SYSDYNET - App and Toolbox for data-driven modeling and diagnostics in dynamic networks

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App download: www.sysdynet.net

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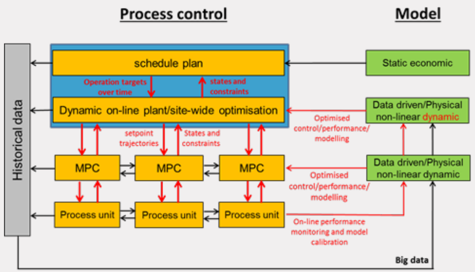
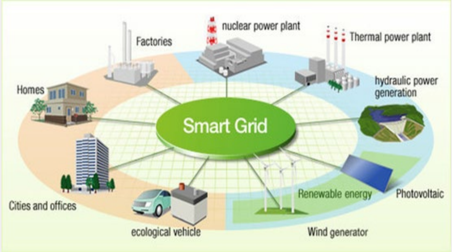
Introduction – dynamic networks

Decentralized process control



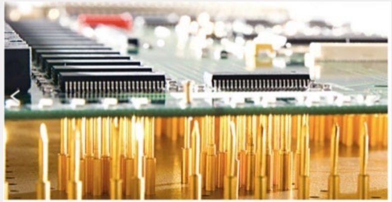
Smart power grid



Betterworldsolutions.eu

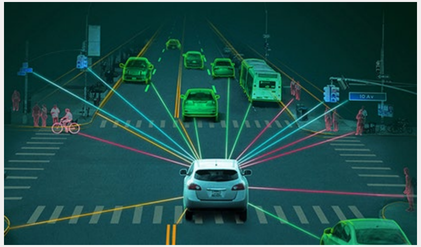
Litography system

PCB testing



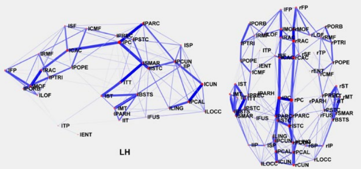
T&M Solutions, Romex BV

Autonomous driving



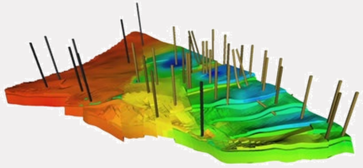
www.envidia.com

Brain network



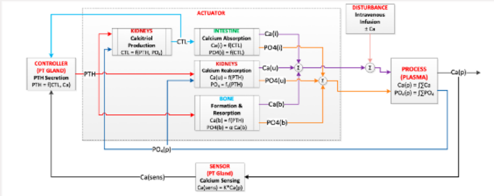
P. Hagmann et al. (2008)

Hydrocarbon reservoirs



Mansoori (2014)

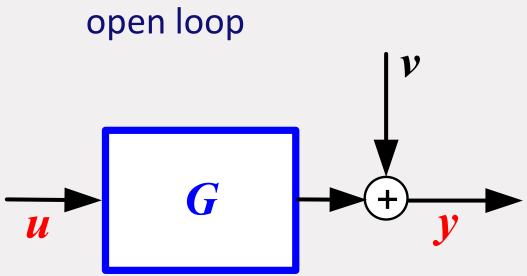
Physiological models

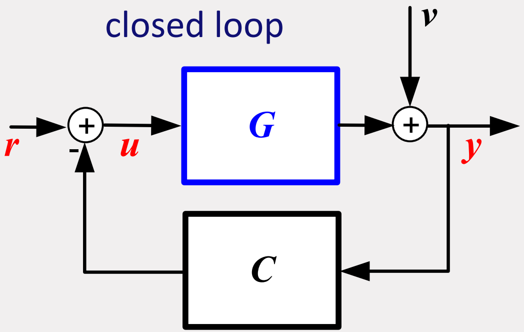


Christie, Achenie and Ogunnaike (2014)

System identification

The classical (multivariable) data-driven modeling problems[1] :



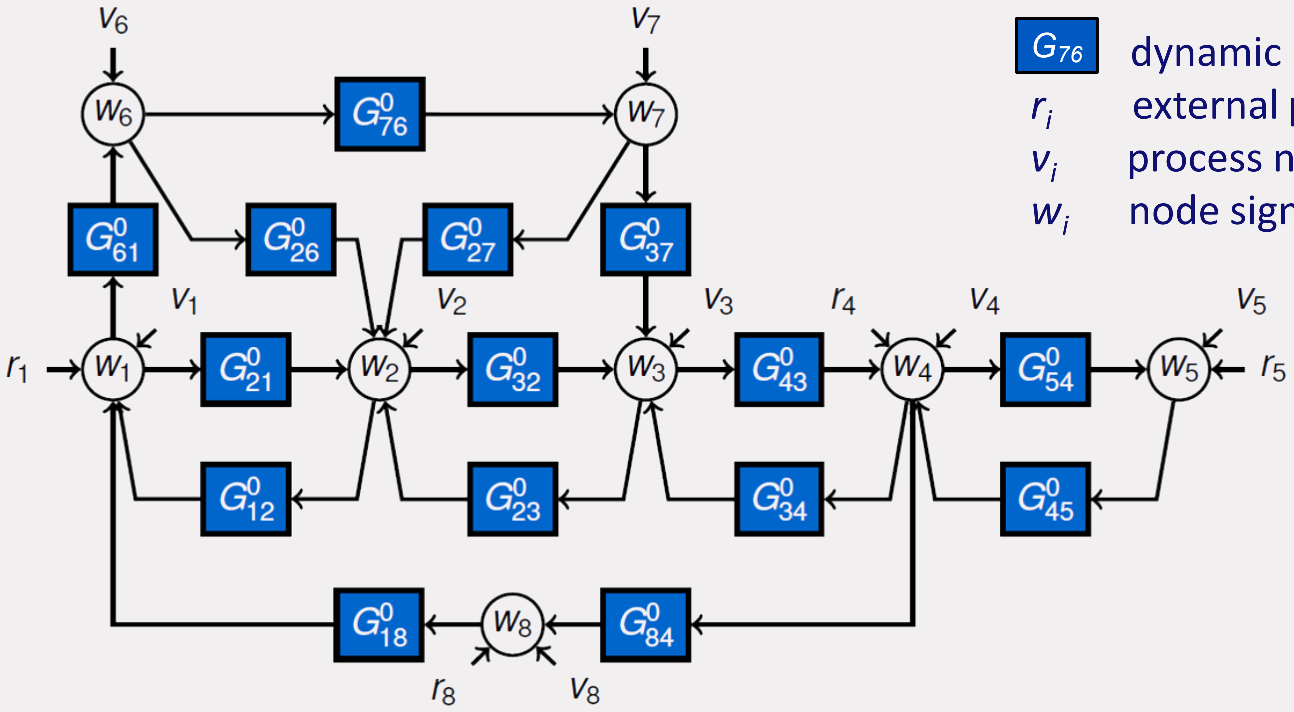


Identify a model of G on the basis of measured signals u, y
(and possibly r), focusing on *continuous LTI dynamics*.

In interconnected systems (networks) the **structure / topology** becomes important to include

[1] Ljung (1999), Söderström and Stoica (1989), Pintelon and Schoukens (2012)

LTI Dynamic network setup



G_{76} dynamic module

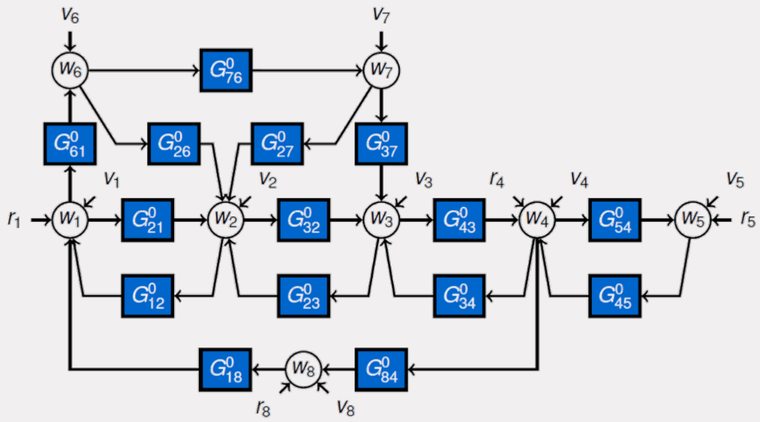
r_i external probing

v_i process noise

w_i node signal

Type of Bayesian network for time series / dynamic systems

LTI Dynamic network setup



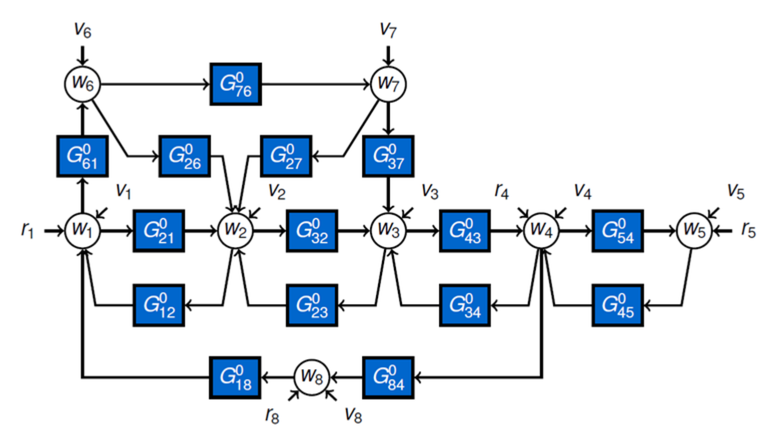
Basic building block:

$$w_j(t) = \sum_{k \in \mathcal{N}_j} G^0_{jk}(q) w_k(t) + v_j(t) + r_j(t)$$

Collecting all equations:

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

Dynamic network setup



Measured time series:

$$\{w_i(t)\}_{i=1,\cdots L};\ \ \{r_j(t)\}_{j=1,\cdots K}$$

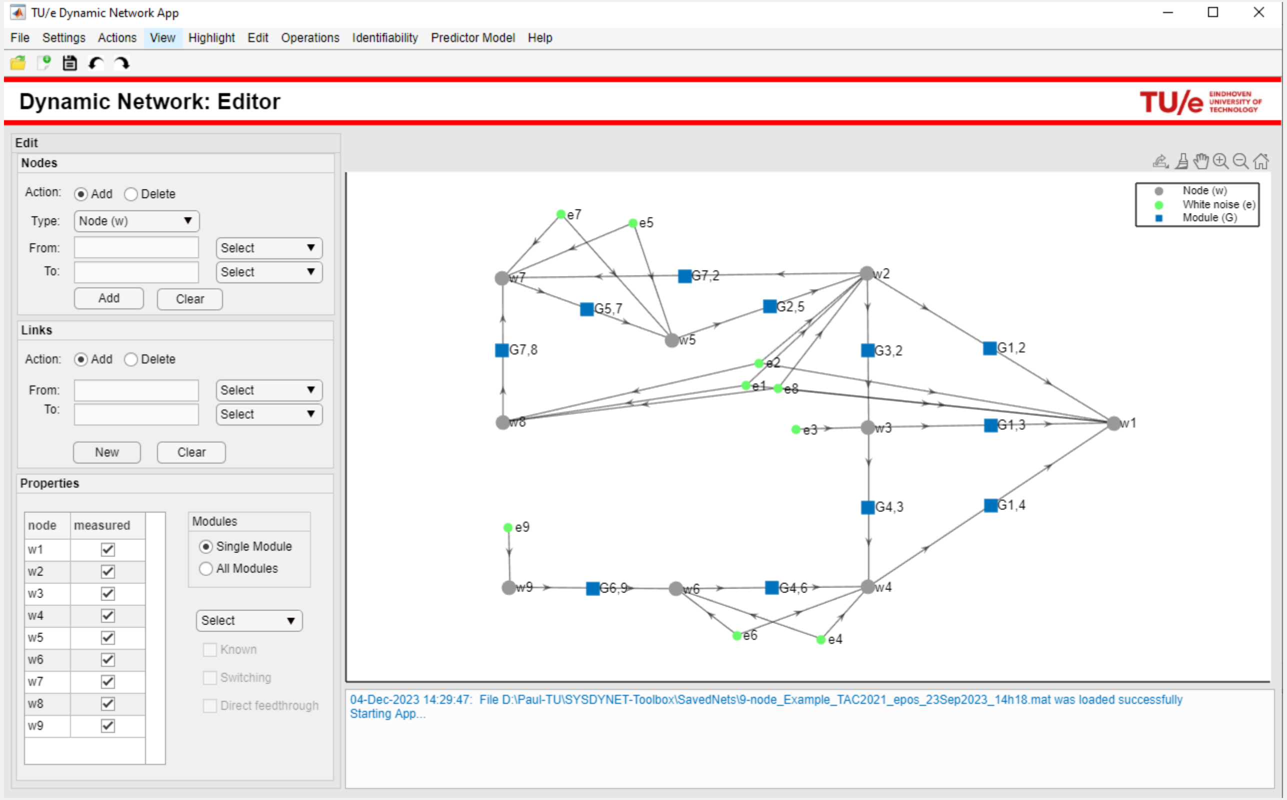
Data-driven modeling questions/tasks:

- **Identifiability** analysis/synthesis of a module / subnetwork / full network
- **Identification** of a module / subnetwork / full network (known topology)

- Typical user choices:
  - Excitation locations (r)
  - Sensor locations (measured nodes)
  - Prior known / parametrized modules

TU/e

Network creation/editing



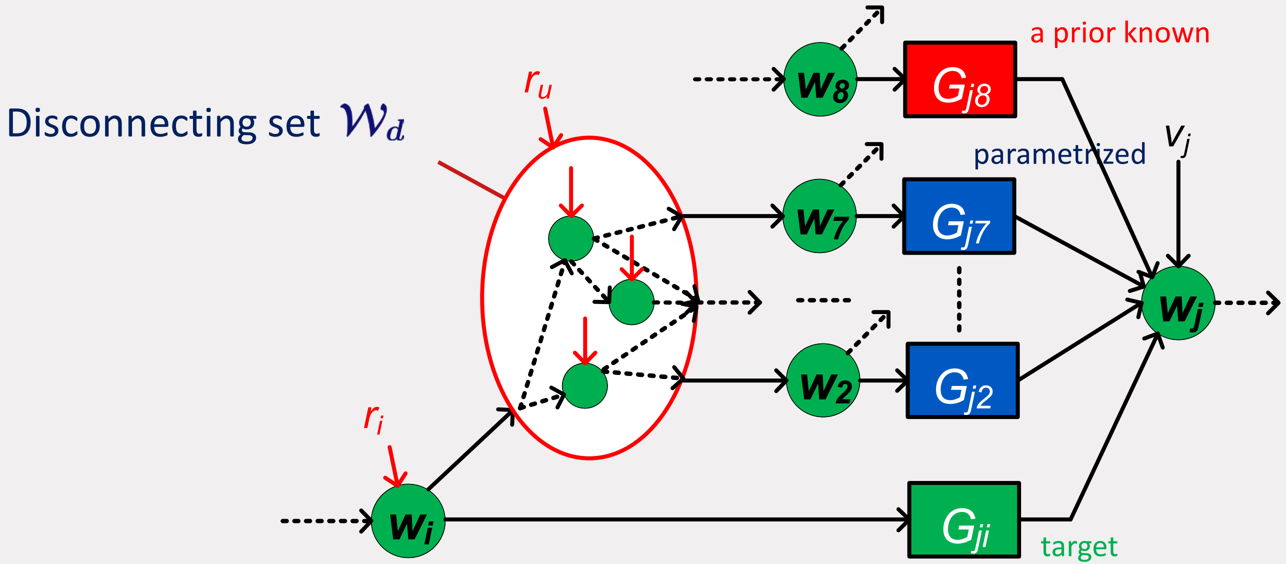
- Network creation
- Adding/removing/replacing nodes/links/external signals
- Editing structural properties of modules/nodes
- Edit through input panel or interactively in plot.
- Highlighting of properties

Network identifiability (new)

- Given the topology of a network.
- Given the location of excitation signals r and the (sub)set of measured nodes w_s
- w_s can be written as $w_s(t) = T_{wr}(q)r(t) + v_s(t)$
- The identifiability question then becomes:
  Can a particular module G_{ji} (or a full network) be uniquely determined from $T_{wr}(q)$ and $\Phi_{v_s}(\omega)$?
- The answer is typically dependent on:
  - The network topology
  - Which modules are known / parametrized?
  - Location of external r's and e's.

Single module identifiability – full measurement

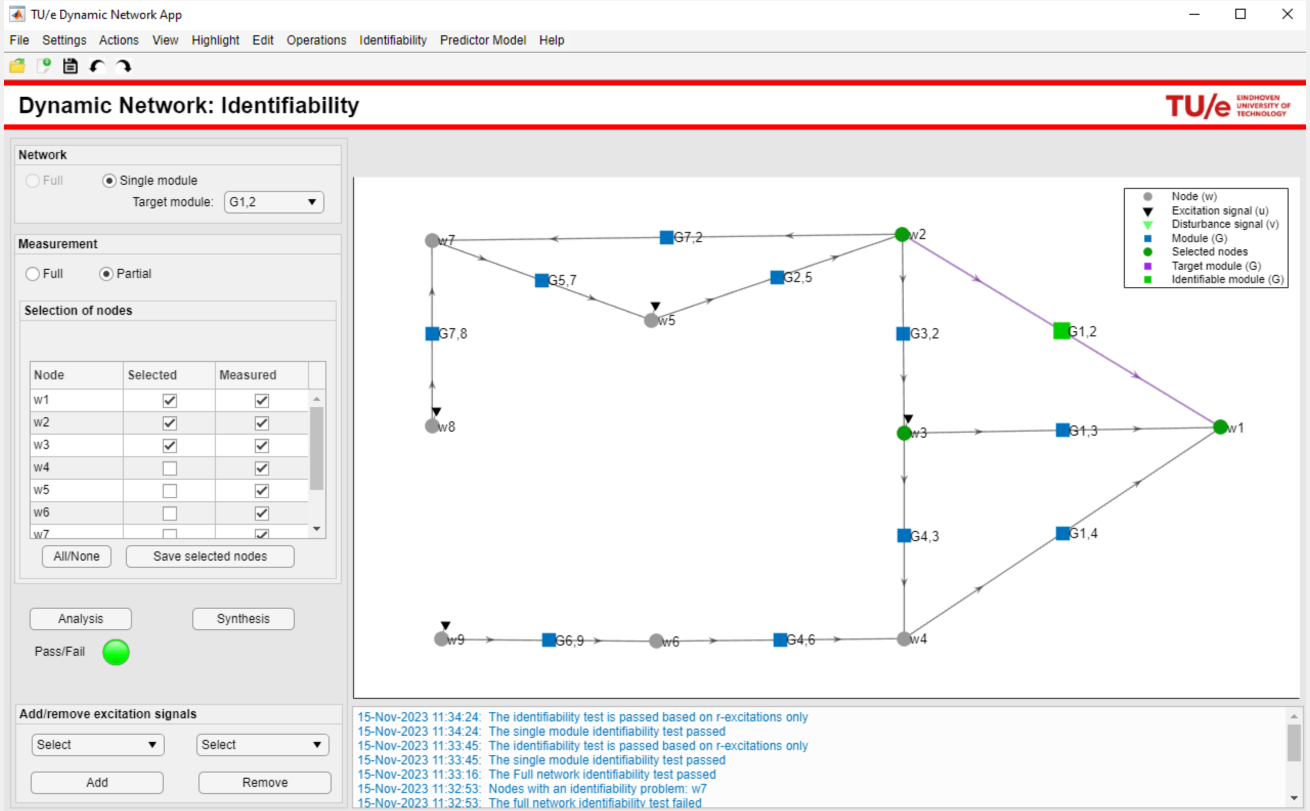
Synthesis question: where to allocate excitation signals?



Result[1]**:** G_{ji} is generically identifiable if independent external signals are added to the nodes in $\mathcal{W}_d$ and w_i. This can be either (independent) noise signals designed excitation signals.

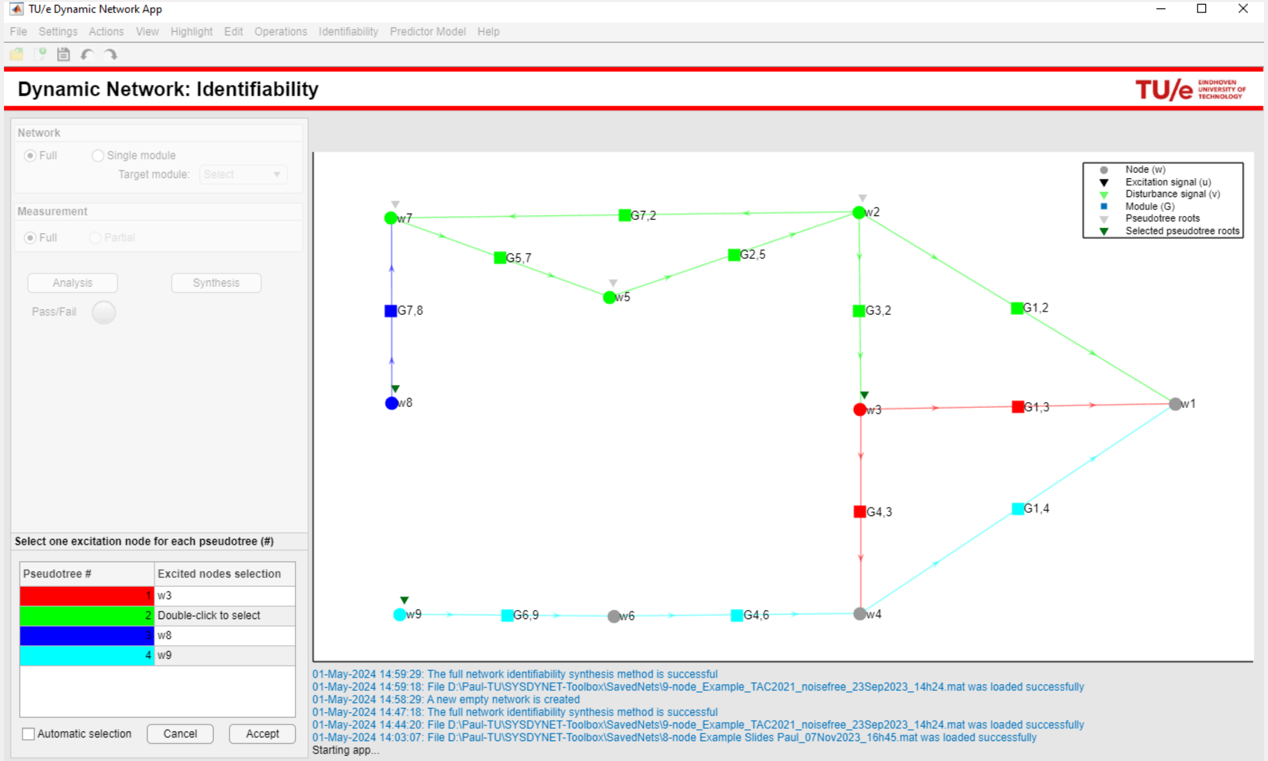
[1] Shi, Cheng, VdHof, IFAC 2020; Automatica 2022.

Identifiability



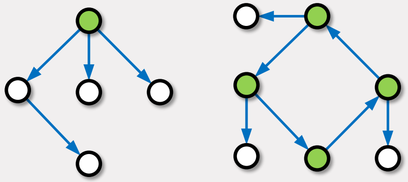
- Analyse identifiabiltiy of a single module / network
- Create (synthesize) identifiability of a single module / network
- User variables: Selected measured nodes + present r-signals

Allocation of external signals for network identifiability

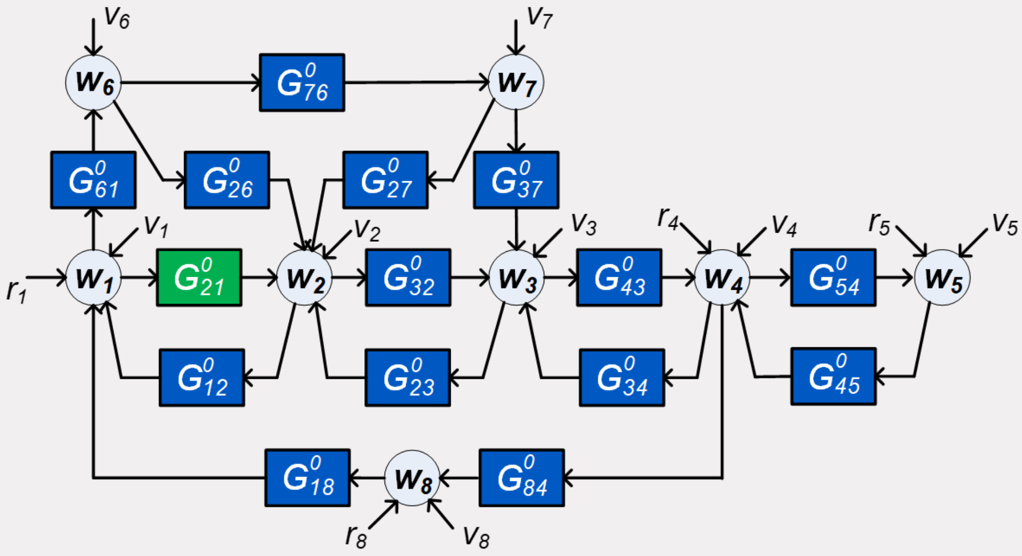


Full measurement case:

- Decomposition of network graph in disjoint pseudotrees
- Have an independent external signal in the root of each pseudotree



Single module identification



Different types of methods:

Indirect methods:

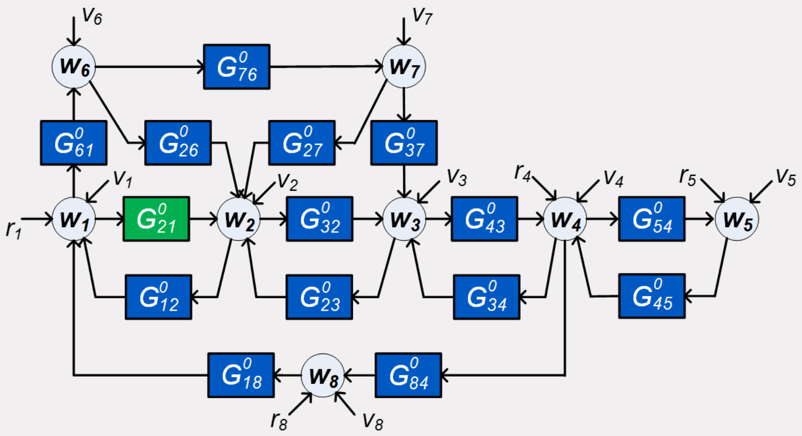
- Rely on mappings $r \rightarrow w$ and on sufficient excitation signals r

Direct methods:

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

Identifiability results indicate which method can be used!

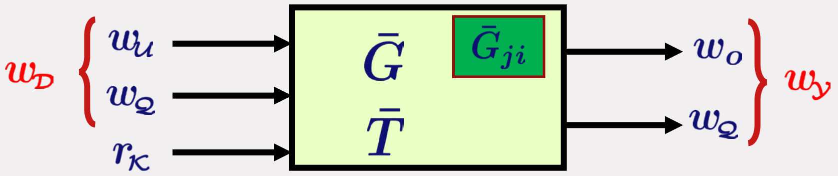
Single module identification



Select a predictor model:

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

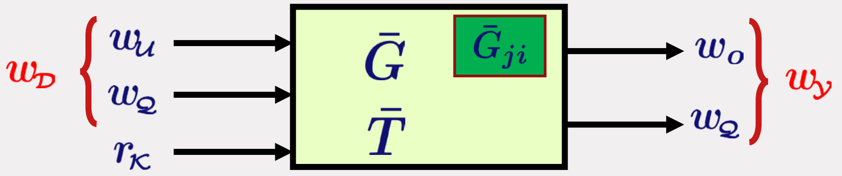
such that prediction error minimization leads to an accurate (reconstructed) estimate of G^0_{21}



+ disturbance model

Note: same node signals can appear in input and output

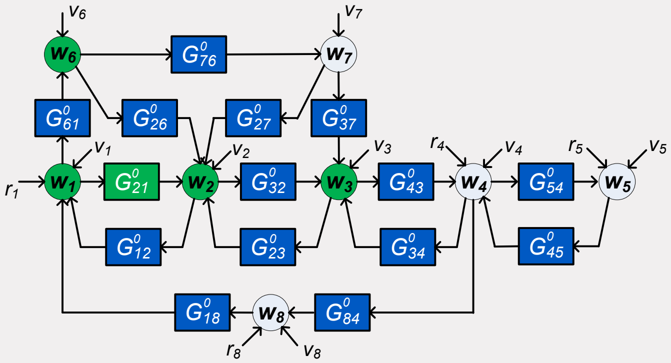
Predictor model for identification of a single module (direct method)

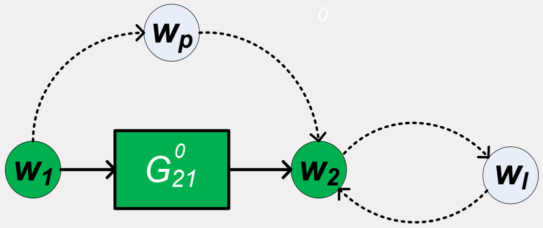


Method-dependent conditions for arriving at an accurate (consistent) model:

1. Module invariance: $\bar{G}_{ji} = G^0_{ji}$ when removing discarded nodes (immersion)
2. Handling of confounding variables
3. Data-informativity
4. *Technical condition on presence of delays*

Single module identification - module invariance





A sufficient condition for module invariance:

All parallel paths, and loops around the output,
should be "blocked" by a measured node that is present in $w_\mathcal{D}$

All other signals can be removed/immersed from the network[2]

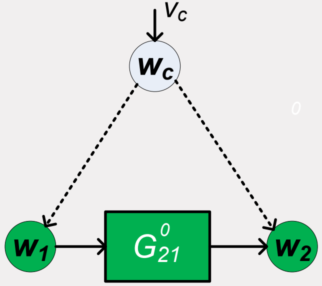
[1] Dankers et al., TAC 2016
[3] Shi et al., Automatica 2022

[2] Generalizations available in Linder&Enqvist (2017), Weerts et al, (2020)

Single module identification - confounding variables

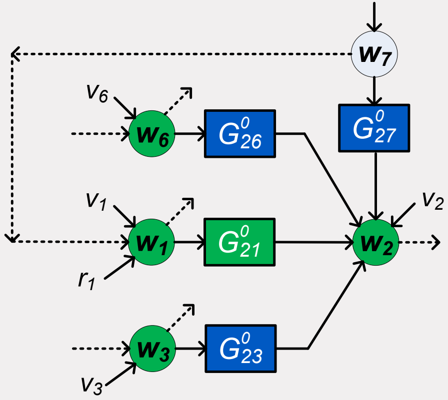
Confounding variable [1][2]**:**

Unmeasured signal that has (unmeasured paths) to both the input and output of an estimation problem.



In networks they can appear in two different ways:

- If disturbances on inputs and outputs are correlated.
- If non-measured in-neighbors of an output affect signals in the inputs.

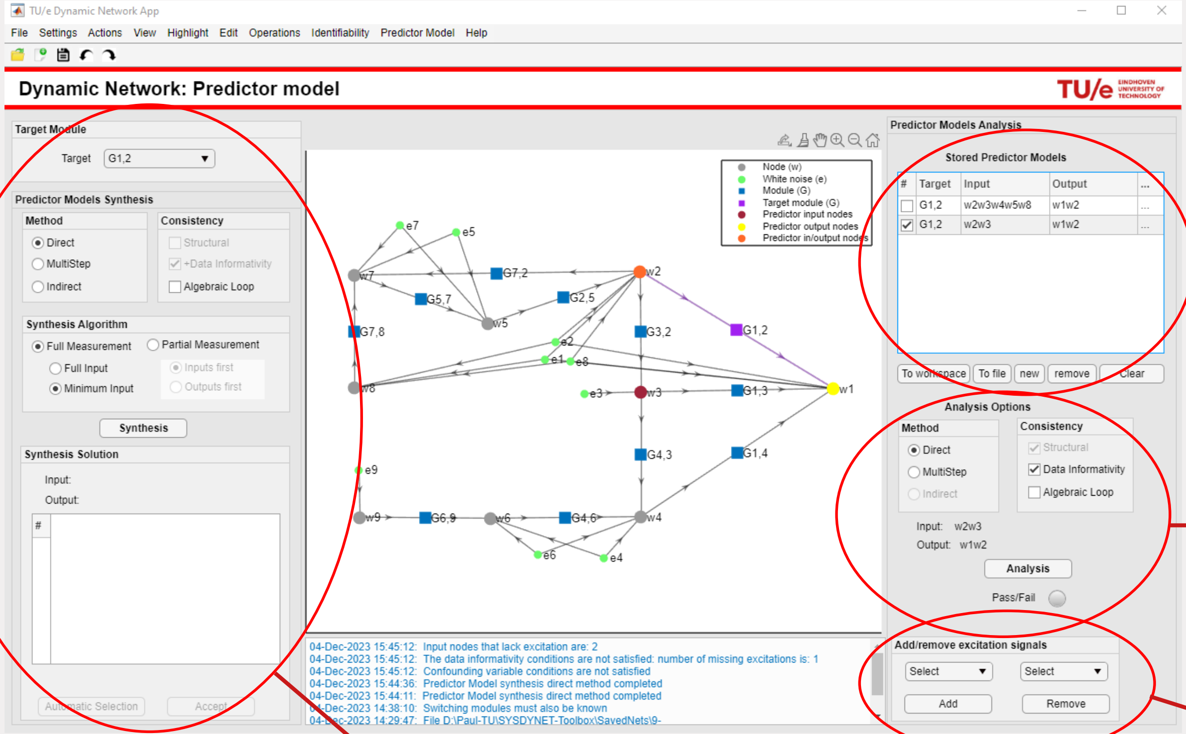


Solutions:

- Add additional nodes as predictor inputs or outputs [3].
- Decorrelate disturbances through a multistep method [4].

[1] J. Pearl, *Stat. Surveys, 3,* 96-146, 2009
[2] A.G. Dankers et al., *Proc. IFAC World Congress*, 2017.
[3] K.R. Ramaswamy et al., IEEE-TAC, 2021.
[4] S.J.M. Fonken et al., Automatica 2022, CDC 2023.

Predictor model construction for single module id



Collection of PM's

Analysis of consistency properties

Adding/removing external signals

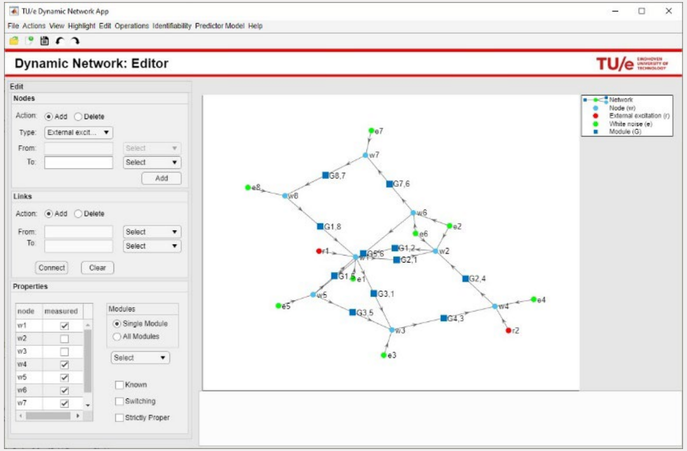
Construction of a PM (synthesis)

Toolbox m-files for actual simulation/identification

- Network simulation
- Full network identification with sequential linear regression (SLS) algorithm [1]
- Single module identification with the local direct method (PEM) [2]
- Single module identification with the multistep method [3]
- …………. (to be extended)

[1] H.H.M. Weerts et al., SYSID 2018.
[2] K.R. Ramaswamy & PVdH, IEEE-TAC, 2021.
[3] S.J.M. Fonken et al., CDC 2023.

SYSDYNET App and Toolbox



Beta-version to be downloaded from www.sysdynet.net

Background material and papers: available on www.sysdynet.eu

Slides/videos of 8 hours course on dynamic network identification , Lyon, April 2024:
http://www.pvandenhof.nl/lyon-spring-school-2024/