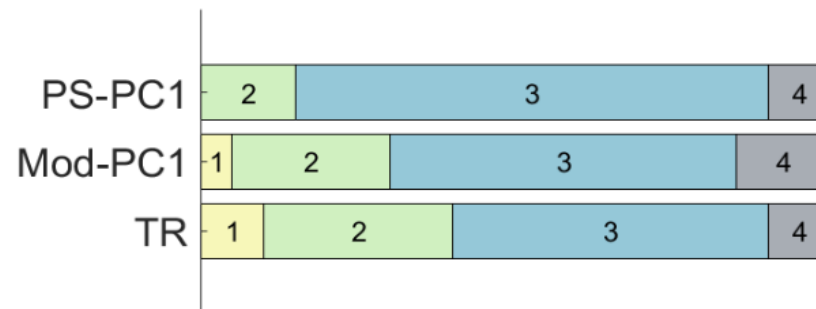


$\alpha = 1 \times 10^{-16}$ (in standard map)
G3 = true root cause location



Usability study - Survey

- 20 responses:
 - ❖ SU final-year/postgraduate students: 10
 - ❖ Employees of an industrial IoT firm: 6
 - ❖ AAP employees: 4 😊
- Main results:
 - ❖ Participants indicated user-friendliness (1 = least user-friendly & 4 = most user-friendly)



- From best to worst: (1) **PS-PCI**, (2) Mod-PCI, (2) TR

- Themes that arose from open-ended questions:
 - ❖ Process knowledge & causality analysis experience
 - The user should have process knowledge AND process knowledge should be incorporated in the causality map itself.
 - Causality analysis training is required for effective and accurate application and interpretation.
 - ❖ Grouping variables
 - Fewer variables allows for easier interpretation.
 - Grouping according to plant sections is preferable, because:
 1. It's more intuitive; it introduces process knowledge
 2. Grouping according to modules adds confusion
 3. Data-based modules can end up with numerous variables

❖ Accuracy during simplification

- “anything that simplifies the map is good (assuming it stays correct)”
- Concern w.r.t. using only PCI to represent a group of variables, as important info can be lost in subsequent PCs
 - Counter-argument: Using more PCs decreases interpretability & PS-PCI in this project identifies correct root cause location

❖ Sliders

- Sliders add confusion, because the maps change completely according to the sliders
- Slightly less confusion when there is only one slider

- Standard conditional GC is not suitable for plant-wide causality analysis:
 - ❖ Requires large amounts of data
 - ❖ AIC is not suitable for model order selection
 - Consider using BIC, cross-validation, or checking known connection strength at different model orders
 - Future studies can treat hyperparameter (e.g. model order) selection as an optimisation problem – although unclear what overall performance function would be
- Incorporating process knowledge decreases spurious connections
 - ❖ Improves confidence in connections
- Visually displaying node rankings is especially helpful for cyclic maps

Conclusions & recommendations

- Sliders add confusion
 - ❖ Rather perform variable selection once-off prior to causality analysis calculation
- Mod-PCI is not wrong; it is just not useful
- PS-PCI is the most promising approach
 - ❖ Clearly identified correct root cause location
 - ❖ Requires less data
 - ❖ Improved interpretability due to fewer nodes



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Thank you!

Any questions?



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