Identification in interconnected systems – modelling and structural aspects
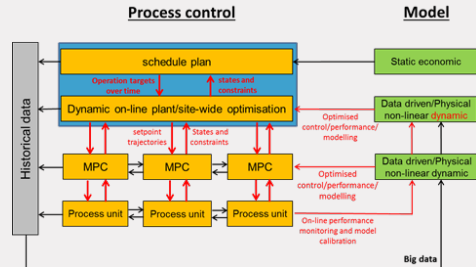
Paul Van den Hof

Five Decades of Systems and Control Theory in Groningen,
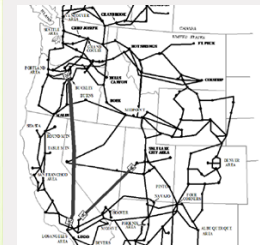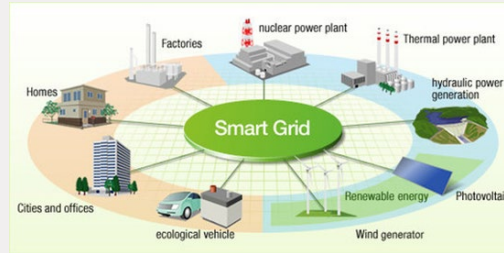University of Groningen
21-22 September 2023

www.sysdynet.eu
www.pvandenhof.nl
p.m.j.vandenhof@tue.nl

Introduction – dynamic networks
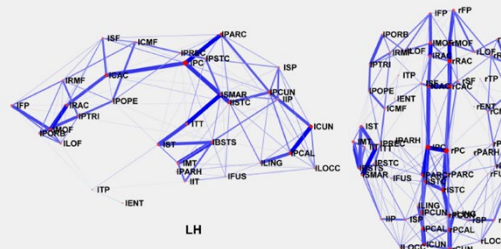
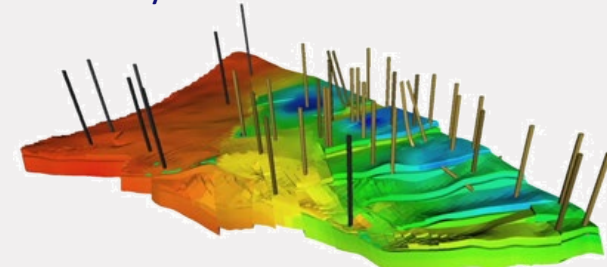## Decentralized process control

Smart power grid

Pierre et al. (2012)

Complex machines

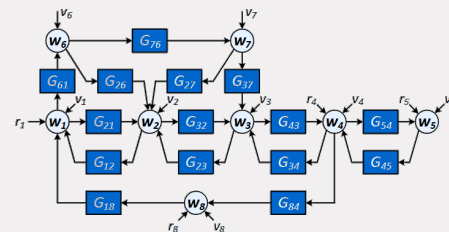
Brain network

P. Hagmann et al. (2008)

Hydrocarbon reservoirs

Mansoori (2014)

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Network models

- scalable, describing the physics
- dynamic elements with cause-effect
- handling feedback loops (cycles)
- combining physical and cyber components
- centered around measured signals
- allow disturbances and probing signals
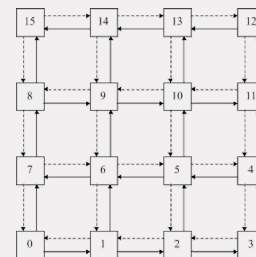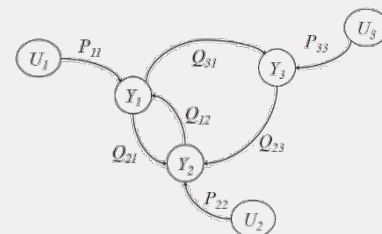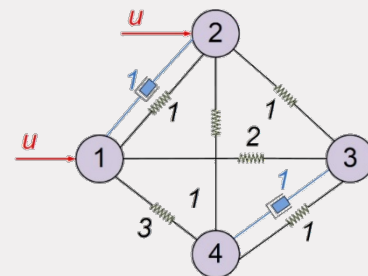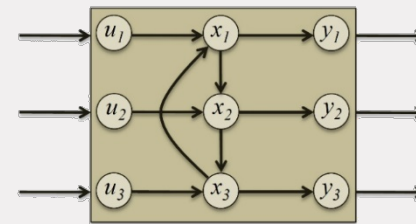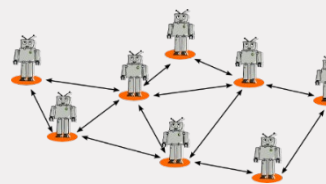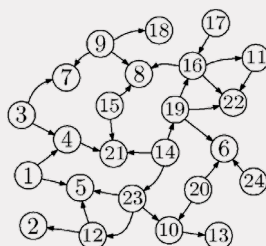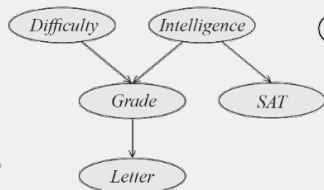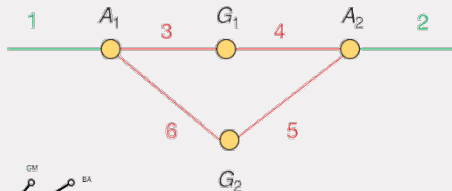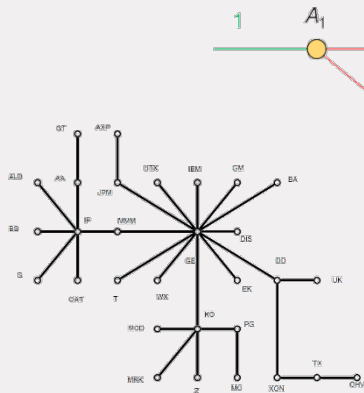
D. Materassi and M.V. Salapaka (2012)

R.N. Mantegna (1999)

www.momo.cs.okayama-u.ac.jp
J.C. Willems (2007)
D. Koller and N. Friedman (2009)

E.A. Carara and F.G. Moraes (2008)

P.E. Paré et al (2013)

P.M.J. Van den Hof et al (2013)
X.Cheng (2019)
E. Yeung et al (2010)

4

Network models
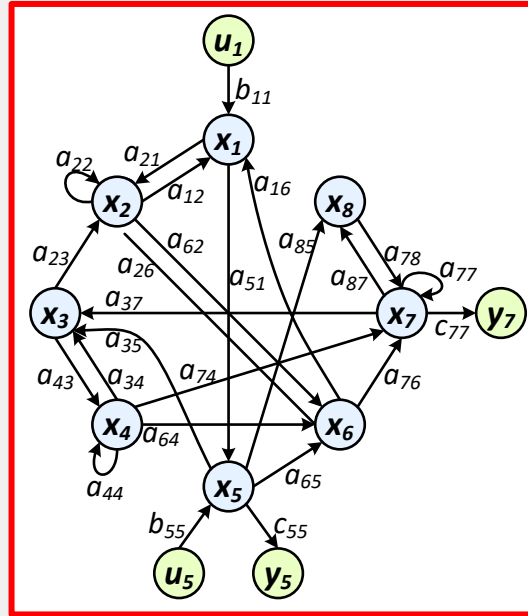
State space representation

$$
\begin{aligned}
x(k+1) &= Ax(k) + Bu(k) \\
y(k) &= Cx(k) + Du(k)
\end{aligned}
$$

- States as **nodes** in a (directed) graph
- State transitions (1 step in time) reflected by a_{ij}
- Transitions are encoded in links
- Ultimate break-down of system structure
- Actuation (u) and sensing (y) reflected by separate links

For data-driven modeling problems:

- Lump unmeasured states in dynamic **modules**

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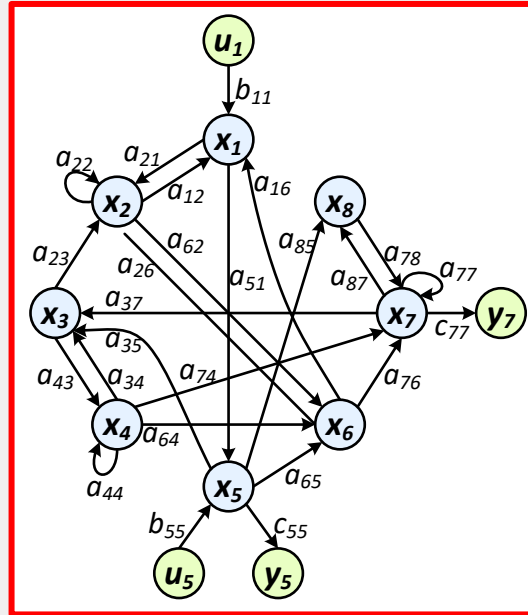
Network models

State space representation [1]
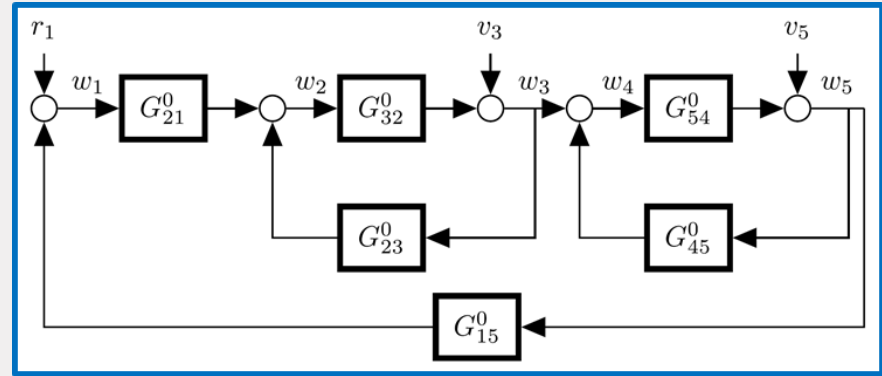
Module representation [2]

[1] Goncalves, Warnick, Sandberg, Yeung, Yuan, Scherpen,…

[2] VdH, Dankers, Goncalves, Warnick, Gevers, Bazanella, Hendrickx, Materassi, Weerts,…

Dynamic network models - zooming
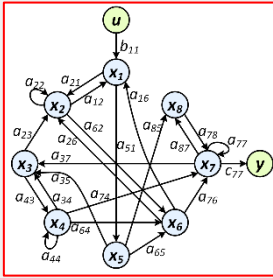
Increasing level of detail
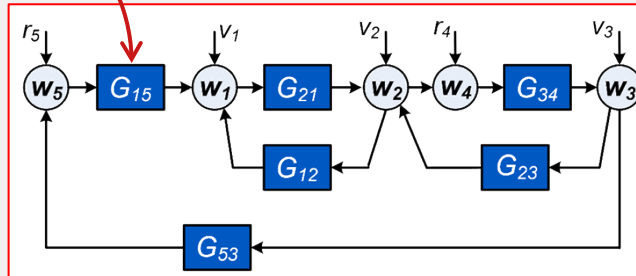
Decreasing structural information

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Dynamic network setup

G_{76}	module
r_i	external excitation
v_i	process noise
w_i	node signal
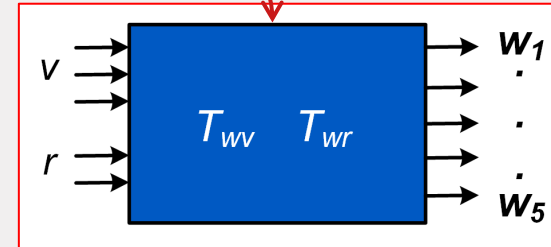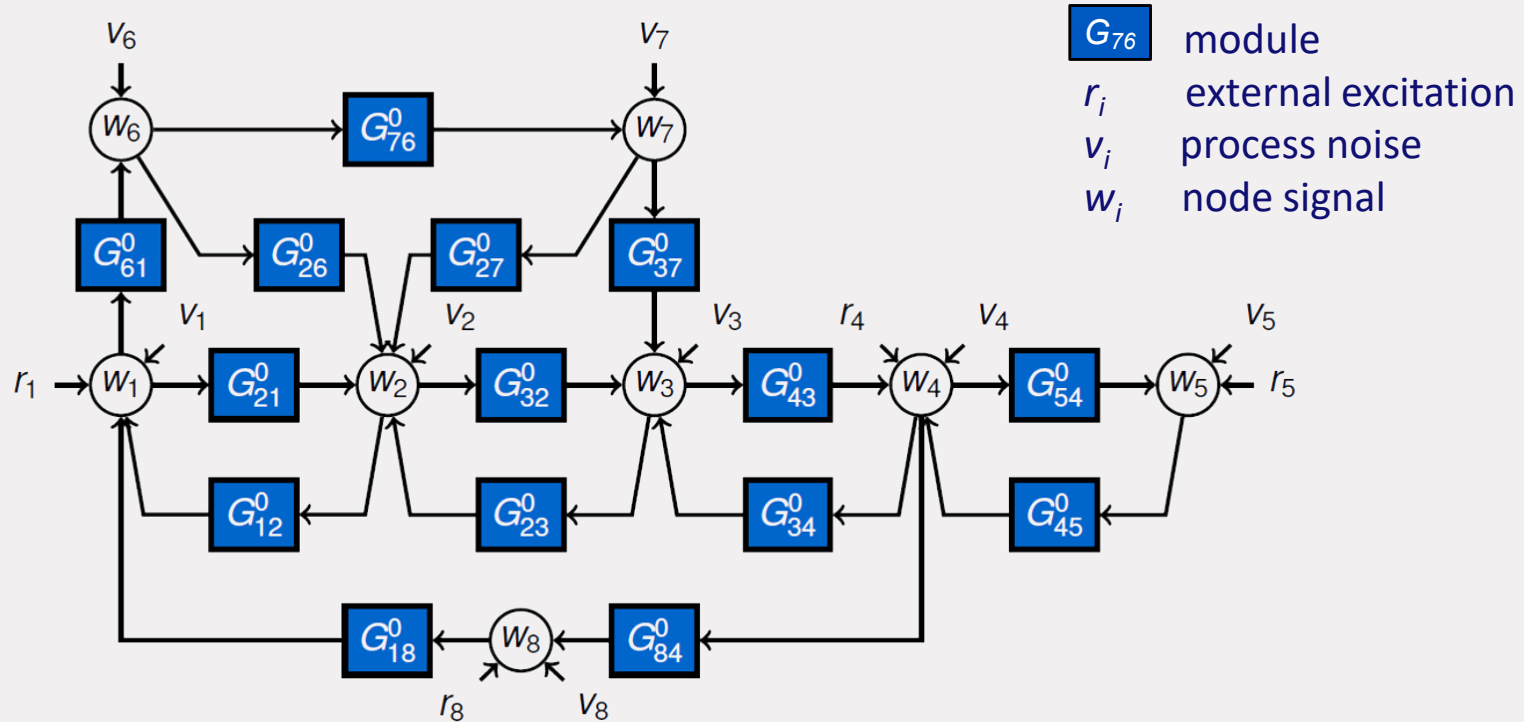
Dynamic network setup

Collecting all equations:

$$
\begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_L \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & G^0_{12} & \cdots & G^0_{1L} \\ G^0_{21} & 0 & \ddots & G^0_{2L} \\ \vdots & \ddots & \ddots & \vdots \\ G^0_{L1} & G^0_{L2} & \cdots & 0 \end{bmatrix}}_{\text{Network matrix } \boldsymbol{G^0(q)}} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_L \end{bmatrix} + R^0 \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_K \end{bmatrix} + H^0 \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_p \end{bmatrix}
$$

$$
w(t) = G^0(q)w(t) + \underbrace{R^0(q)r(t)}_{\boldsymbol{u(t)}} + v(t); \qquad v(t) = H^0(q)e(t); \quad cov(e) = \Lambda
$$

- Typically R^0 is just a (static) selection matrix, indicating which nodes have an excitation signal.

- The topology of the network is encoded in the structure (non-zero entries) of G^0.

- r and e are called external signals.

J. Gonçalves and S. Warnick, IEEE TAC, 2008.
PVdH et al., Automatica, 2013.

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Dynamic network setup
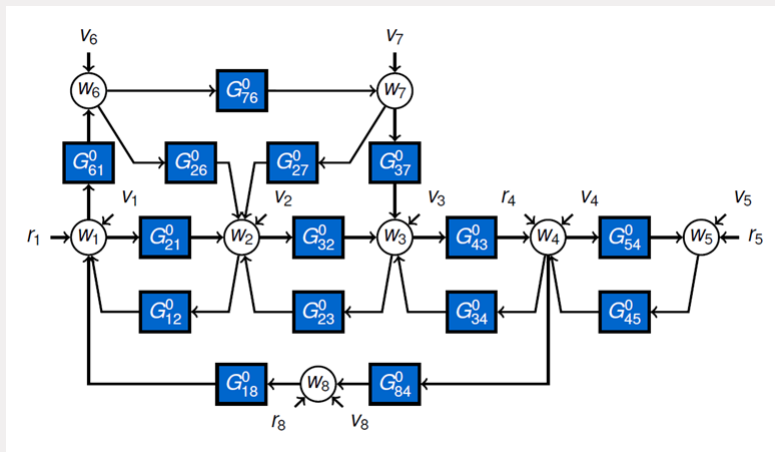
Measured time series:
$$\{w_i(t)\}_{i=1,\cdots L}; \quad \{r_j(t)\}_{j=1,\cdots K}$$

Many challenging data-driven modeling and diagnostics challenges appear

- Identification of a local module (known topology)
- Identification of the full network
- Topology estimation
- Identifiability
- Sensor and excitation allocation
- Diagnostics and fault detection
- User prior knowledge of modules
- Distributed identification
- Scalable algorithms

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Application: Printed Circuit Board (PCB) Testing
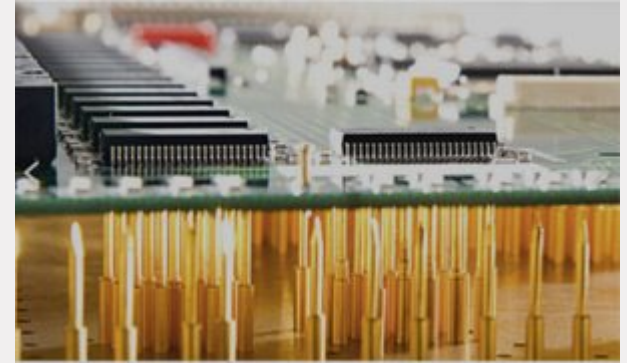
Source: Altium

Detection of

- component failures

- parasitic effects

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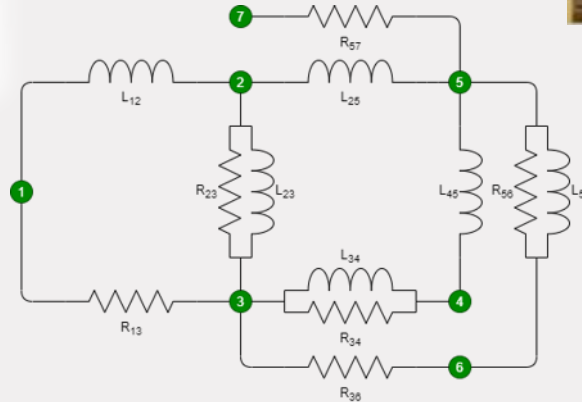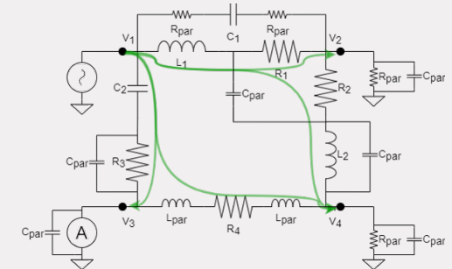
Single module identification

Single module identification
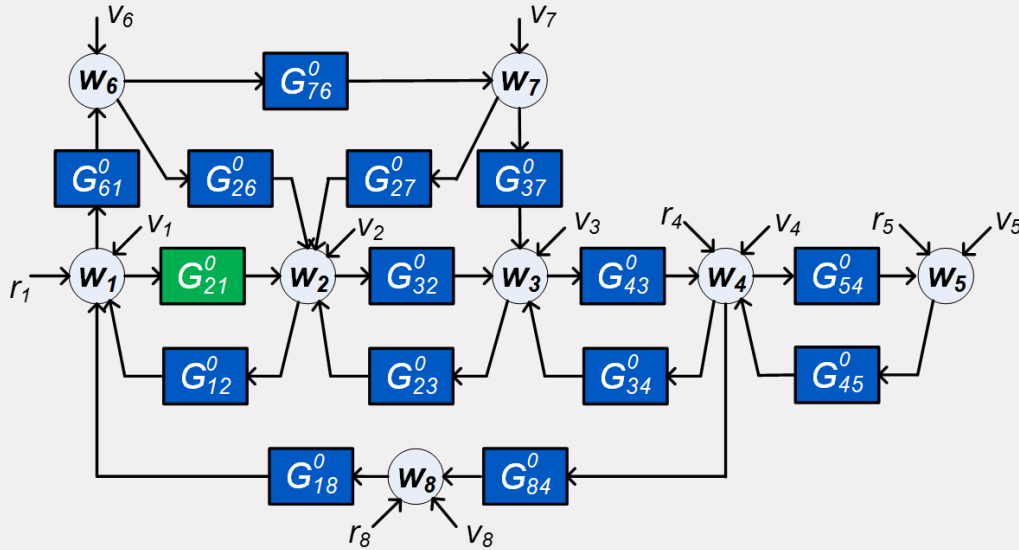
For a network with **known topology**:

- Identify G_{21}^0 on the basis of measured signals
- Which signals to measure? Preference for local measurements
- When is there enough excitation / data informativity?

Single module identification
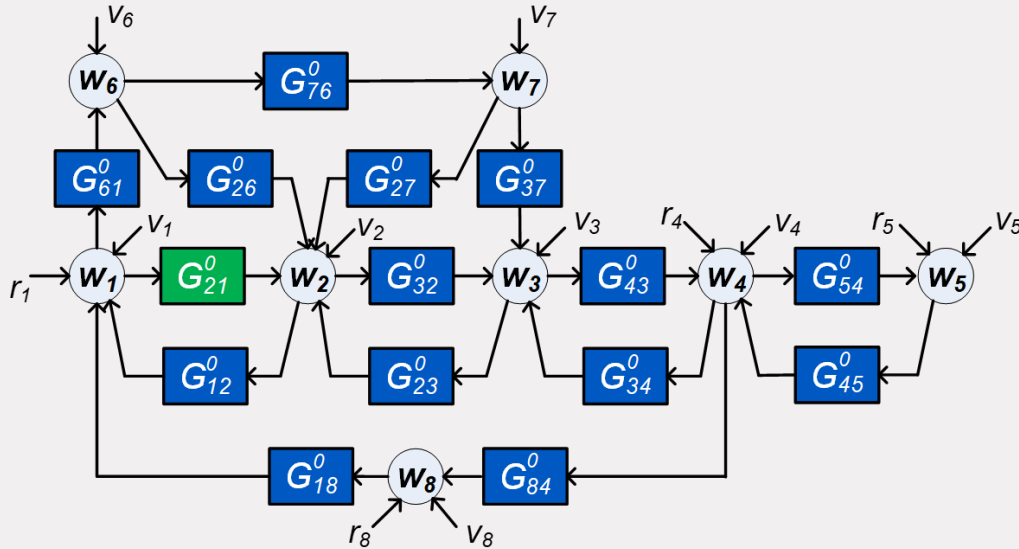
Different types of methods:

Indirect methods:

- Rely on mappings $r \rightarrow w$ and on sufficient excitation signals r

Direct methods:

- Rely on mappings $w \rightarrow w$ and use excitation from both r and v signals

Single module identification – local direct method

Select a subnetwork:

- Predicted outputs: $w_{\mathcal{Y}}$
- Predictor inputs: $w_{\mathcal{D}}$

such that prediction error minimization leads to an accurate estimate of G_{21}^0
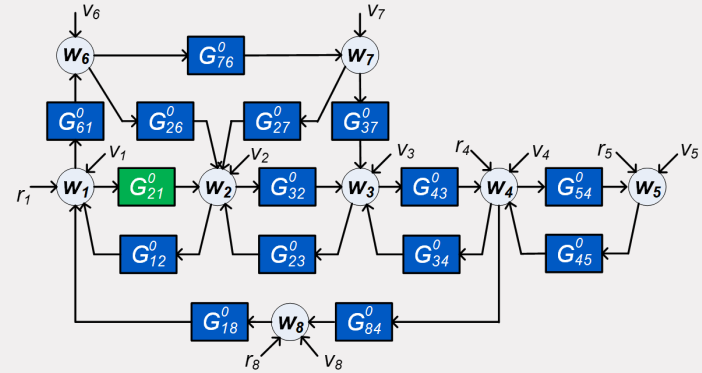
$$w_{\mathcal{Y}}(t) = \bar{G}(q,\theta)w_{\mathcal{D}}(t) + \bar{H}(q,\theta)\xi_{\mathcal{Y}}(t) + \bar{J}(q,\theta)u_{\mathcal{K}}(t) + \bar{S}u_{\mathcal{P}}(t)$$
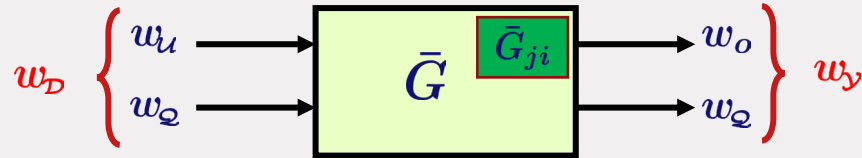
Note: same node signals can appear in input and output
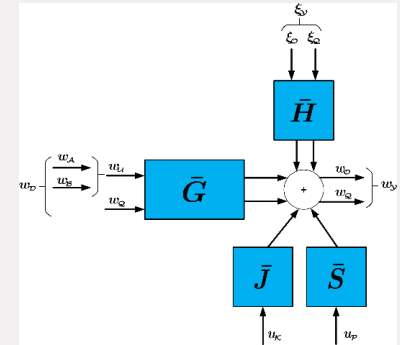
TU/e

Single module identification
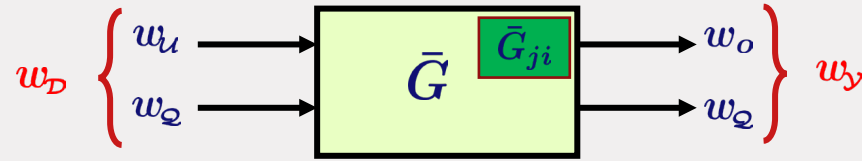
Conditions for arriving at a consistent model estimate:

1. Module invariance: $\bar{G}_{ji} = G_{ji}^0$

2. Handling of confounding variables

3. Data-informativity

4. *Technical conditions on presence of delays*

Path-based conditions on the selected signals and the network graph

Single module identification
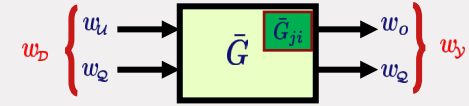
Conditions for arriving at a consistent model estimate:

1. Module invariance: $\bar{G}_{ji} = G_{ji}^0$
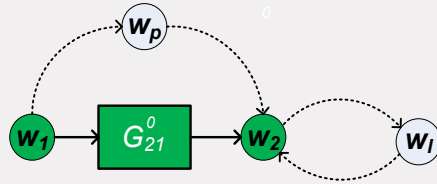
PPL condition: all parallel paths and loops around the output should be blocked by a measured node that is present in $w_{\mathcal{D}}$

2. Handling of confounding variables
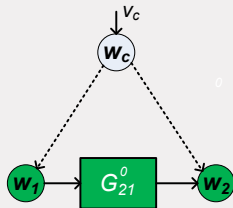
No correlated disturbances between $w_{\mathcal{Y}}$ and signals in $w_{\mathcal{U}}$ that are in-neighbors of $w_{\mathcal{Y}}$

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Single module identification
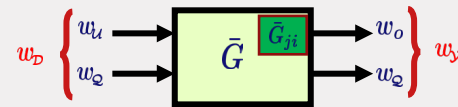
Conditions for arriving at a consistent model estimate:

3. Data informativity:

$$w_{\mathcal{Y}}(t) = \bar{G}(q,\theta)w_{\mathcal{D}}(t) + \bar{H}(q,\theta)\xi_{\mathcal{Y}}(t) + \bar{J}(q,\theta)u_{\mathcal{K}}(t) + \bar{S}u_{\mathcal{P}}(t)$$

The inputs of the predictor model should receive enough excitation from external signals (e- and u-signals)

Sufficient condition: $\boxed{\Phi_{\kappa}(\omega) > 0 \text{ for almost all } \omega}$ for $\kappa(t) := \begin{bmatrix} w_{\mathcal{D}}(t) \\ \xi_{\mathcal{Y}}(t) \\ u_{\mathcal{K}}(t) \end{bmatrix}$

κ persistently exciting holds **generically** if there are $dim(\kappa)$ **vertex disjoint paths** between external signals $\{u,e\}$ and κ

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Data informativity (classical definition)

Predictor model: $\hat{w}_y(t, \theta) = W(q, \theta) z(t)$

for a model set $\mathcal{M}$ parametrized by $\theta \in \Theta$

Then a data sequence $\{z(t)\}_{t=0,\ldots}$ is informative with respect to $\mathcal{M}$ if for any two models in $\mathcal{M}$:

$$\bar{\mathbb{E}}[(W_1(q) - W_2(q)) z(t)]^2 = 0 \implies W_1(e^{i\omega}) \equiv W_2(e^{i\omega})$$

A sufficient condition for this is that z is persistently exciting:

$$\Phi_z(\omega) > 0 \quad \text{for almost all } \omega$$

[1] L. Ljung, Englewood Cliffs, NJ: Prentice-Hall, 1999

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Single module identification

Different synthesis algorithms can provide predictor models that satisfy the conditions

Multiple solutions
for either full/partial
measurement

Typical result:

required excitation signals
increases with
increasing # outputs
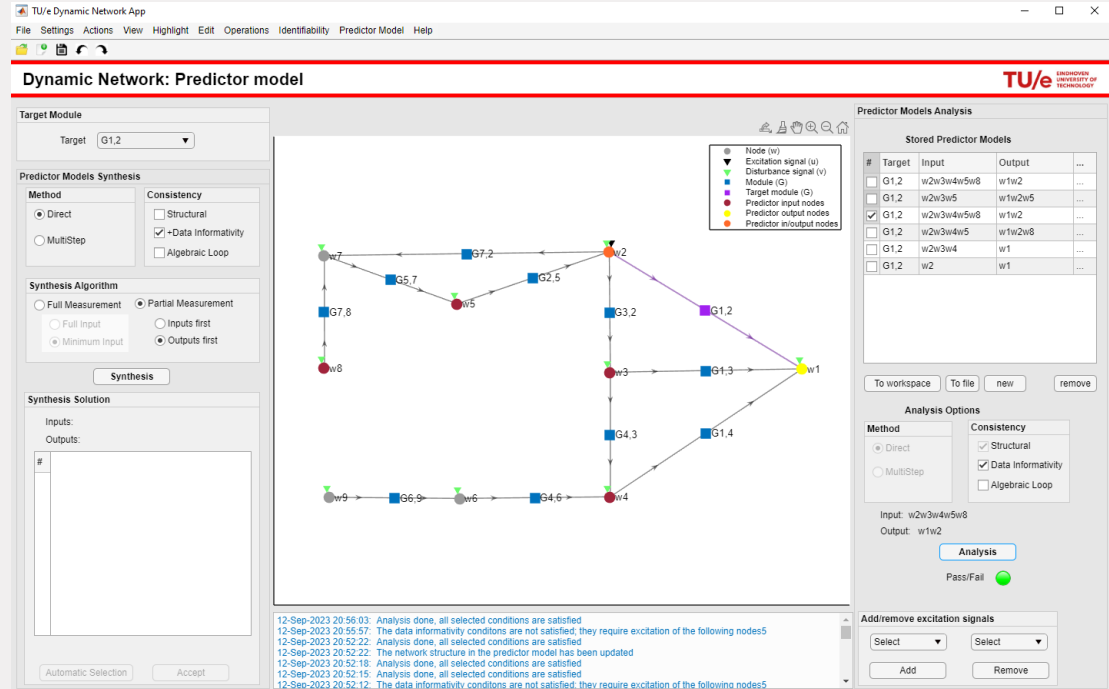
[1] K.R. Ramaswamy et al., IEEE-TAC, 2021. [3] Control Systems Group TU/e, SYSDYNET Toolbox for MATLAB, 2023, www.sysynet.net.

[2] S.J.M. Fonken et al., CDC, 2023.

Summary single module identification

- Path-based conditions that the predictor model should satisfy

- Different algorithms for synthesizing predictor model

- Degrees of freedom in sensor / actuator placement

- Onec a predictor model is constructed, estimation comes down to a "classical" MISO/MIMO estimation problem

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Generic network identifiability

Full network identification
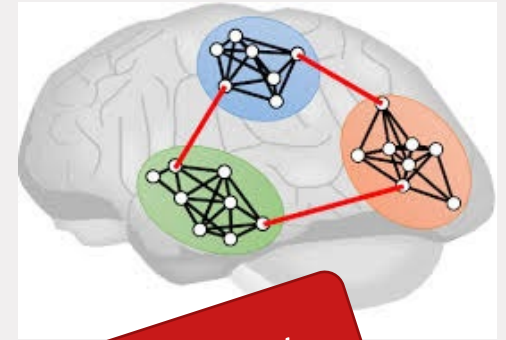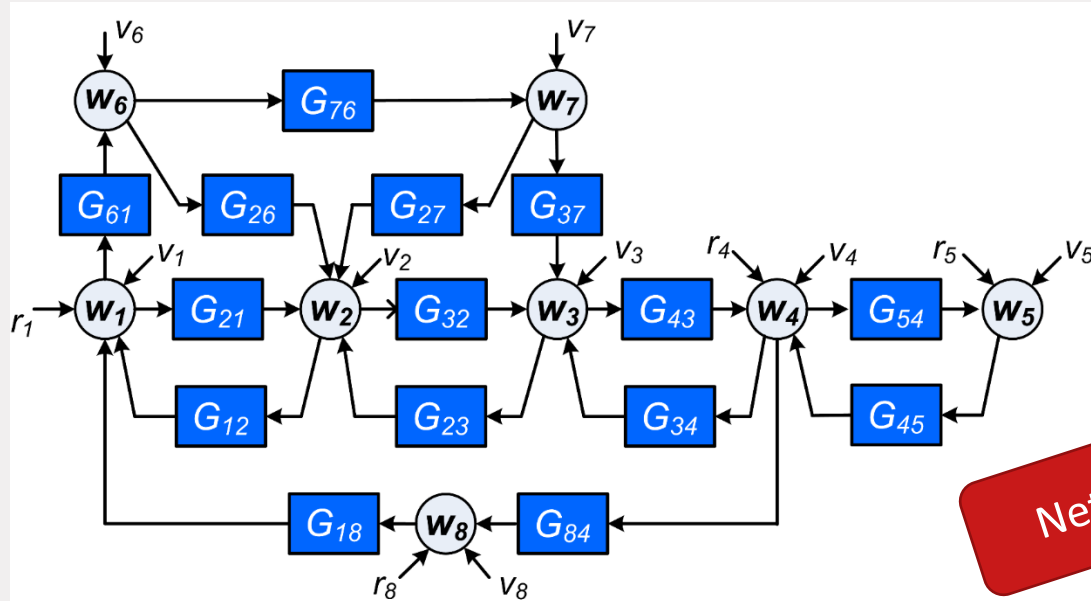
Network identifiability

Under which conditions can we estimate the topology and/or dynamics of the full network?

Network identifiability
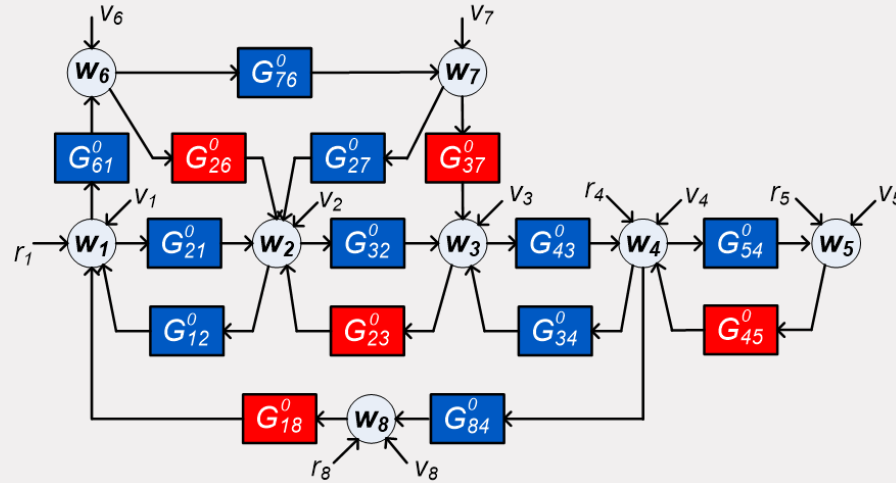
blue = unknown
red = known

Question: Can different dynamic networks be *distinguished* from each other from measured signals *w , r* ?

Network identifiability

The identifiability problem:

The network **model**:

$$w(t) = G(q)w(t) + R(q)r(t) + \underbrace{H(q)e(t)}_{v(t)}$$

can be transformed with any rational $P(q)$:

$$P(q)w(t) = P(q)\{G(q)w(t) + R(q)r(t) + H(q)e(t)\}$$

to an **equivalent model**:

$$w(t) = \tilde{G}(q)w(t) + \tilde{R}(q)r(t) + \tilde{H}(q)e(t)$$

➡ **Nonuniqueness,** unless there are structural constraints on G, R, H.
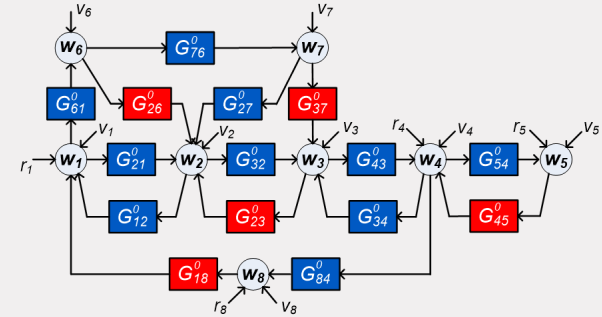
[1] Weerts, Linder et al., Automatica, 2019.
[2] Bottegal et al., SYSID 2017

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Network identifiability

Consider a **network model set**:

$$\mathcal{M} = \{(G(\theta), R(\theta), H(\theta))\}_{\theta \in \Theta}$$

representing structural constraints on the considered models:
- modules that are fixed and/or zero (topology)
- locations of excitation signals
- disturbance correlation

Generic identifiability of $\mathcal{M}$:

    - There do not exist distinct equivalent models (generating the same data)
    - for almost all models in the set.

[1] Weerts et al., SYSID2015; Weerts et al., Automatica, March 2018;
[2] Bazanella, CDC2017; Hendrickx et al., IEEE-TAC, 2019.

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Example 5-node network

Conditions for identifiability ➡ rank conditions on transfer function
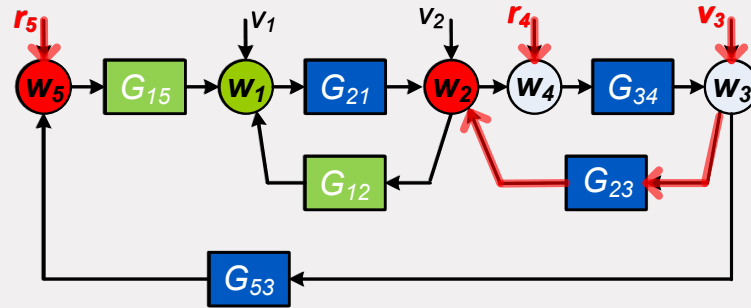
Full row rank of mapping

| External signals that do not enter w_j through a parametrized module | ➡ | Node signals that enter w_j through a parametrized module |

For the **generic case**, the rank can be calculated by a graph-based condition[1],[2] :

Generic rank = number of vertex-disjoint paths

2 vertex-disjoint paths → full row rank 2 ✅
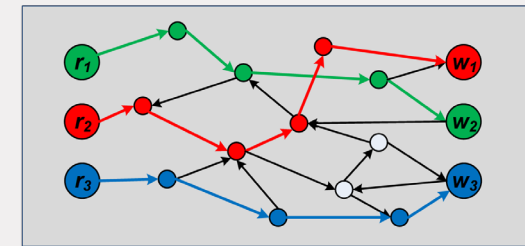
The rank condition has to be checked for all nodes.

[1] Van der Woude, 1991.
[2] Hendrickx, Gevers & Bazanella, CDC 2017, TAC 2019.
[3] H. van Waarde et al., TAC, 2019.

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Synthesis solution for network identifiability

Allocating external signals for generic identifiability:

1. Cover the graph of the network model set by a set of **disjoint pseudo-trees**

   Pseudo-trees:

   Tree with root in green   Cycle with outgoing trees;
                                    Any node in cycle is root
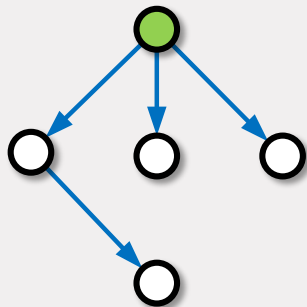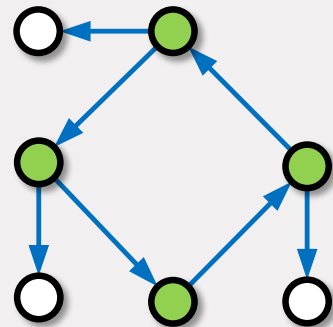
   Indegree of all nodes ≤ 1

   Edges are **disjoint** and all out-neighbours of a node are in the same pseudo-tree

2. Assign an independent external signal (r or e) at a root of each pseudo-tree.

   This guarantees generic identifiability of the model set.

[1] X. Cheng, S. Shi and PVdH, TAC, February 2022.

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Where to allocate external excitations for network identifiability?
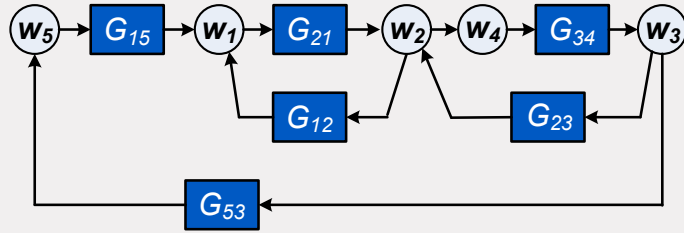
All indicated modules are parametrized
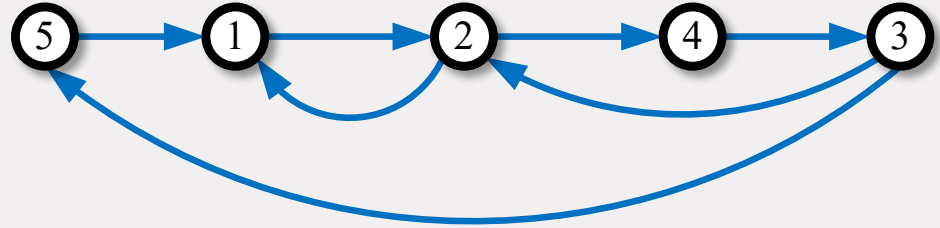
Two disjoint pseudo-trees
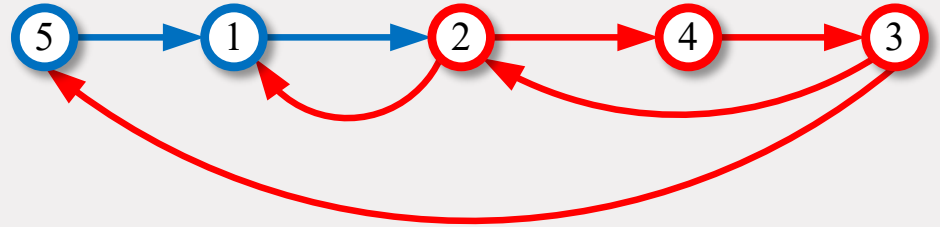
Where to allocate external excitations for network identifiability?
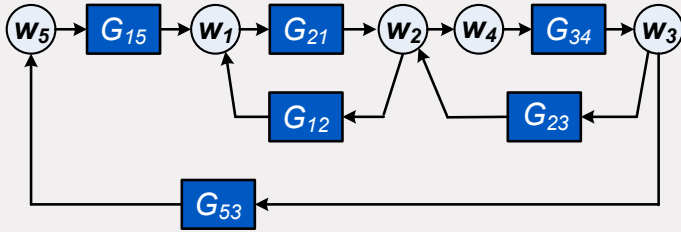
Two independent excitations
guarantee
generic network identifiability

[1] X. Cheng, S. Shi and PVdH, CDC 2019.

TU/e

Where to allocate external excitations for network identifiability?

Pseudo-tree
merging
algorithm [1]
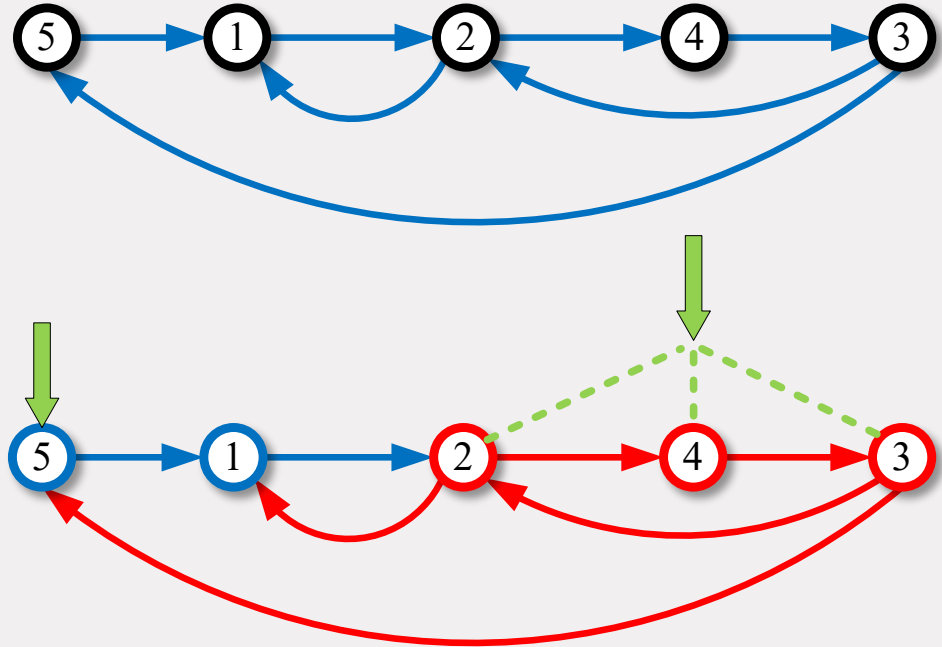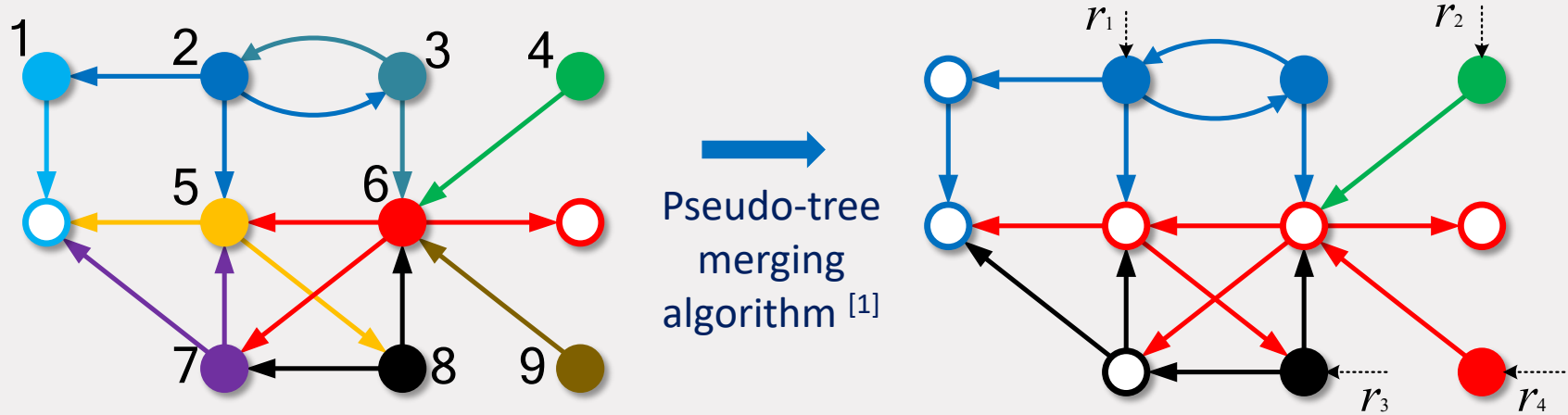
- Nodes are signals w and external signals (r, e) that are input to a parametrized link

- Known (nonparametrized) links do not need to be covered

[1] X. Cheng, S. Shi and PVdH, TAC, February 2022.

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Merging algorithm

Consider the disjoint pseudotree covering: $\{\mathcal{T}_1, \cdots \mathcal{T}_n\}$

Construct the mergability matrix $\mathfrak{M}$ with

$$\mathfrak{M}_{ij} = \begin{cases} 1 & \text{if } \mathcal{T}_i \text{ is mergeable to } \mathcal{T}_j \\ \varnothing & \text{if there are no common vertices in } \mathcal{T}_i \text{ and } \mathcal{T}_j, \\ 0 & \text{otherwise} \end{cases}$$

Merging is represented by an algebraic row- and column operation on $\mathfrak{M}$

Final reduction step

After allocation, evaluate (path-based test) whether any of the excitation signals is superfluous

8-node example

When 4 (dashed) edges are known
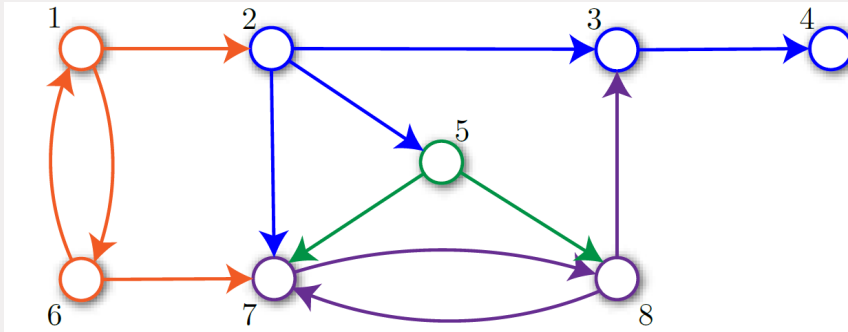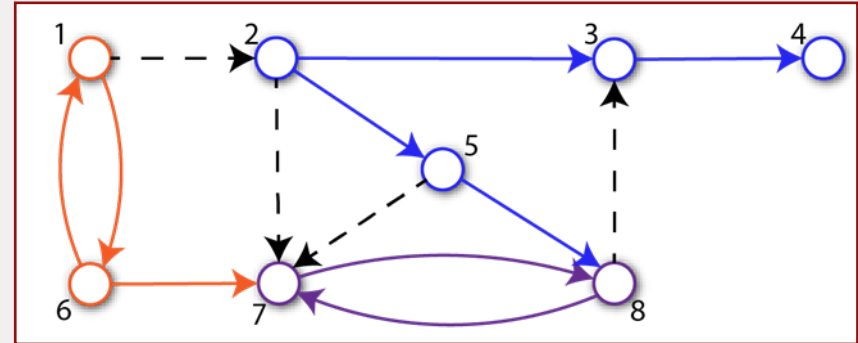
Network graph covered by 4 edge-disjoint pseudo-trees
Four external signals added for identifiability: (1 or 6), (7 or 8), 2 and 5

Network graph covered by 3 edge-disjoint pseudo-trees
Three external signals added for identifiability: (1 or 6), (7 or 8), and 2

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Conservatism of current solution

2 pseudo-trees for all edges parametrized

Dashed edges are fixed.
Parametrized edges covered by 2 pseudo-trees (4-2-3, 5-1)

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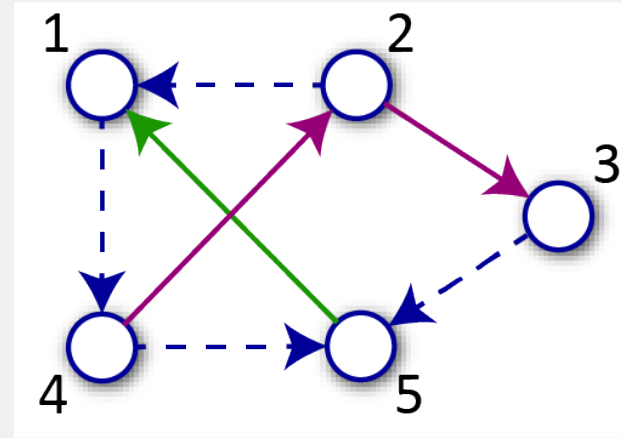
Conservatism of current solution
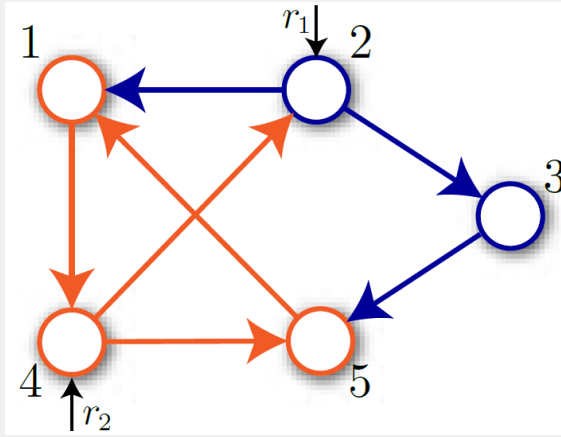
2 pseudo-trees for all edges parametrized
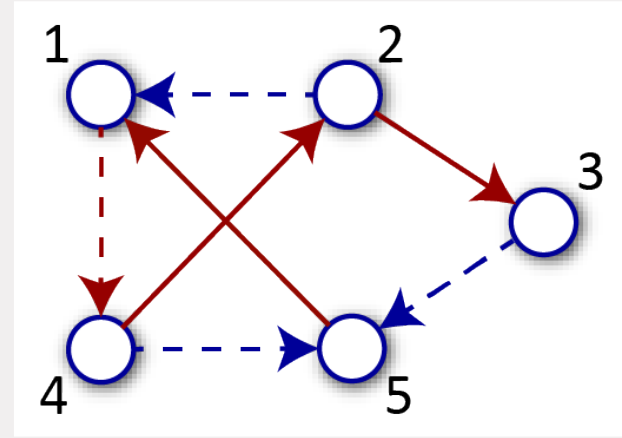
Dashed edges are fixed.
Parametrized edges covered by 2 pseudo-trees (4-2-3, 5-1)

But: all parametrized edges can be covered by 1 pseudo-tree: (5-1-4-2-3)

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New approach: explicit incorporation of fixed edges

Define **multi-rooted graph:** directed graph for which there is a nonempty set of roots from all of which there exist paths to every vertex in the graph.

Define **single source identifiable multi-rooted graph (SIMUG):** multi-rooted graph where each vertex has an indegree *of parametrized edges* ≤ 1.

Define **edge-disjoint SIMUGs:** no common edges and for each vertex all outgoing edges are in the same SIMUG.

Result:
Generic network identifiability holds if:
- All *parametrized edges* in the network graph are covered by edge-disjoint SIMUGs, and
- An external signal (r or e) is applied to one vertex in the root set of every SIMUG.

[1] M. Dreef et al, CDC 2022.

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Examples of SIMUGs
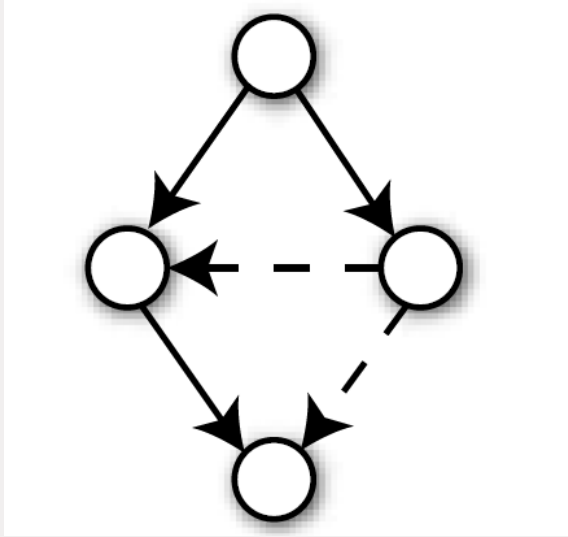
One SIMUG
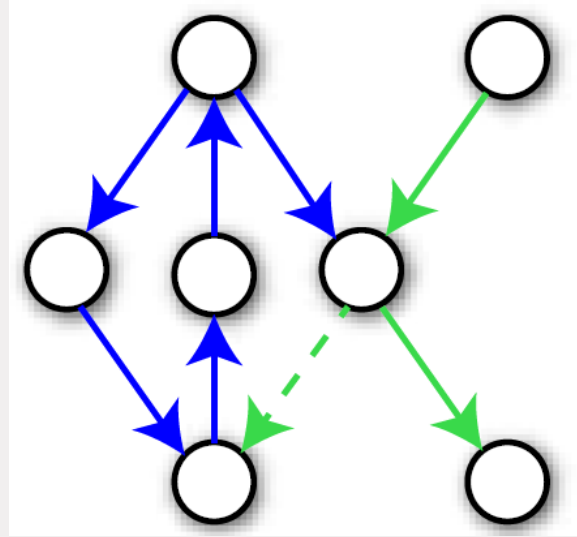
Two edge-disjoint SIMUGs
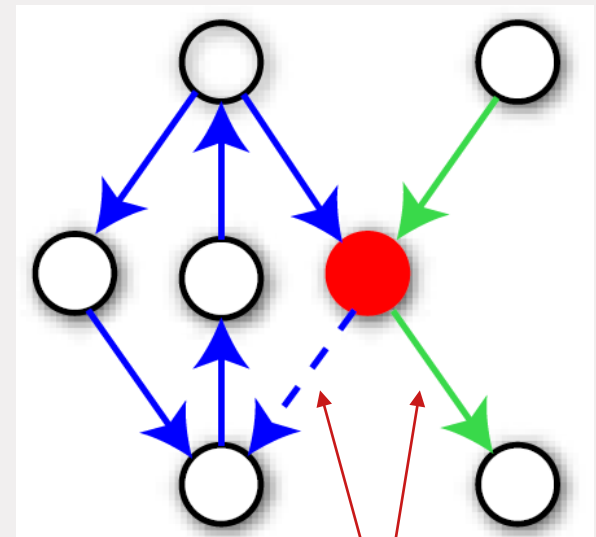
Two SIMUGs,
but not edge-disjoint

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Applied to 8-node example with fixed links:

Dashed links are fixed (known modules)
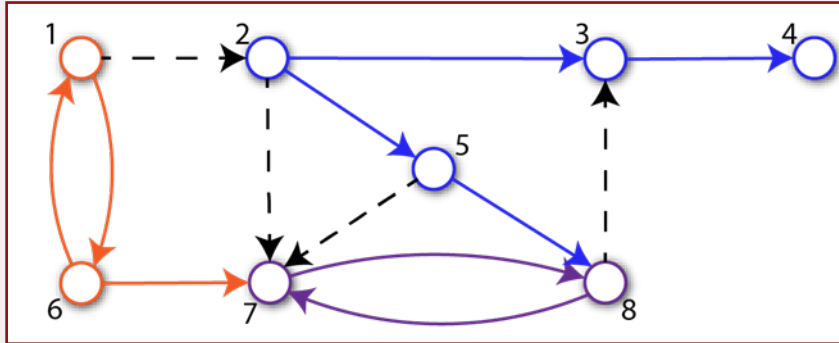
Network graph covered by 3 edge-disjoint pseudo-trees
Three external signals added for identifiability: (1 or 6), (7 or 8), and 2
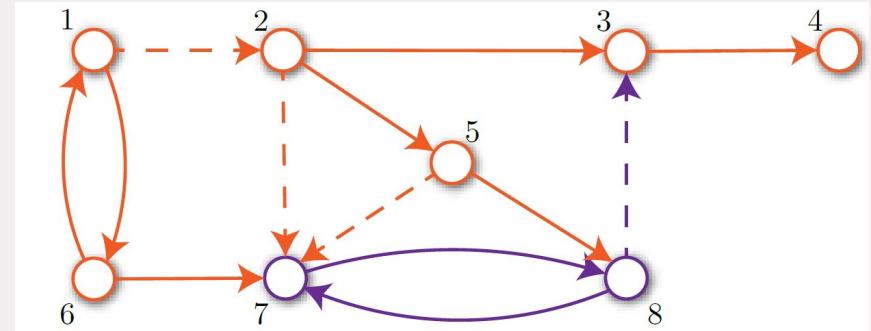
Network graph covered by 2 edge-disjoint SIMUGs
Two external signals required for identifiability: (1 or 6) and (7 or 8)

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Synthesis algorithm available in the SYSDYNET toolbox:

[1] Control Systems Group TU/e, SYSDYNET Toolbox for MATLAB, 2023, www.sysynet.net.
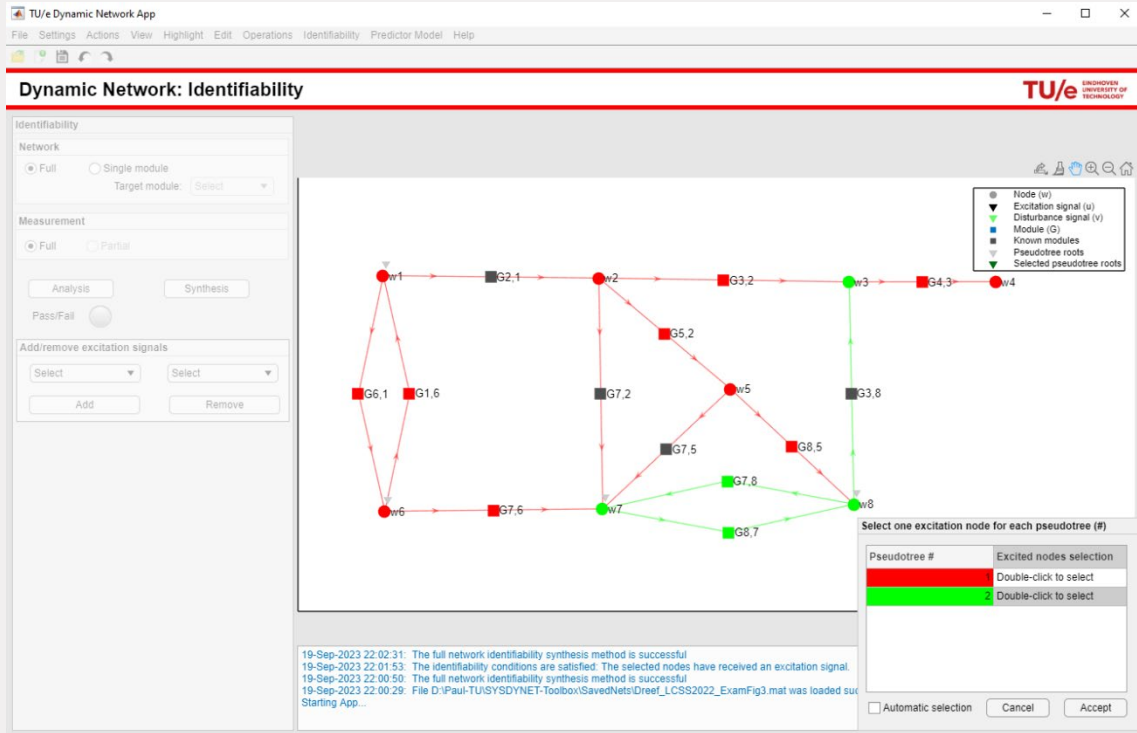
Merging algorithm – slight adaptation

Consider the disjoint SIMUG covering: $\{\mathcal{T}_1, \cdots \mathcal{T}_n\}$
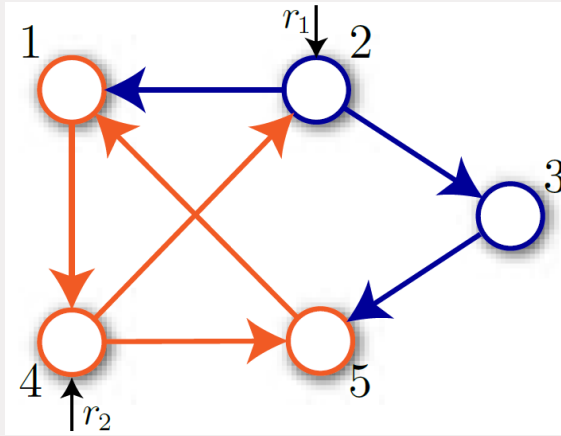
Construct the mergability matrix $\mathfrak{M}$ with

$$\mathfrak{M}_{ij} = \begin{cases} 1 & \text{if } \mathcal{T}_i \text{ is mergeable to } \mathcal{T}_j \\ \varnothing & \text{if there are no vertices in } \mathcal{T}_i \cup \mathcal{T}_j \text{ with multiple parametrized incoming links,} \\ 0 & \text{otherwise} \end{cases}$$

Merging is represented by an algebraic row- and column operation on $\mathfrak{M}$

Summary

Identifiability of network model sets is determined by

- Presence and location of external signals,
- Correlation of disturbances
- Topology of network: parametrized/fixed modules

- Graph-based method for synthesizing allocation of external signals

- that effectively exploits the presence of fixed (known) modules

- and can be executed through algebraic operations

- But reaching the minimum number of excitations is not guaranteed

Extensions:
- Situations where not all node signals are measured [1,2]

[1] A. Bazanella, CDC 2019.
[2] X. Cheng et al., TAC-TN, 2023.

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Diffusively coupled networks

Back to the basics of physical interconnections

In connecting physical systems, there is often no predetermined direction of information [1]
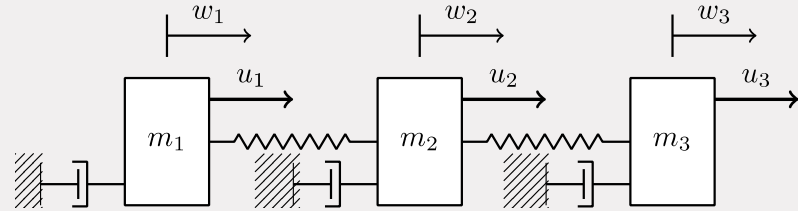
Example: resistor / spring connection in electrical / mechanical system:

Resistor

Spring

$$I = \frac{1}{R}(V_1 - V_2)$$

$$F = K(x_1 - x_2)$$

Difference of node signals drives the interaction: **diffusive coupling**

[1] J.C. Willems (1997,2010)

Diffusively coupled physical network
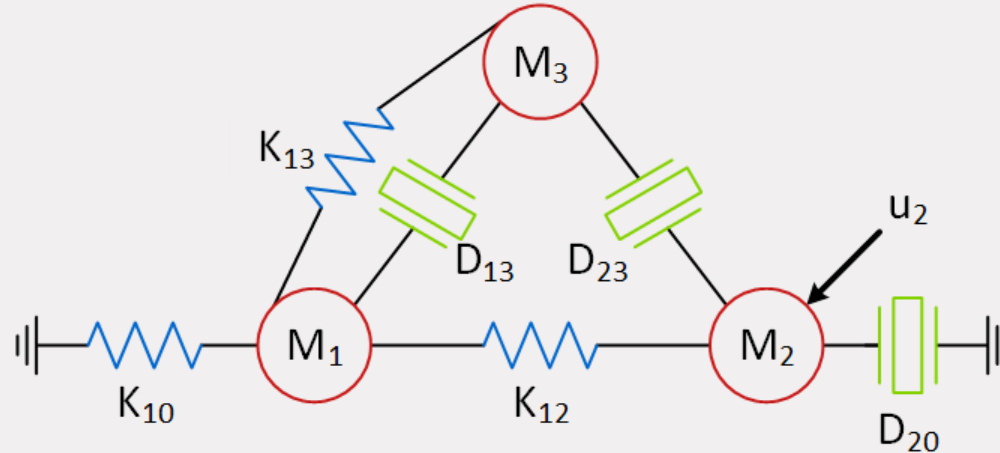
Equation for node j:

$$M_j \ddot{w}_j(t) + D_{j0}\dot{w}_j(t) + \sum_{k \neq j} D_{jk}(\dot{w}_j(t) - \dot{w}_k(t)) + K_{j0}w_j(t) + \sum_{k \neq j} K_{jk}(w_j(t) - w_k(t)) = u_j(t),$$

Mass-spring-damper system

- Masses M_j
- Springs K_{jk}
- Dampers D_{jk}
- Input u_j
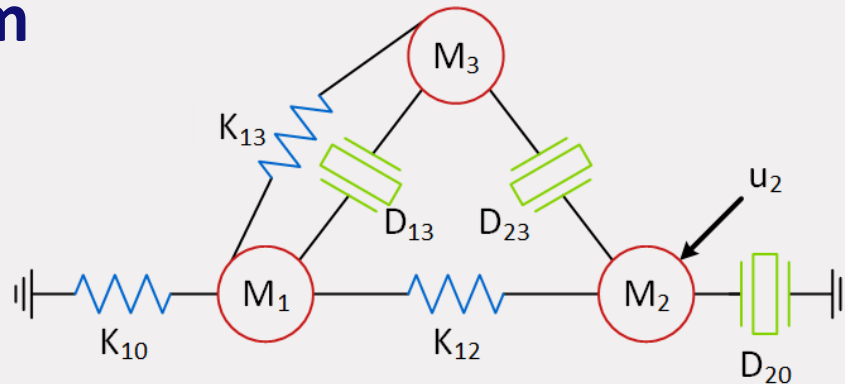
$$\begin{bmatrix} M_1 & & \\ & M_2 & \\ & & M_3 \end{bmatrix} \begin{bmatrix} \ddot{w}_1 \\ \ddot{w}_2 \\ \ddot{w}_3 \end{bmatrix} + \begin{bmatrix} 0 & & \\ & D_{20} & \\ & & 0 \end{bmatrix} \begin{bmatrix} \dot{w}_1 \\ \dot{w}_2 \\ \dot{w}_3 \end{bmatrix} + \begin{bmatrix} K_{10} & & \\ & 0 & \\ & & 0 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}$$

$$+ \begin{bmatrix} D_{13} & 0 & -D_{13} \\ 0 & D_{23} & -D_{23} \\ -D_{13} & -D_{23} & D_{13}+D_{23} \end{bmatrix} \begin{bmatrix} \dot{w}_1 \\ \dot{w}_2 \\ \dot{w}_3 \end{bmatrix} + \begin{bmatrix} K_{12}+K_{13} & -K_{12} & -K_{13} \\ -K_{12} & K_{12} & 0 \\ -K_{13} & 0 & K_{13} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} = \begin{bmatrix} 0 \\ u_2 \\ 0 \end{bmatrix}$$

$$[\underbrace{X(p)}_{diagonal} + \underbrace{Y(p)}_{Laplacian}] w(t) = u(t) \qquad X(p), Y(p) \text{ polynomial} \qquad p = \frac{d}{dt}$$

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Mass-spring-damper system

$$[\underbrace{X(p)}_{diagonal} + \underbrace{Y(p)}_{Laplacian}] w(t) = u(t) \qquad X(p), Y(p) \text{ polynomial}$$

$$[\underbrace{Q(p)}_{diagonal} - \underbrace{P(p)}_{hollow\&symmetric}] w(t) = u(t)$$

This fully fits in the earlier module representation:

$$w(t) = Gw(t) + \underbrace{Rr(t) + He(t)}_{Q^{-1}(p)u(t)}$$

with the additional condition that:

$$G(p) = Q(p)^{-1} P(p) \qquad Q(p), P(p) \text{ polynomial}$$

$$P(p) \text{ symmetric}, \ Q(p) \text{ diagonal}$$

Module representation

Consequences for node interactions:
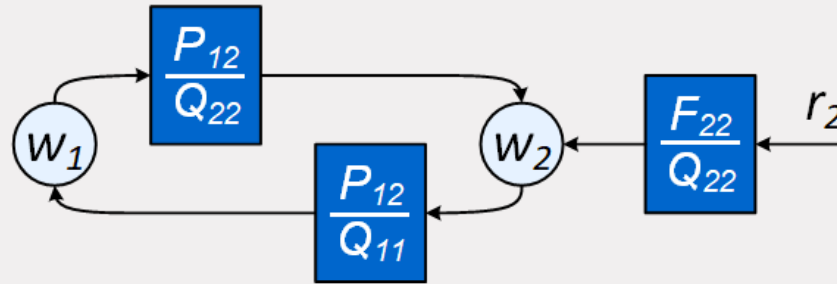
- Node interactions come in pairs of modules
- Where numerators are the same

Framework for network identification remains the same

- Symmetry can be incorporated in identifiability/identification

[1] E.M.M. Kivits et al., CDC 2019.

Polynomial representation

More attractive: stay within the polynomial domain (discrete-time now)

$$[\underbrace{Q(q^{-1})}_{diagonal} - \underbrace{P(q^{-1})}_{hollow\&symmetric}] w(t) = u(t)$$

$$A(q^{-1})w(t) = \underbrace{B(q^{-1})r(t) + v(t)}_{u(t)}$$

with $A(q^{-1})$ symmetric and nonmonic

i.e. $A(q^{-1}) = A_0 + A_1 q^{-1} + \cdots A_n q^{-n}$

with $A_0 \neq I$

Network identifiability[1]

New analysis, based on $T_{wr}(q)$ only (noise discarded because of algebraic loops):

$$A(q^{-1})w(t) = B(q^{-1})r(t)$$

$$\Pi(q^{-1}) \left[A(q^{-1})w(t) = B(q^{-1})r(t) \right]$$

Identifiability conditions:

- At least 1 excitation signal $r(t)$ present
- $A(q^{-1})$ and $B(q^{-1})$ left coprime
- diagonality constraint on $\begin{bmatrix} A_0 \cdots A_n & B_0 \cdots B_n \end{bmatrix}$
- $A(q^{-1})$ symmetric
- 1 parametric constraint in $A(q^{-1})$ or $B(q^{-1})$

- $B(q^{-1})$ present
- $\Pi(q^{-1})$ unimodular
- Π diagonal
- $\Pi = \alpha I$
- $\Pi = I$

[1] E.M.M. Kivits and PVdH, TAC 2023.

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Polynomial representation - identifiability

- **Identifiability conditions** are **strongly relaxed** (compared to module framework) in terms of number of excitation signals required.

- Diffusive couplings strongly limit the **degrees of freedom** in the network model

- Identification **algorithms** are available for both full network[1] and local identification[2].

[1] E.M.M. Kivits and PVdH, TAC 2023.
[2] E.M.M. Kivits and PVdH, CDC 2022.

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Summary diffusively coupled networks

- Interesting class of models, not extensively studied in identification

- Non-directed graphs

- Adhering to physical interconnections

- Framework is fit for representing **combined networks**
  (combining physical bi-directional links, and cyber uni-directional links)[1].

[1] E.M.M. Kivits, PhD-Thesis 2024 (to appear).

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Algorithms implemented in SYSDYNET Toolbox
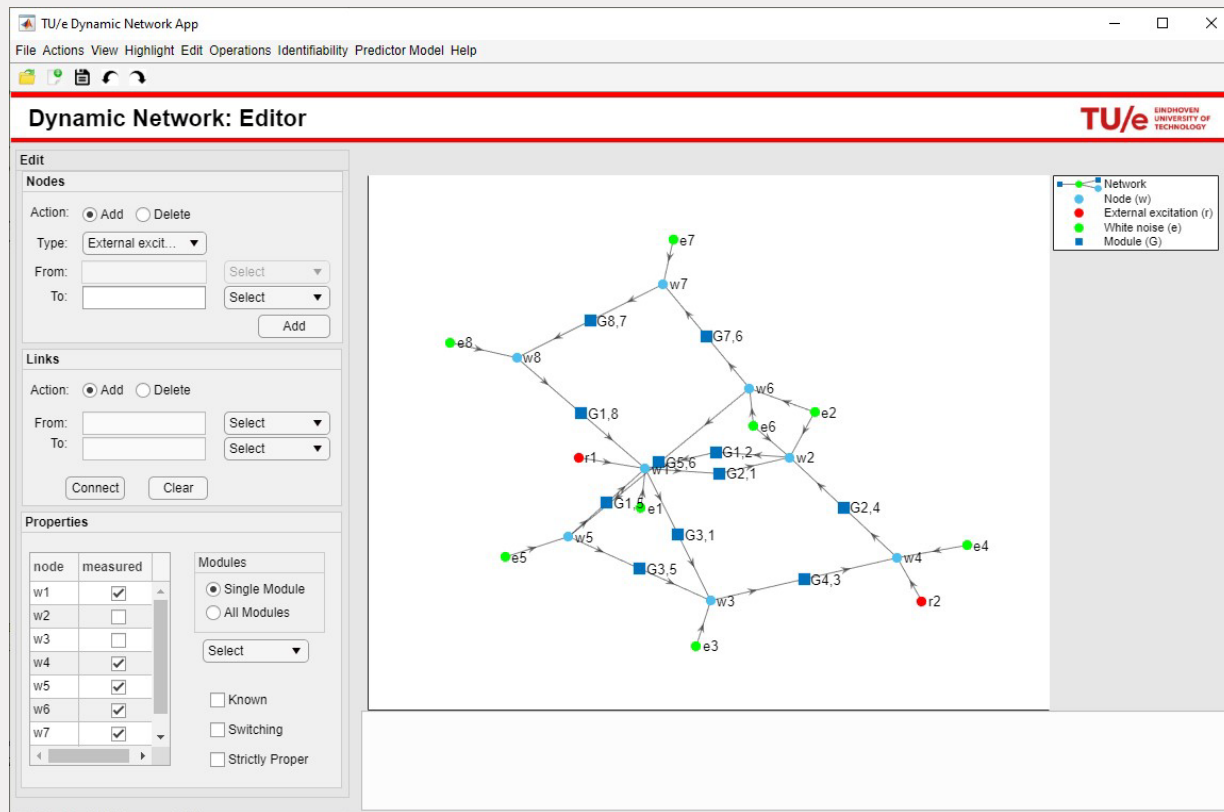
Structural analysis and operations on dynamic module networks

- Edit and manipulate
- Assign properties to nodes and modules
- Immersion of nodes, PPL test
- Generic identifiability analysis and synthesis
- Predictor model selection for single module ID

to be complemented with

- estimation algorithms for single module and full network ID;
- topology estimation

Beta-version 0.2.0, September 2023, to be downloaded from www.sysdynet.net

ERC SYSDYNET Team: data-driven modeling in dynamic networks

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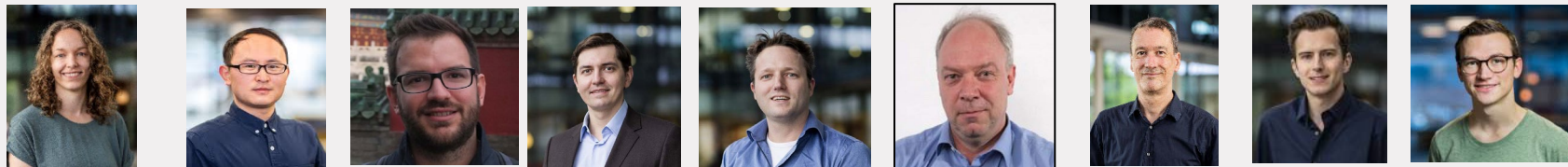
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Further reading

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Papers available at www.sysdynet.eu

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The end