The evolving landscape of data-driven modeling in dynamic networks

Retrospect and Prospect

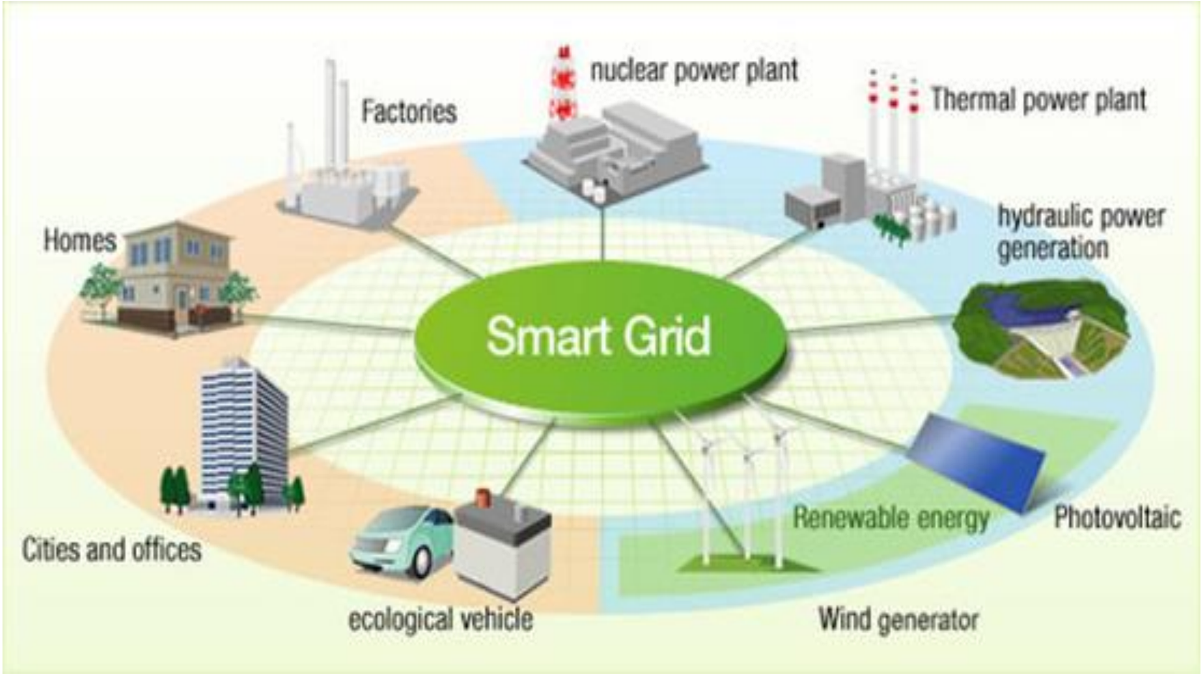
Dr. Ir. Karthik Raghavan Ramaswamy

ASML Research - Mechatronics and Control

Dynamic networks

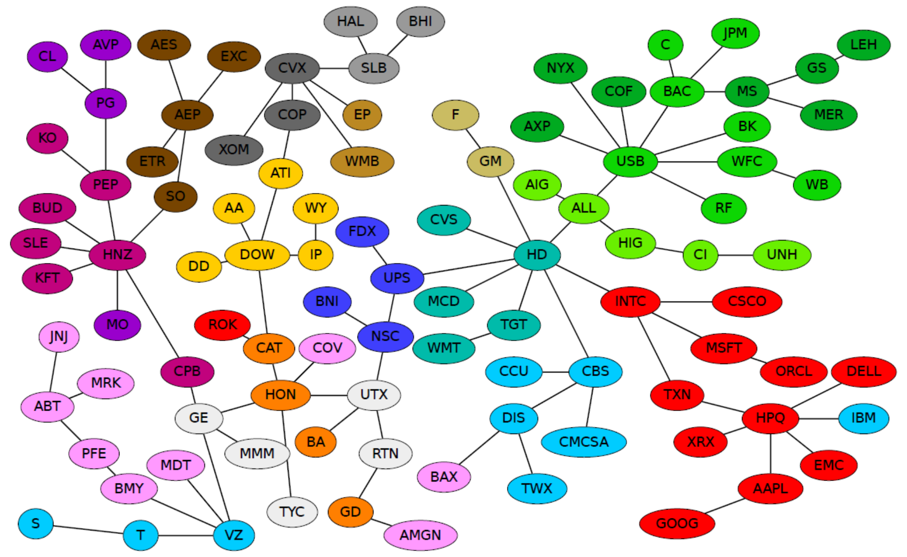
High-tech machines

Smart power grid



Betterworldsolutions.eu

Stock market



Materassi and Innocenti, 2010

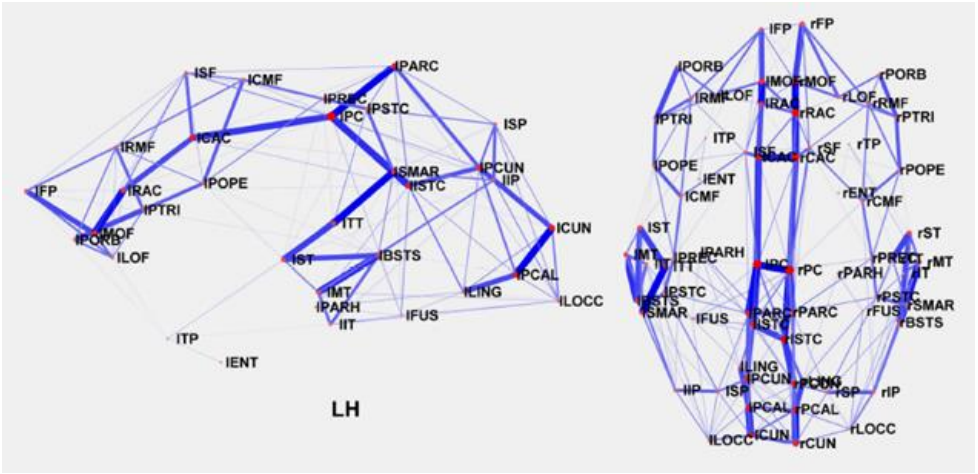
PCB testing

T&M Solutions, Romex BV

Autonomous driving

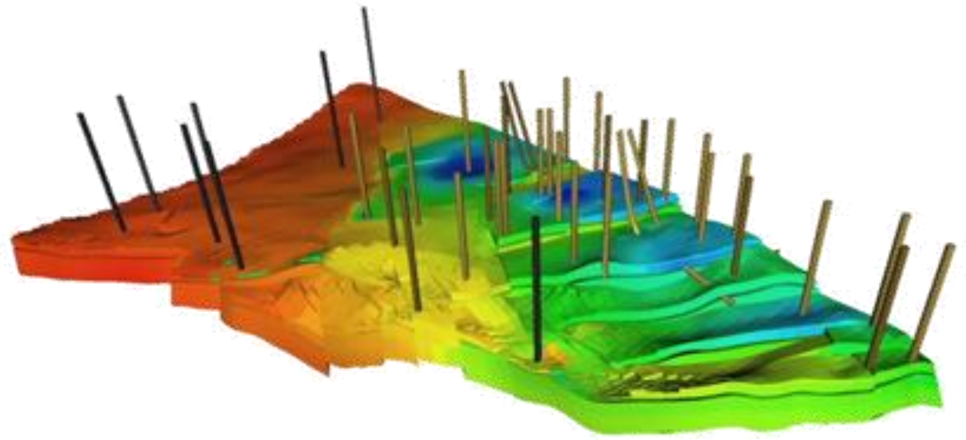
www.envidia.com

Brain network



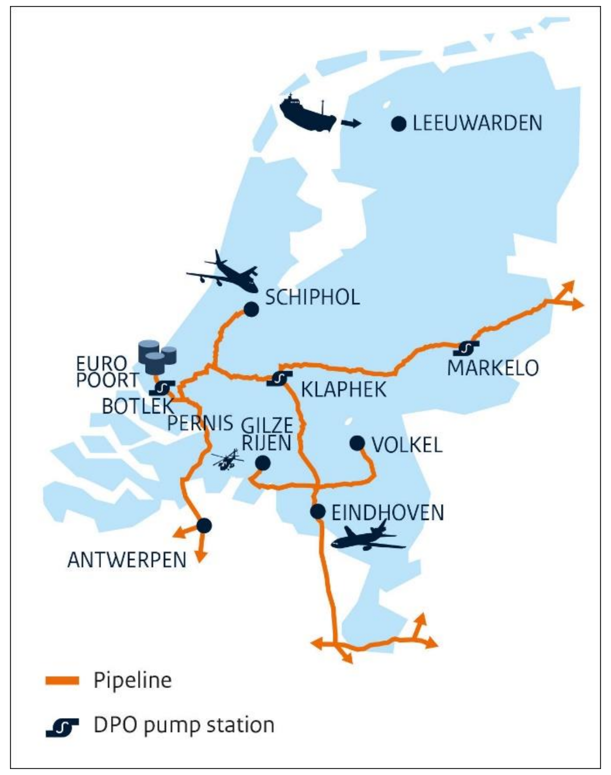
P. Hagmann et al. (2008)

Hydrocarbon reservoirs



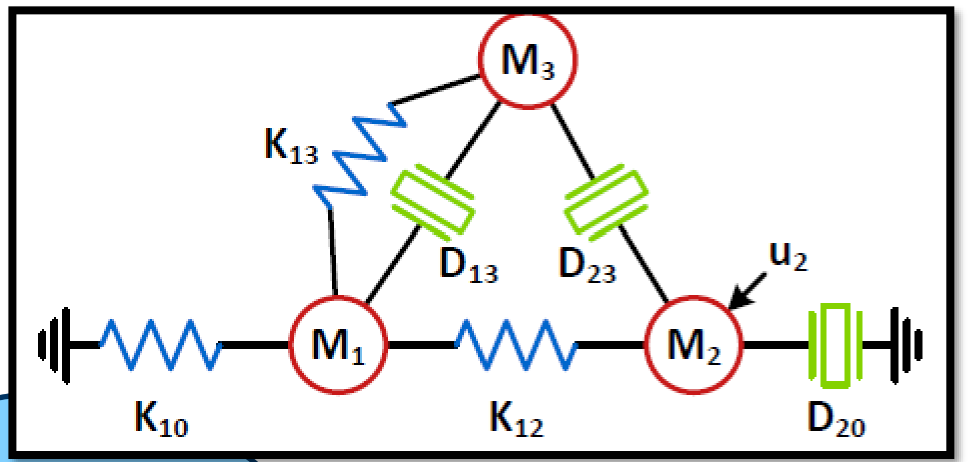
Mansoori (2014)

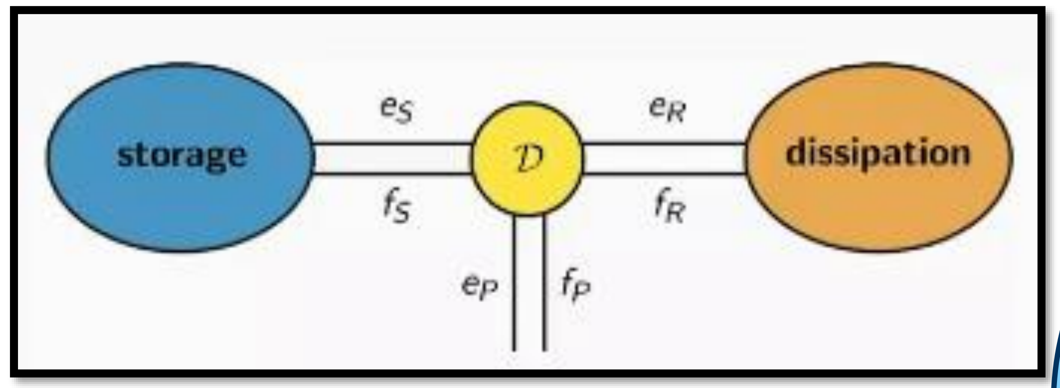
Pipeline networks

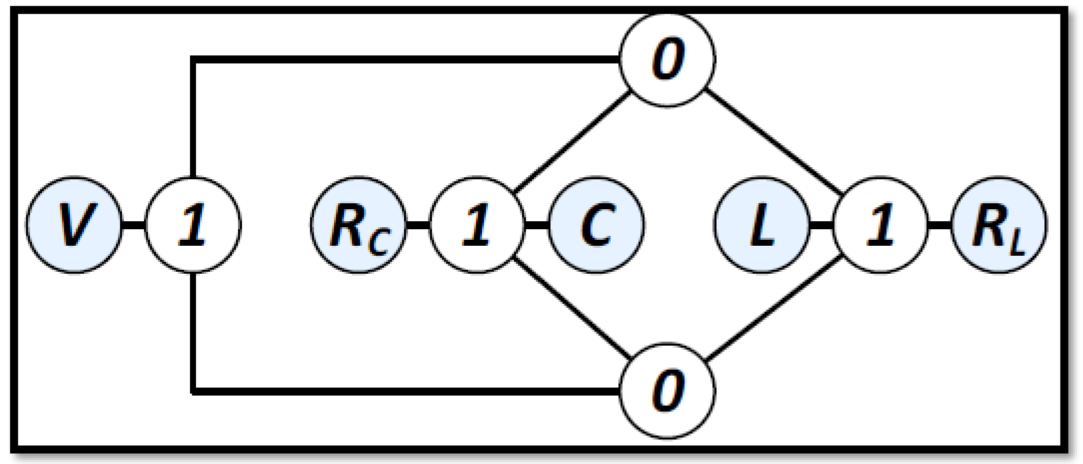


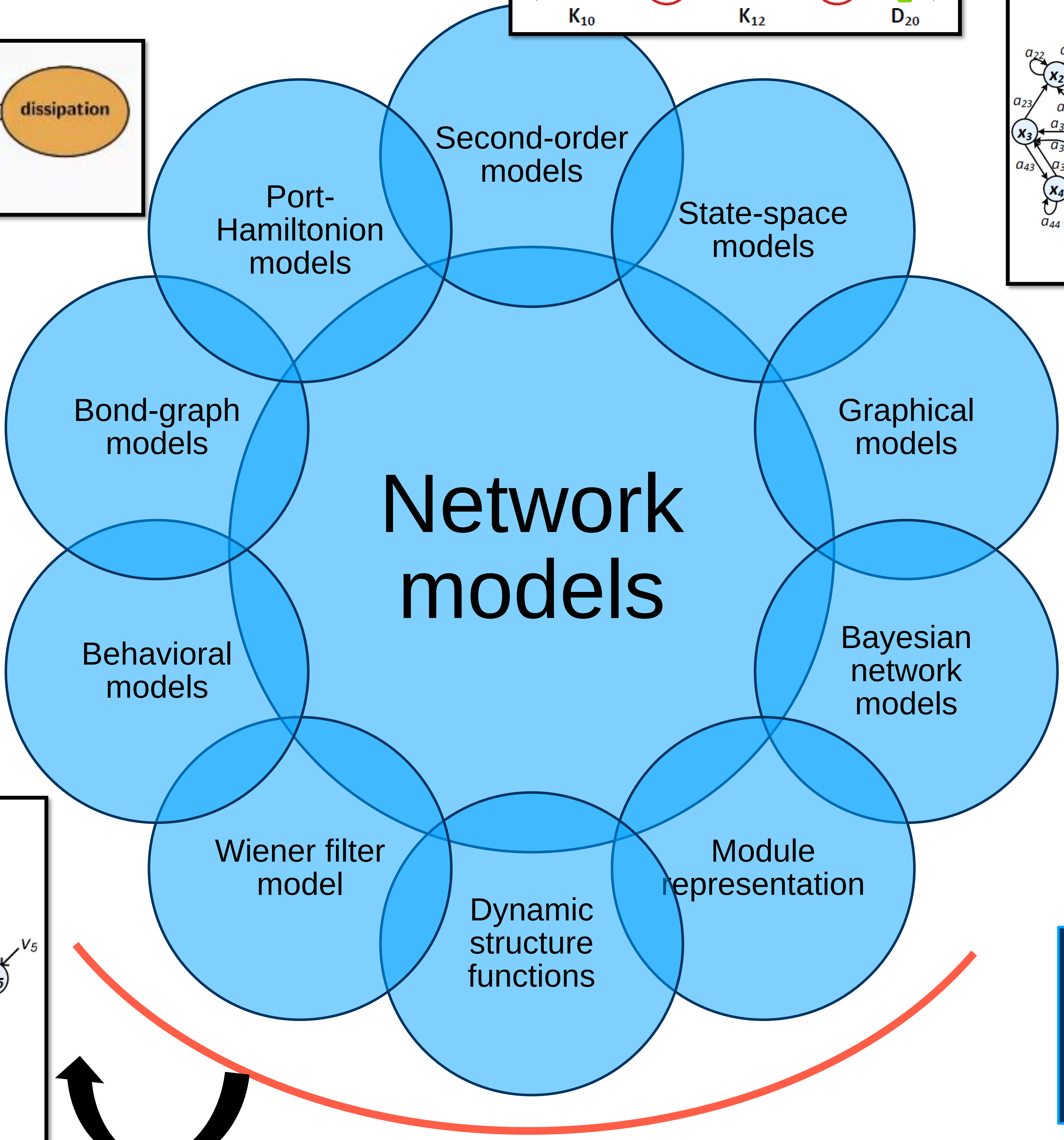
wwww.defensie.nl

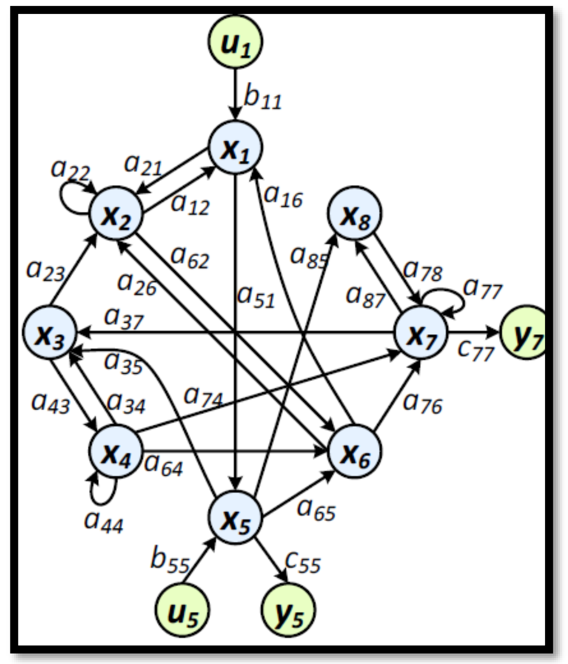
Network models

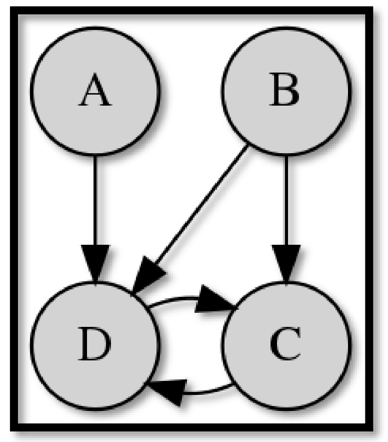


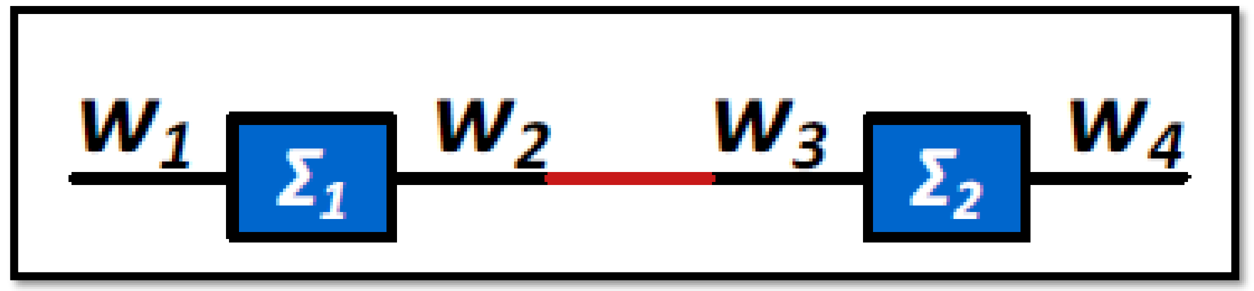


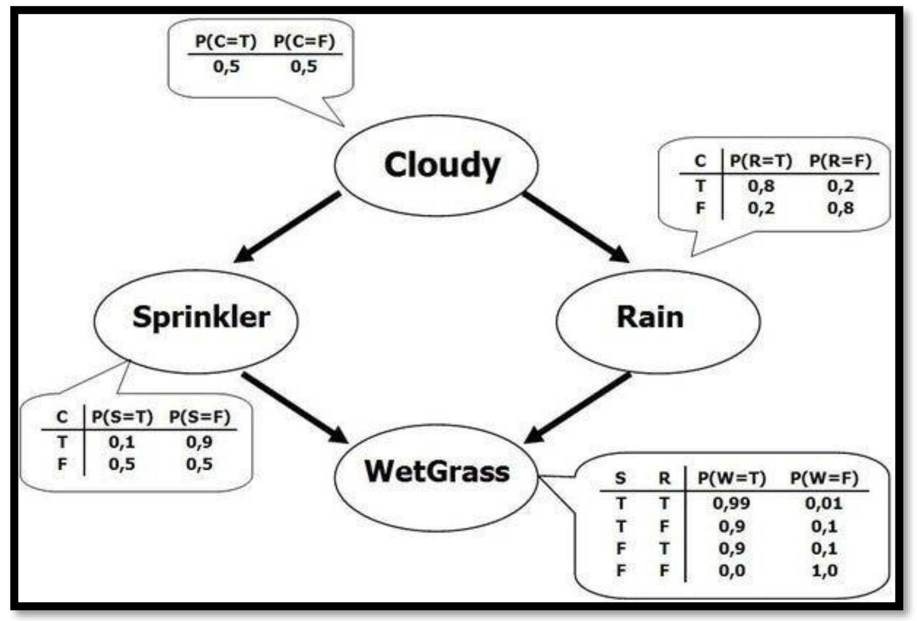


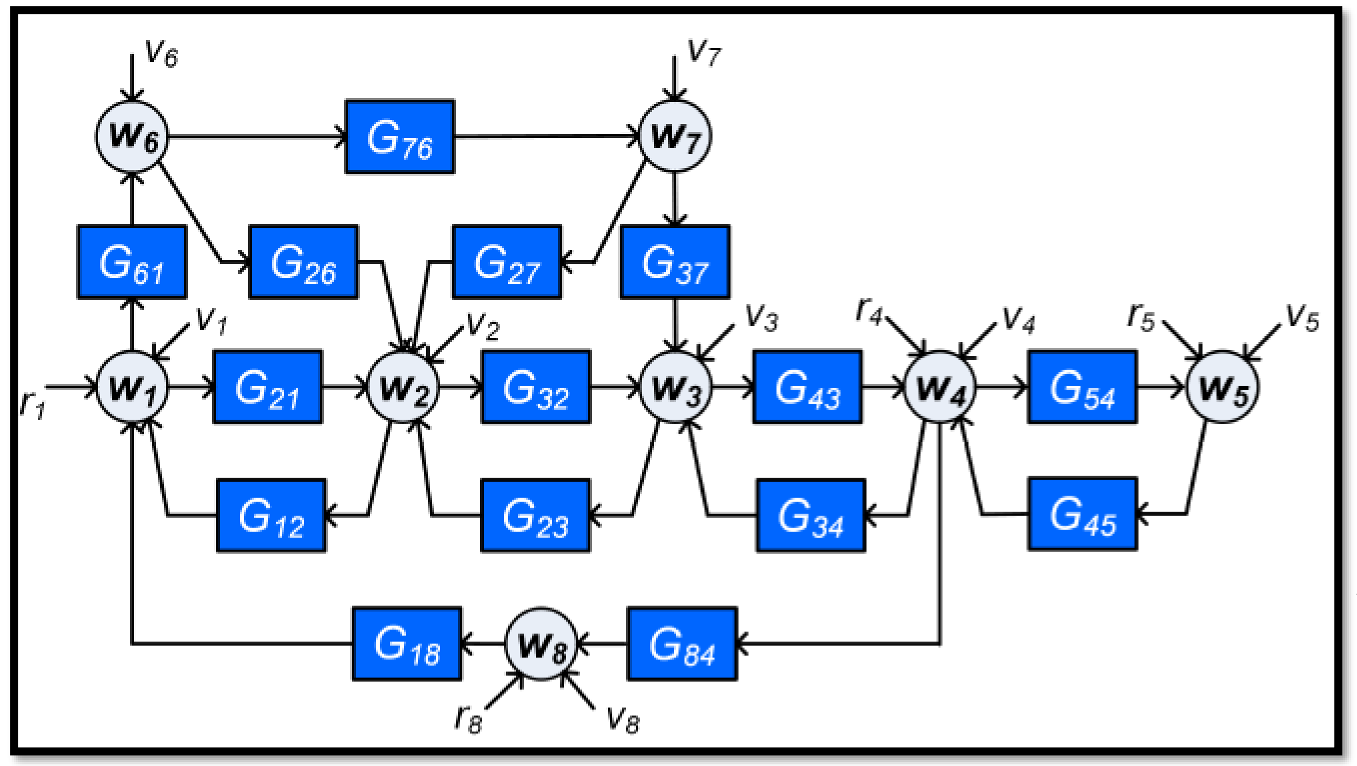








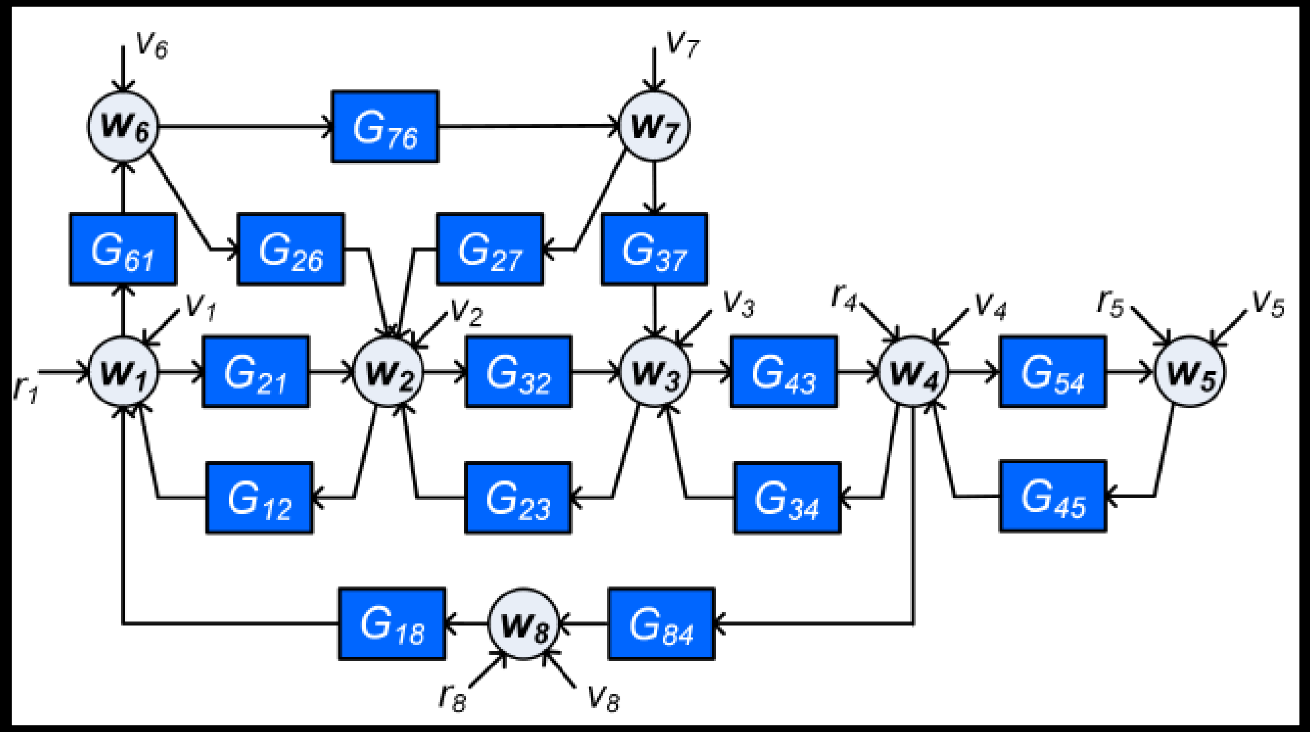




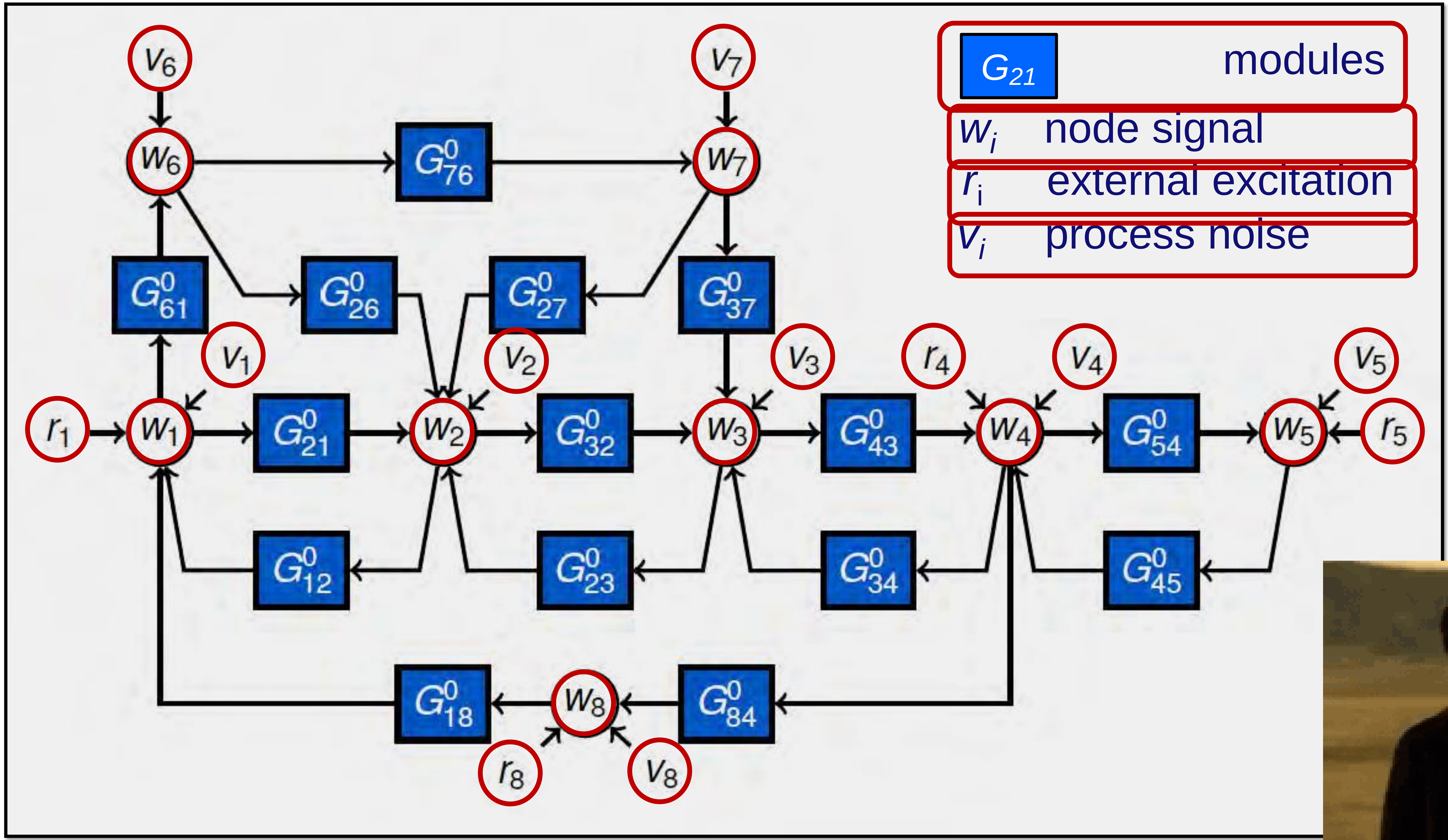
Many candidate network models to choose from

This is me !!


Yay ! It's Vacation Time


v_6
v_7
w_6
G_{76}
w_7
G_{61}
G_{26}
G_{27}
G_{37}
v_1
v_2
v_3
r_4
v_4
r_5
v_5
r_1
w_1
G_{21}
w_2
G_{32}
w_3
G_{43}
w_4
G_{54}
w_5
G_{12}
G_{23}
G_{34}
G_{45}
G_{18}
w_8
G_{84}
r_8
v_8

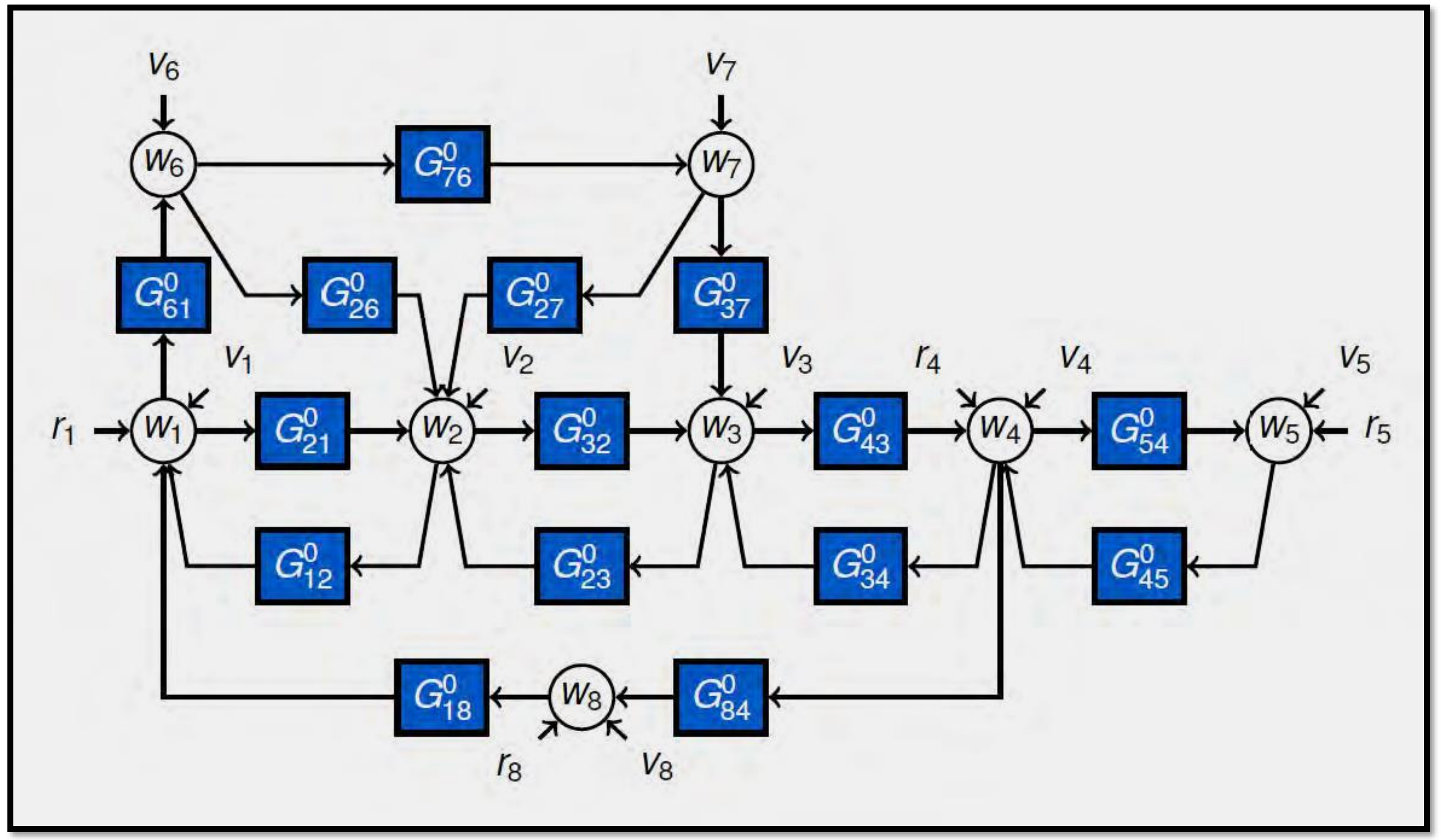
Dynamic network – module representation



[1] J. Gonçalves and S. Warnick, IEEE TAC, 2008.

[2] P. M.J. Van den Hof et al., Automatica, 2013

Dynamic network – module representation



DATA

Topology encoded

Measured time series

External excitations

$$\begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_L \end{bmatrix} = \begin{bmatrix} 0 & G^0_{12} & \cdots & G^0_{1L} \\ G^0_{21} & 0 & \cdots & G^0_{2L} \\ \vdots & \ddots & \ddots & \vdots \\ G^0_{L1} & G^0_{L2} & \cdots & 0 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_L \end{bmatrix} + \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_L \end{bmatrix} + \underbrace{\begin{bmatrix} H^0_{11} & H^0_{12} & \cdots & H^0_{1L} \\ H^0_{21} & H^0_{22} & \cdots & H^0_{2L} \\ \vdots & \vdots & \ddots & \vdots \\ H^0_{L1} & H^0_{L2} & \cdots & H^0_{LL} \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_L \end{bmatrix}}_{v = H^0 e}$$

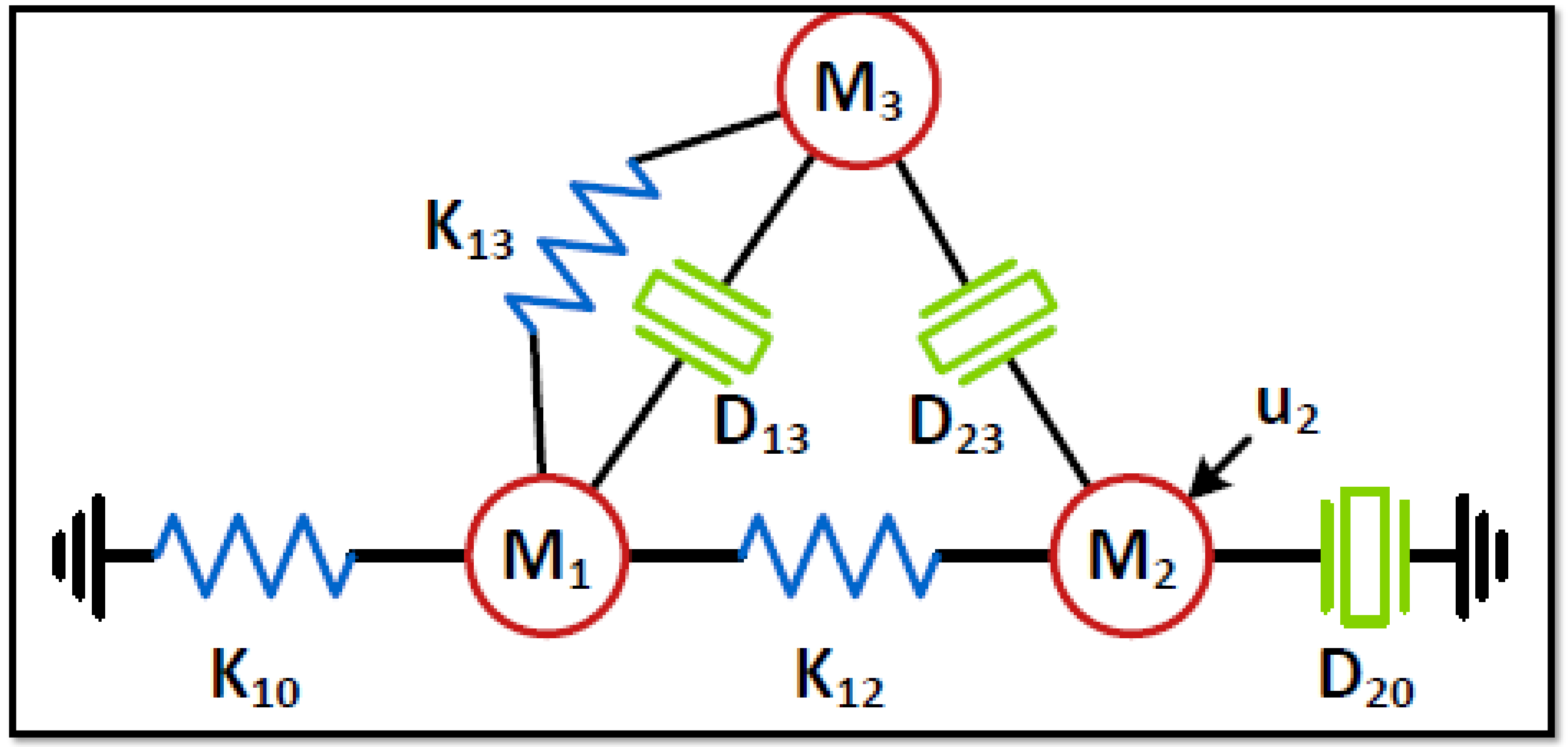
$$w = G^0(q)w + r + v \qquad \underbrace{w = (I - G^0)^{-1}(r + v)}_{\textit{Input-output form (MIMO)}}$$

correlated disturbances

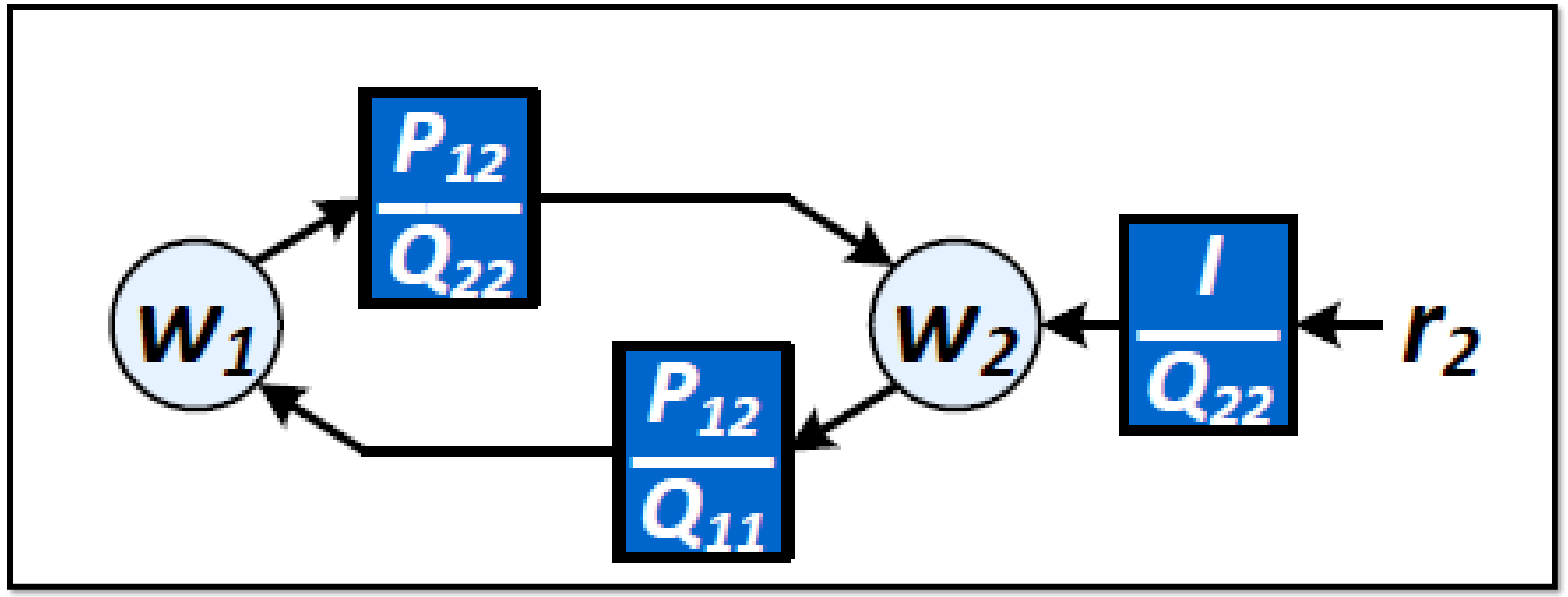
J. Gonçalves and S. Warnick, IEEE TAC, 2008.

P. M. J. Van den Hof et al., Automatica, 2013..

Physical linear systems



Physical systems – Second order model



Module representation

$$\begin{bmatrix} M_1 & & \\ & M_2 & \\ & & M_3 \end{bmatrix}\begin{bmatrix} \ddot{w}_1 \\ \ddot{w}_2 \\ \ddot{w}_3 \end{bmatrix} + \begin{bmatrix} 0 & & \\ & D_{20} & \\ & & 0 \end{bmatrix}\begin{bmatrix} \dot{w}_1 \\ \dot{w}_2 \\ \dot{w}_3 \end{bmatrix} + \begin{bmatrix} K_{10} & & \\ & 0 & \\ & & 0 \end{bmatrix}\begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}$$
$$+ \begin{bmatrix} D_{13} & 0 & -D_{13} \\ 0 & D_{23} & -D_{23} \\ -D_{13} & -D_{23} & D_{13}+D_{23} \end{bmatrix}\begin{bmatrix} \dot{w}_1 \\ \dot{w}_2 \\ \dot{w}_3 \end{bmatrix} + \begin{bmatrix} K_{12}+K_{13} & -K_{12} & -K_{13} \\ -K_{12} & K_{12} & 0 \\ -K_{13} & 0 & K_{13} \end{bmatrix}\begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} = \begin{bmatrix} 0 \\ u_2 \\ 0 \end{bmatrix}$$

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

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

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

with $\quad G(p) = Q(p)^{-1}P(p)$

E. M. M. Kivits et al., CDC 2019.

Evolved directions

LOCAL NETWORK IDENTIFICATION

TOPOLOGY IDENTIFICATION

NETWORK IDENTIFIABILITY

FULL NETWORK IDENTIFICATION

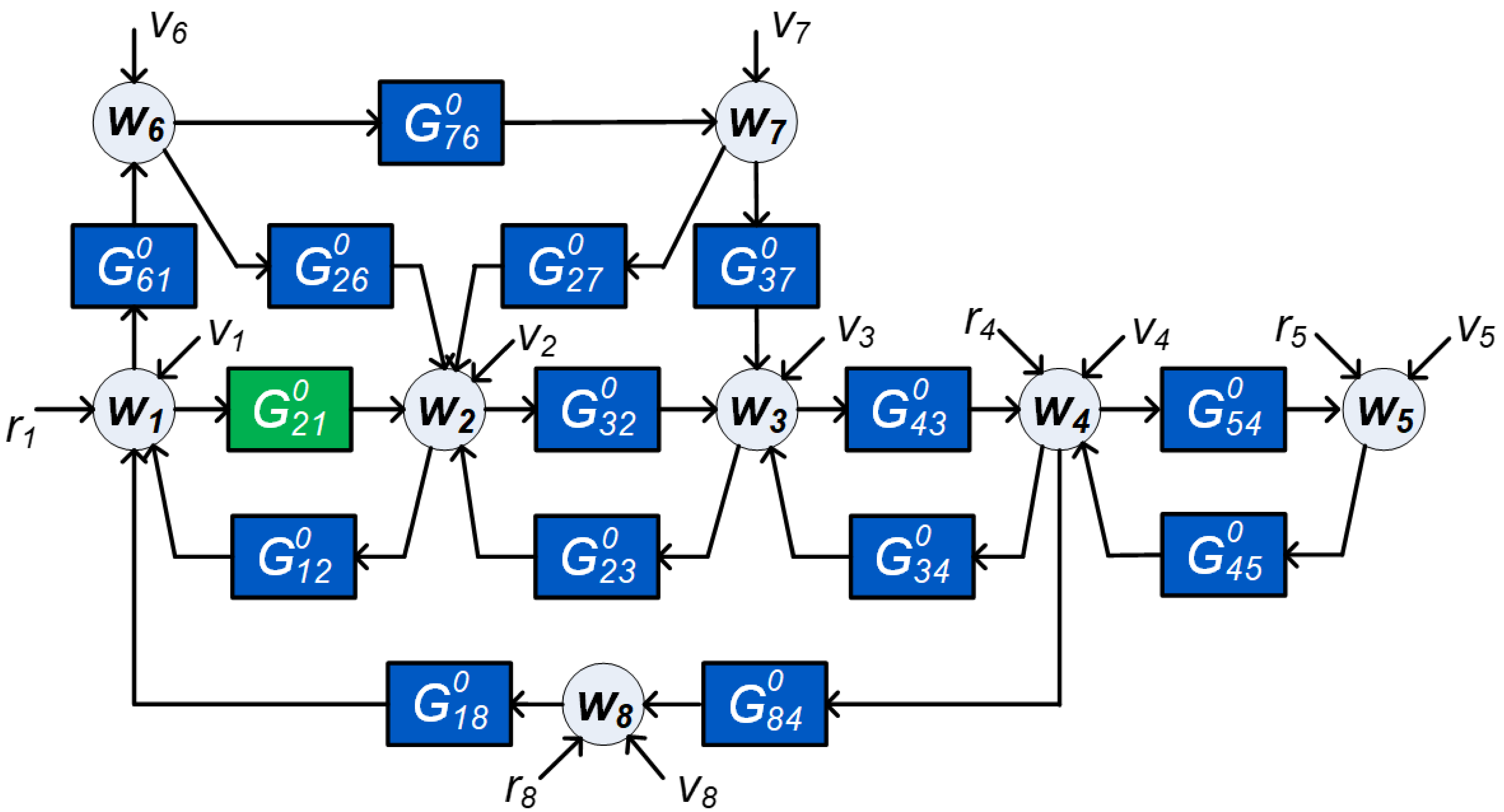
DATA-INFORMATIVITY

SCALABLE AND EFFECTIVE ALGORITHMS

EXPERIMENT DESIGN

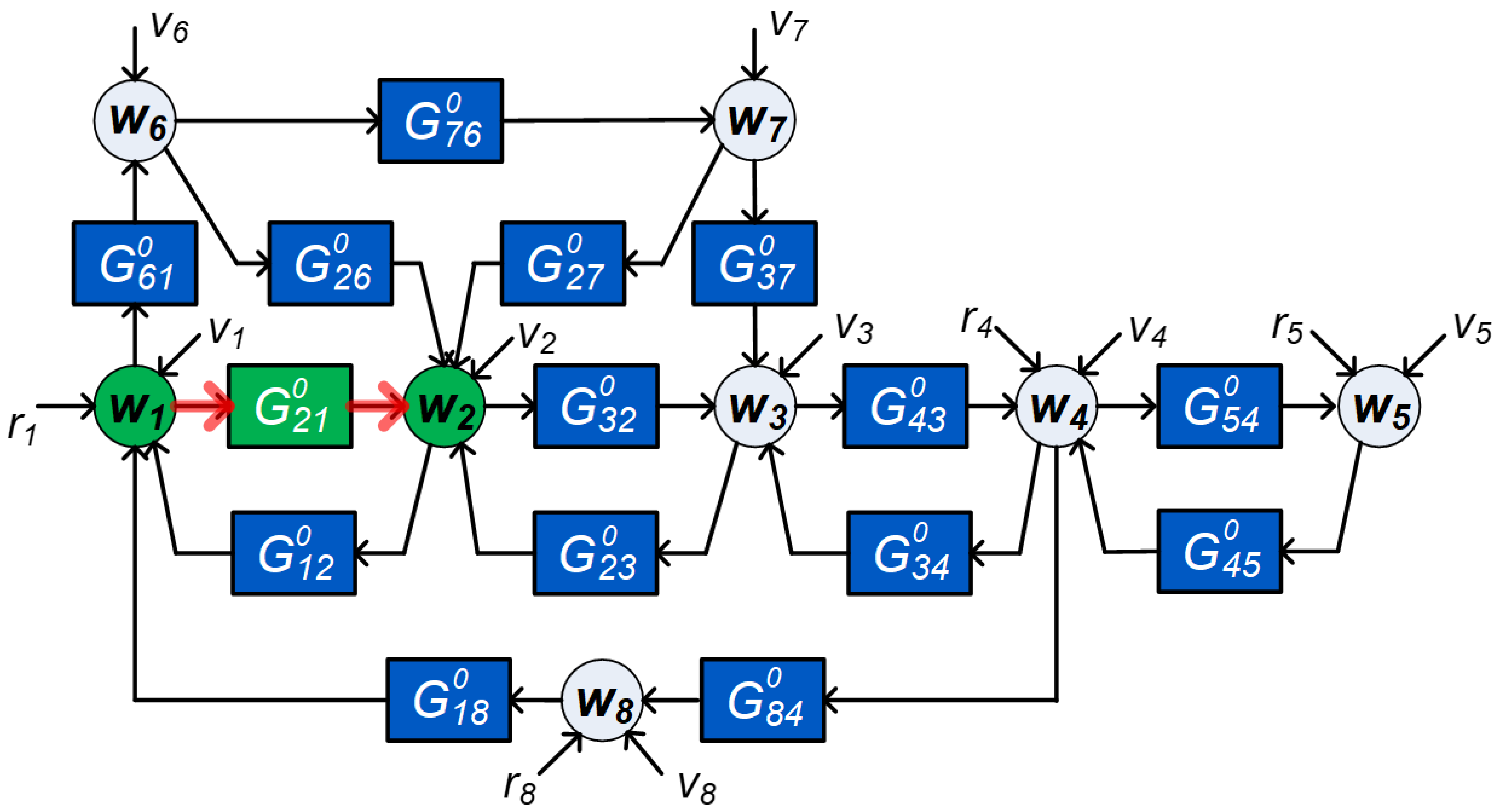
SOFTWARE

Single module identification



- ➢ Identify G_{21}^0 on the basis of measured signals
- ➢ Preference for “local” measurements and limited excitation

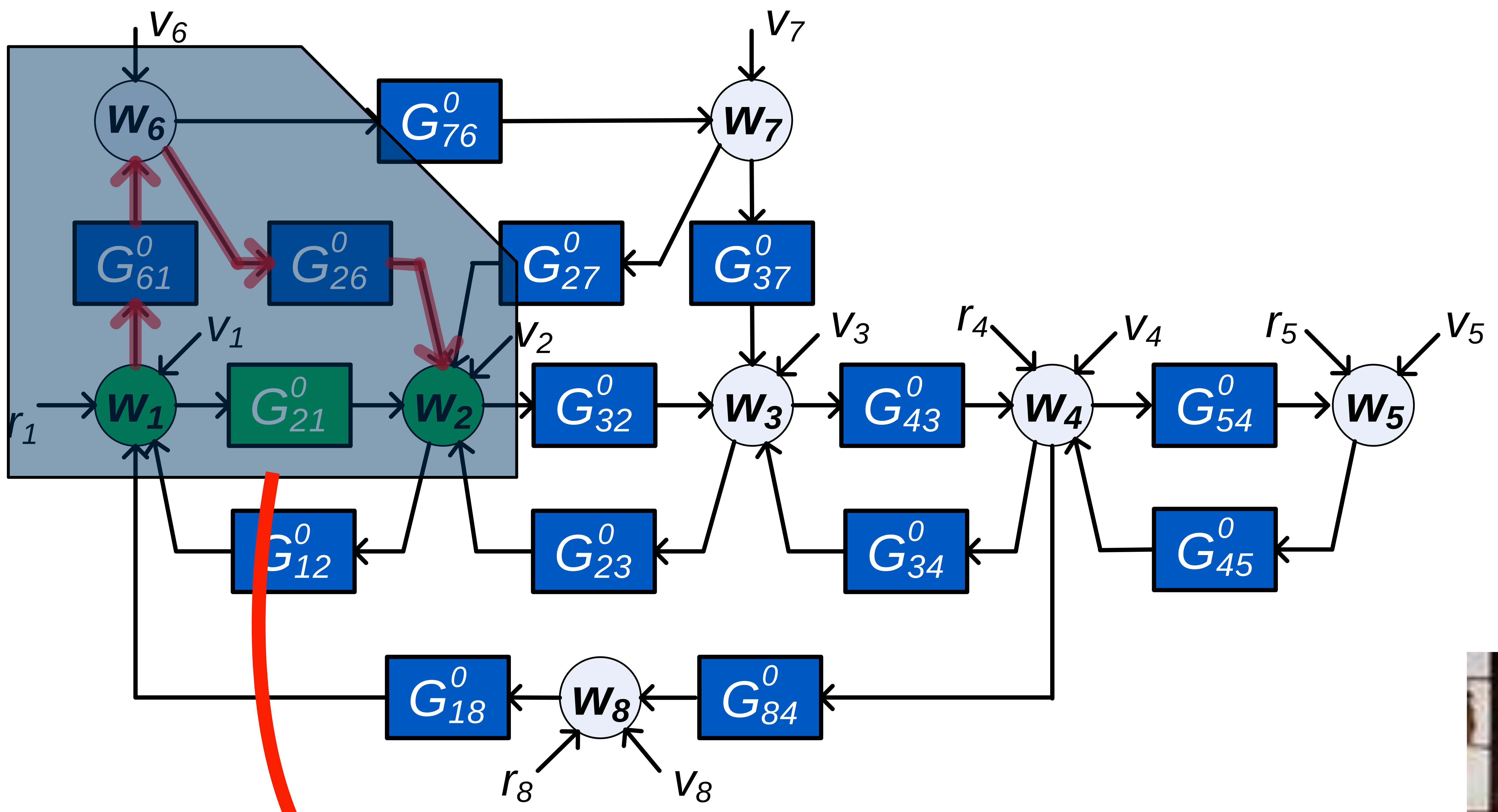
Single module identification



Naïve approaches:

- identify based on w_2 and w_1 ; or
- identify based on $T_{w_2r_1}T^{-1}_{w_1r_1}$

Single module identification



We identify $G^0_{21} + G^0_{26}G^0_{61}$

Naïve approaches:

- ➢ identify based on w_2 and w_1 ; or
- ➢ identify based on $T_{w_2 r_1} T^{-1}_{w_1 r_1}$

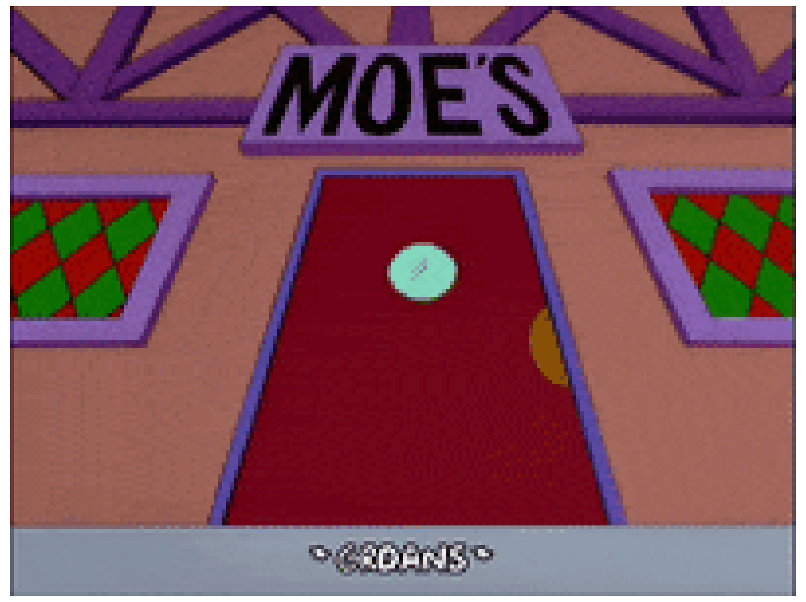
do not work,

e.g. because of parallel paths

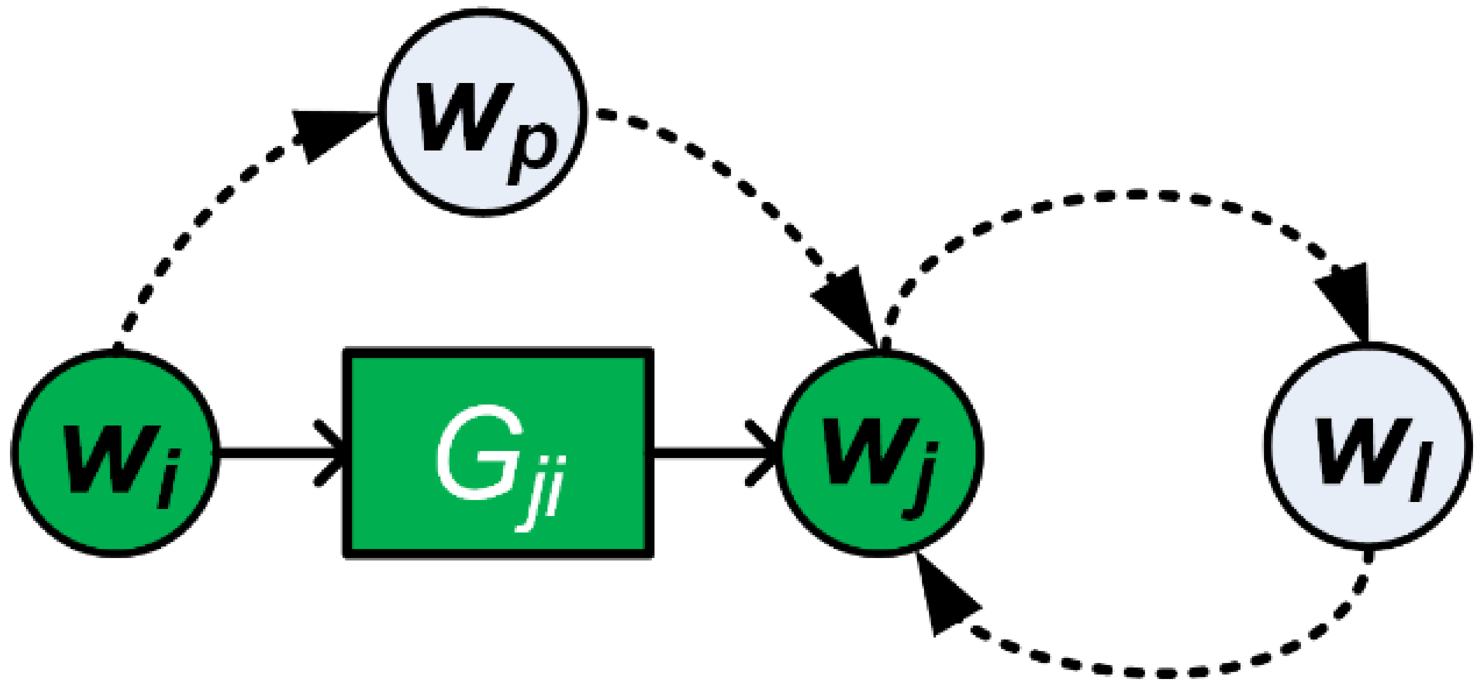
What are all the causes for it? How to achieve module invariance?

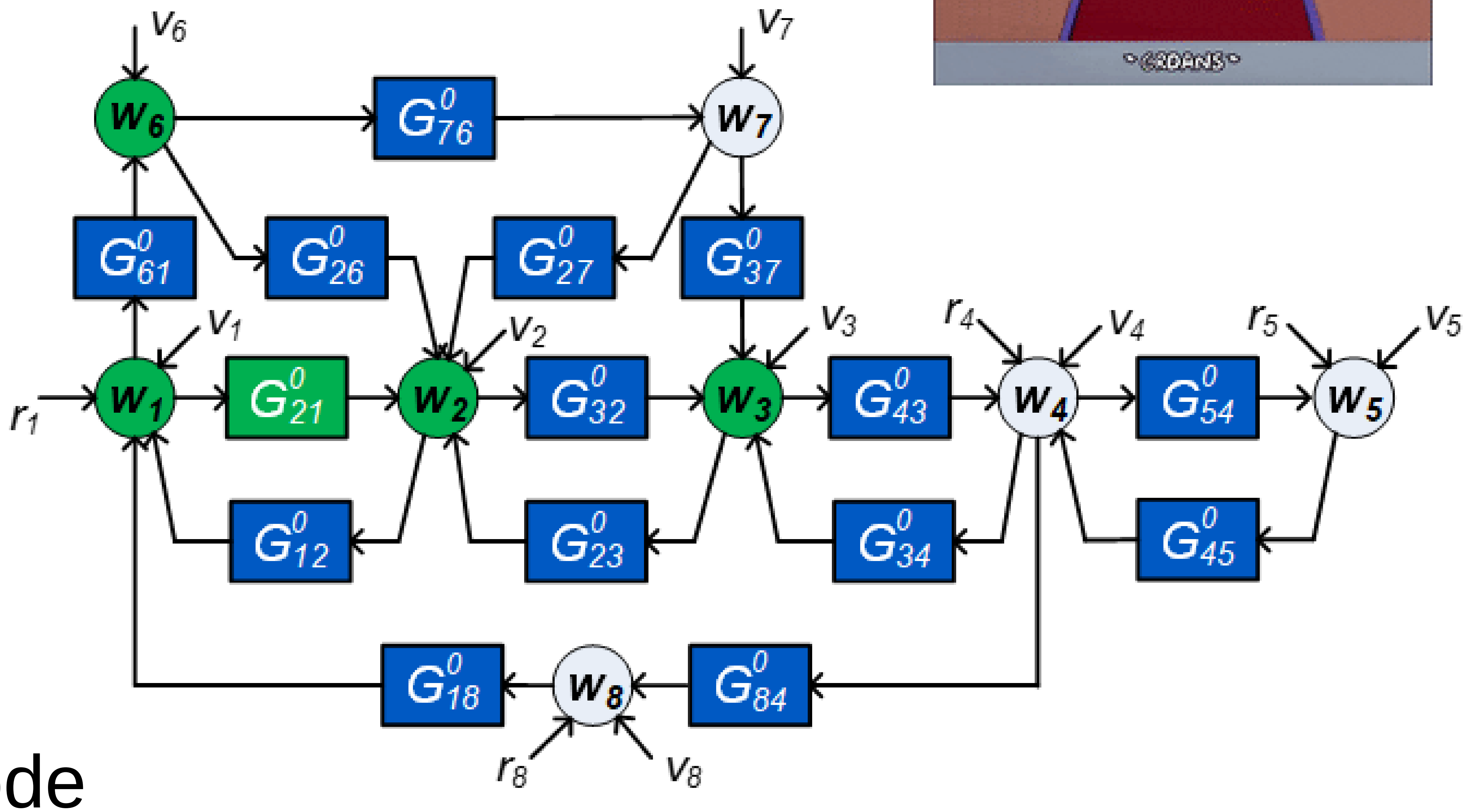
Immersion

- Kicking out node signals, but leaving the remaining node signals invariant (modules and noise signals are adapted)
- We do this when we estimate a module with limited number of node signals
- We need to disentangle the local dynamics from the global network behavior`



Parallel path and loop condition

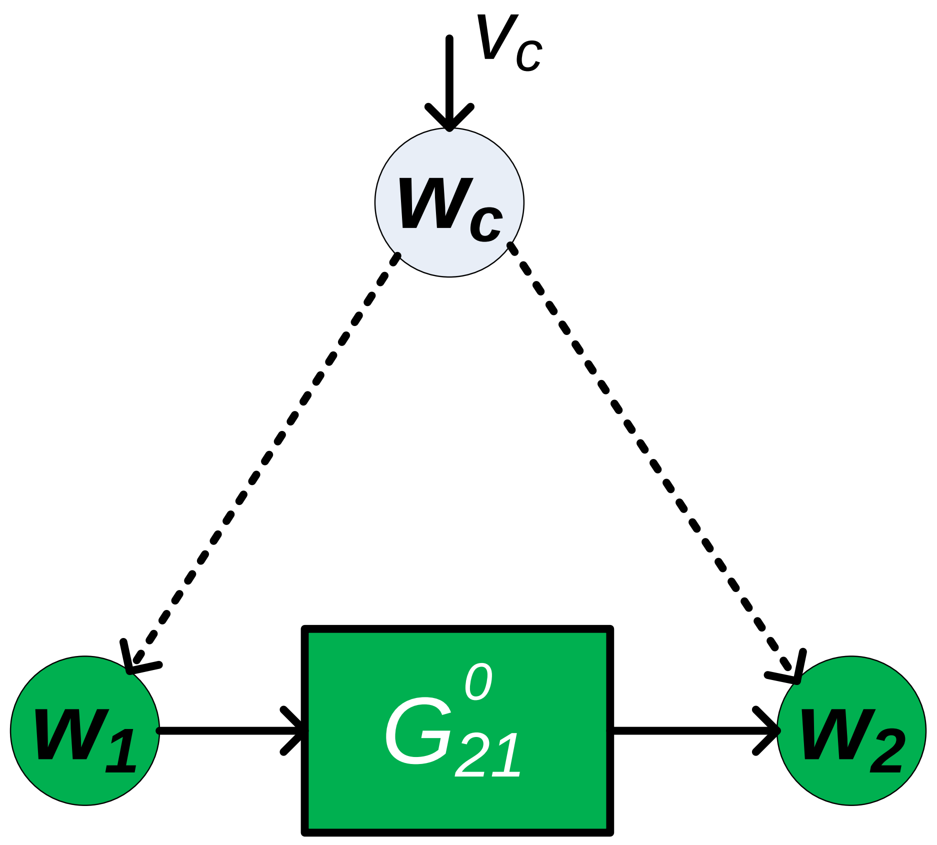




All parallel paths, and loops around the output, should pass through a measured node

A. Dankers et al., TAC 2016.

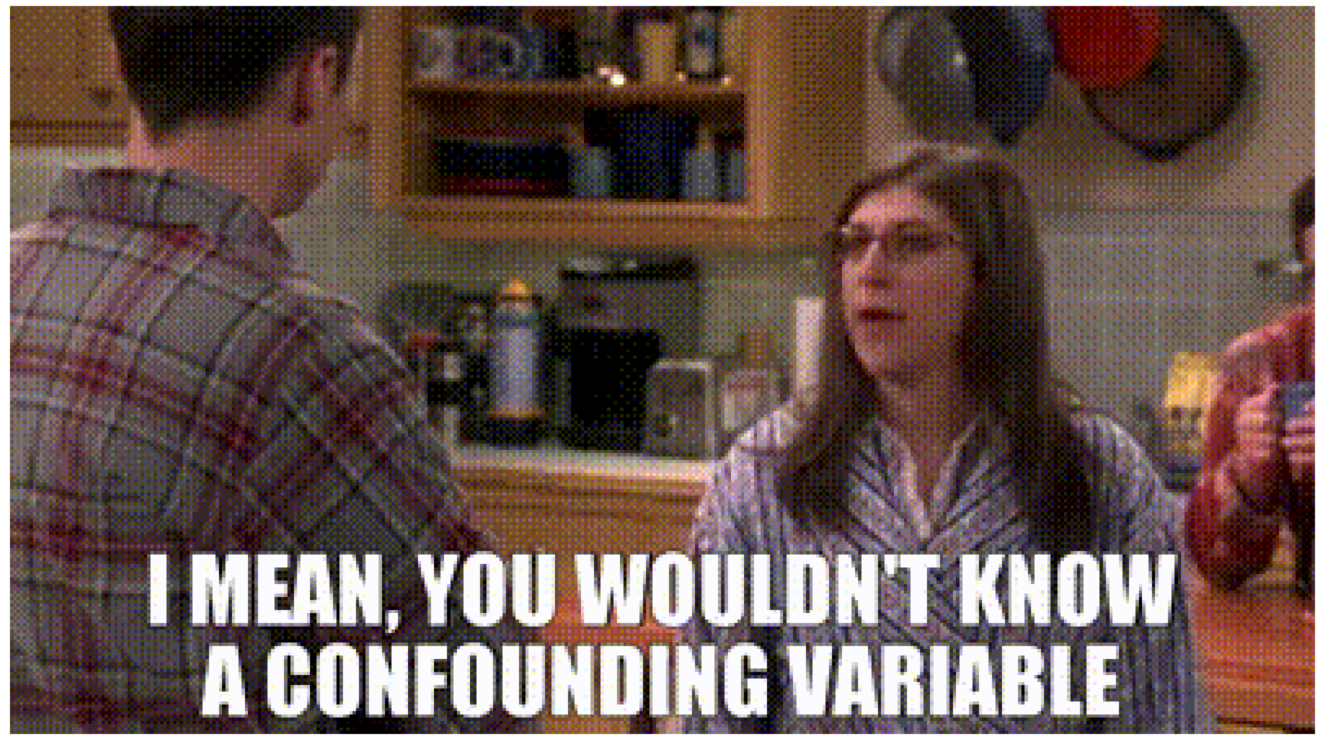
Confounding variable



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:[3]



Direct:

If disturbances on inputs and outputs are correlated.

Indirect:

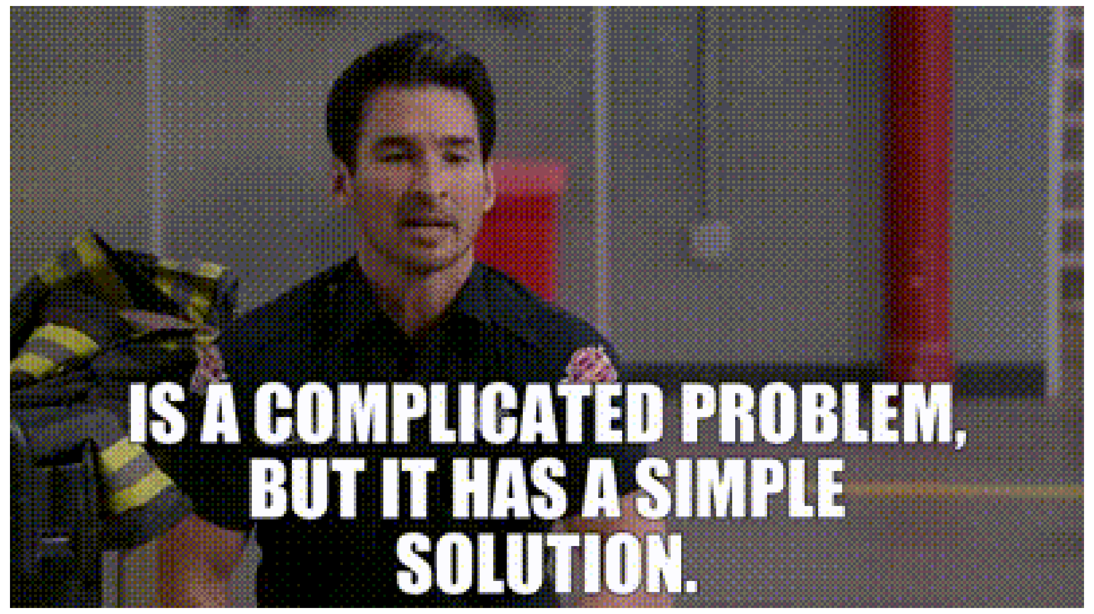
If non-measured in-neighbors of an output affect signals in the inputs.

[1] J. Pearl, Stat. Surveys, 3, 96-146, 2009

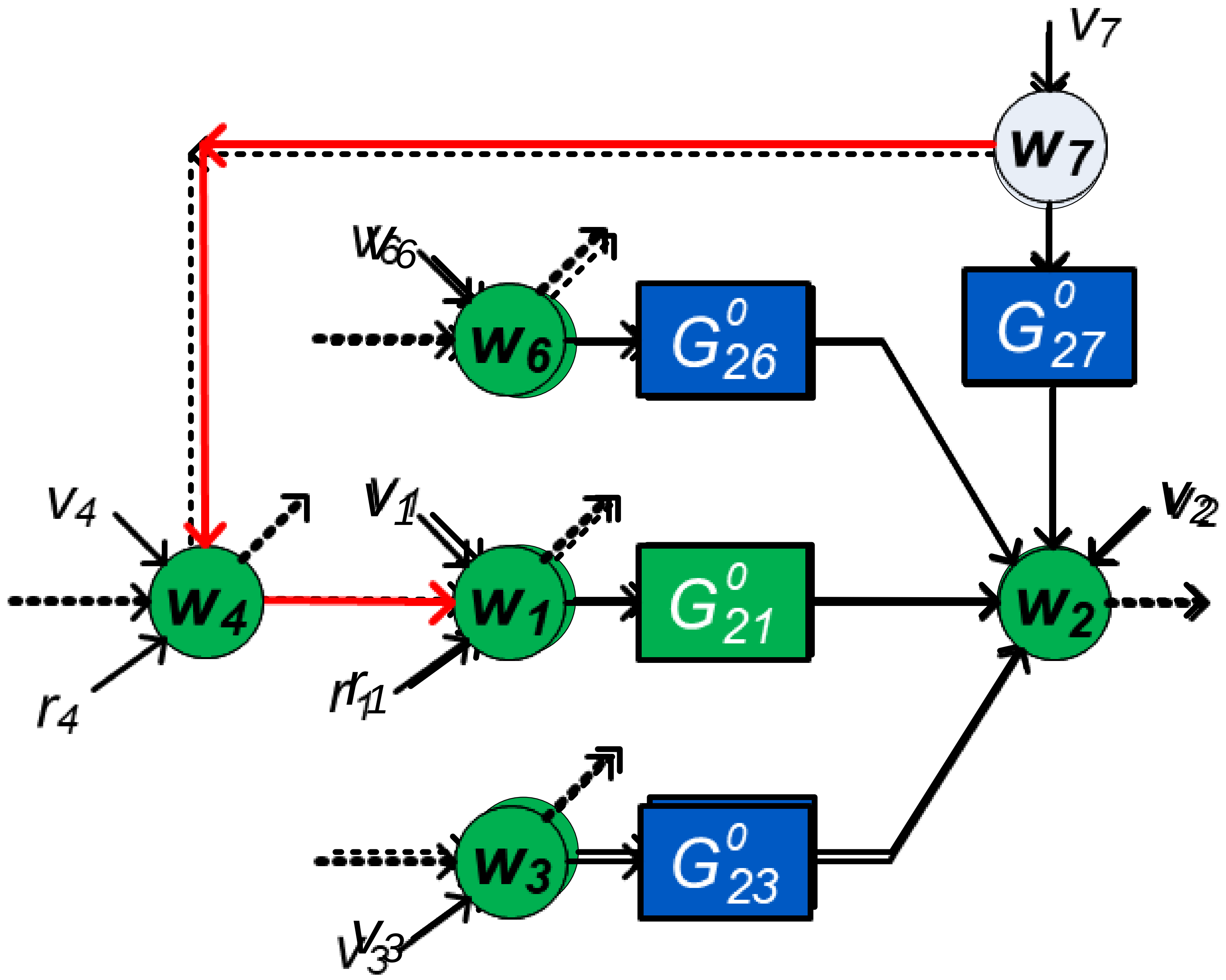
[2] A.G. Dankers et al., Proc. IFAC World Congress, 2017.

[3] K.R. Ramaswamy et al., IEEE-TAC, 2021.

Confounding variables



Non-measurable w_7 is a confounding variable



Two possible solutions:

1. Include w_4 ➡ add predictor input

$$w_{\mathcal{D}} = \{w_1, w_3, w_4, w_6\} \quad w_{\mathcal{Y}} = \{w_2\}$$

2. Predict w_1 too ➡ add predictor output

$$w_{\mathcal{D}} = \{w_1, w_3, w_6\} \quad w_{\mathcal{Y}} = \{w_1, w_2\}$$

There are degrees of freedom in choosing the predictor model

K.R. Ramaswamy et al., IEEE-TAC, 2021.

The two sides of the coin!!

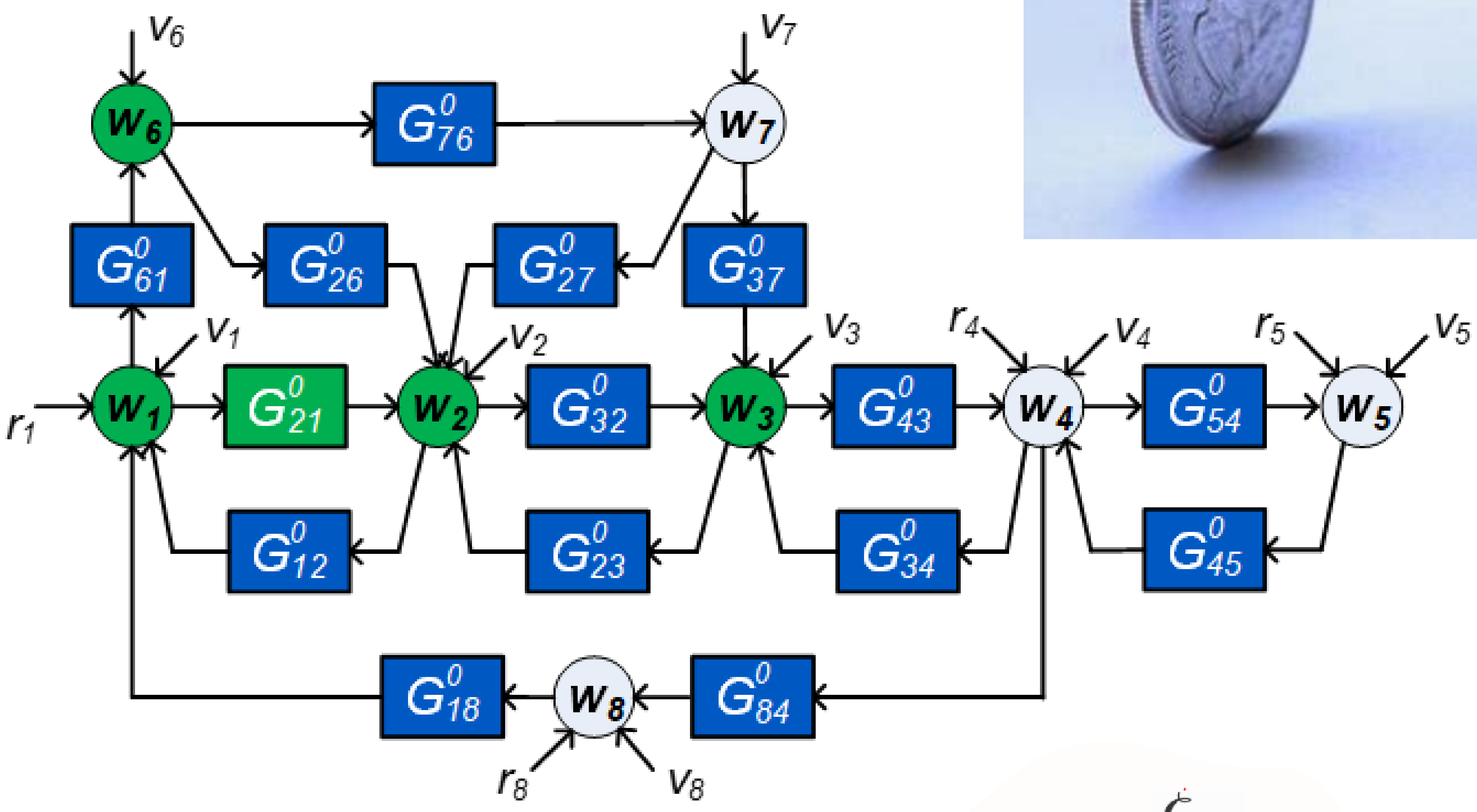
Single module identification

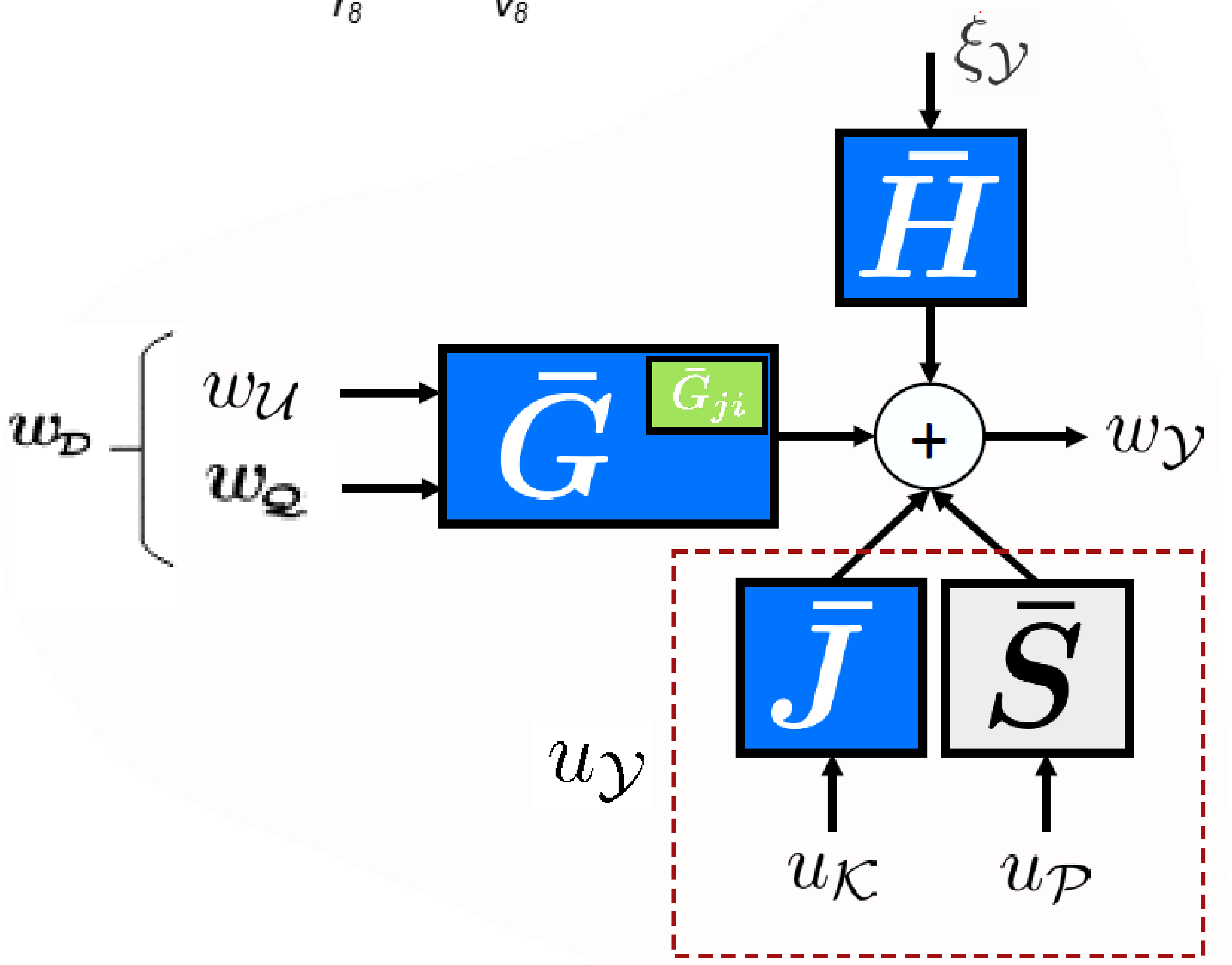
How to formulate the predictor model?

Which signals to select?	What should be the input and output of the estimation problem?

How to perform the identification in complex networks with less computational complexity?

Effective algorithms





K.R. Ramaswamy, PhD Thesis, 2022.

Public

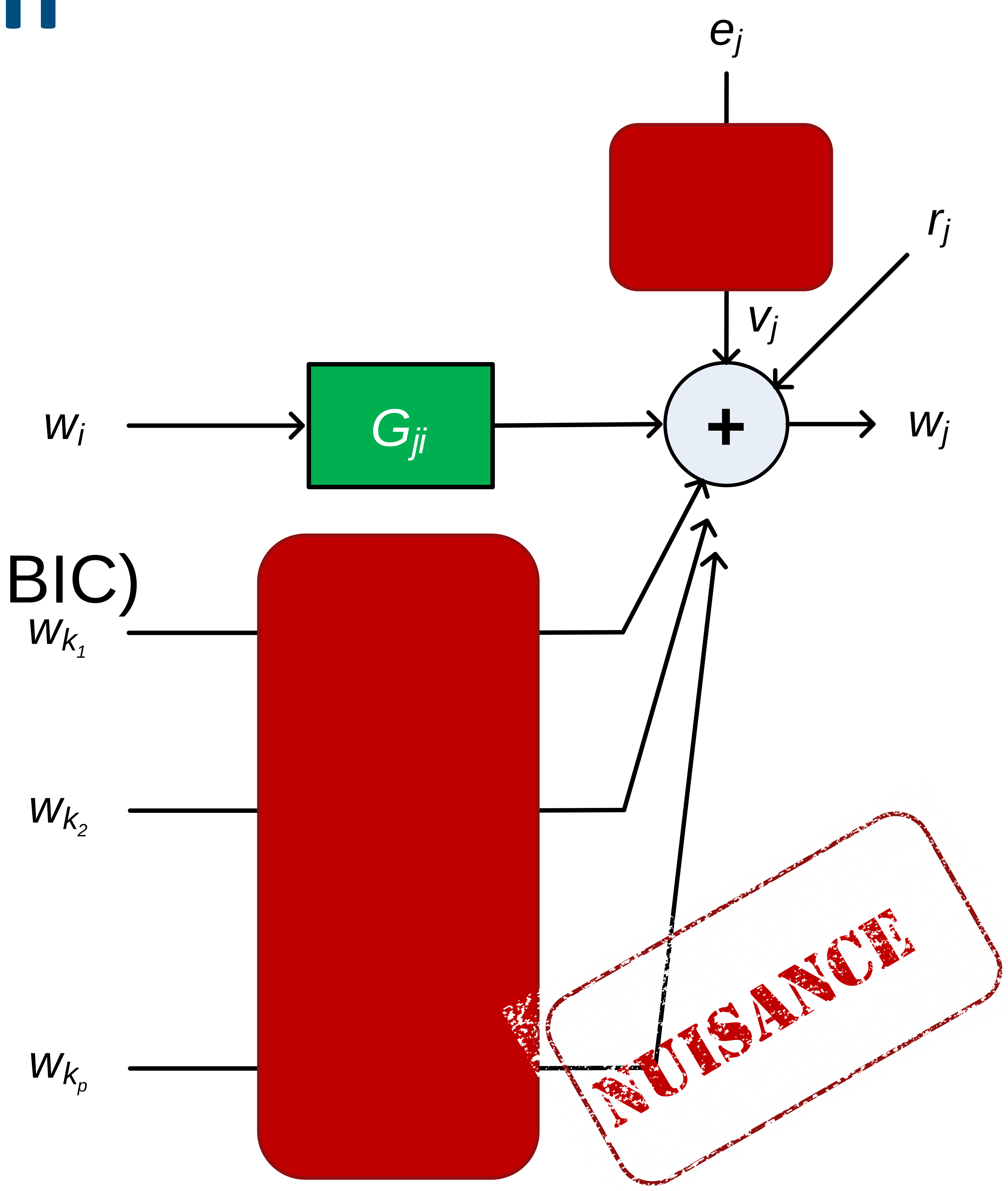
Machine learning in local identification

- ➢ MISO identification with all modules parameterized
- ➢ Brings in two major problems :
  - ➢ Large number of parameters to estimate
  - ➢ Model order selection step for each module (CV, AIC, BIC)

- For 5 modules, combinations = 244,140,625

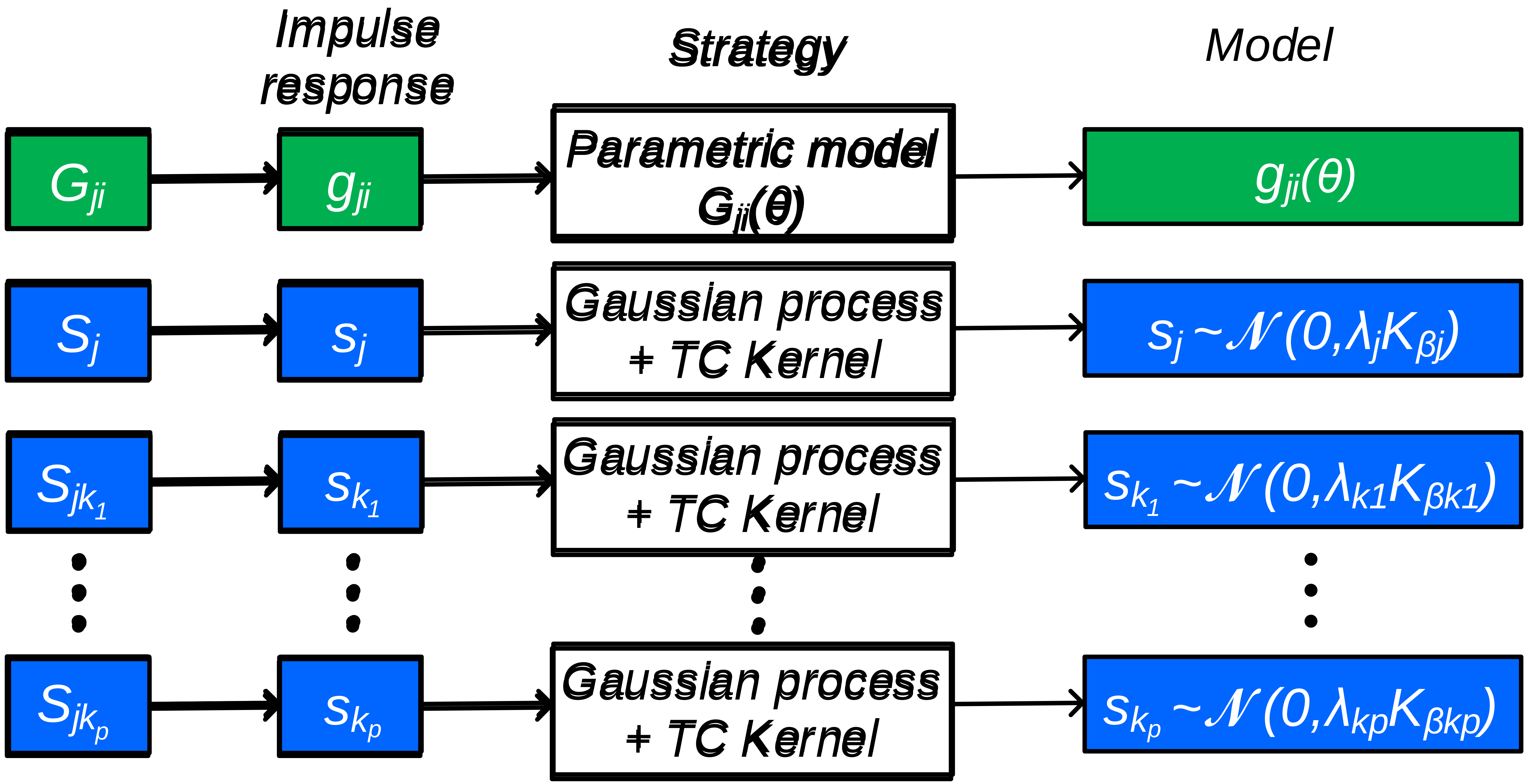
Increases variance

Computationally challenging



  - ➢ We need only the target module. No NUISANCE!

Empirical Bayes method



$$[\boldsymbol{K}_{\boldsymbol{\beta}}]_{\boldsymbol{x},\boldsymbol{y}} = \boldsymbol{\beta}^{\mathbf{max}(\boldsymbol{x},\boldsymbol{y})}$$

$$\boldsymbol{\beta_j} \in [\mathbf{0}, \mathbf{1}), \quad \boldsymbol{\lambda} \geq \mathbf{0}$$

Maximize marginal likelihood of output data: $\hat{\eta} = \underset{\eta}{\operatorname{argmax}}\, p(w_j; \eta)$

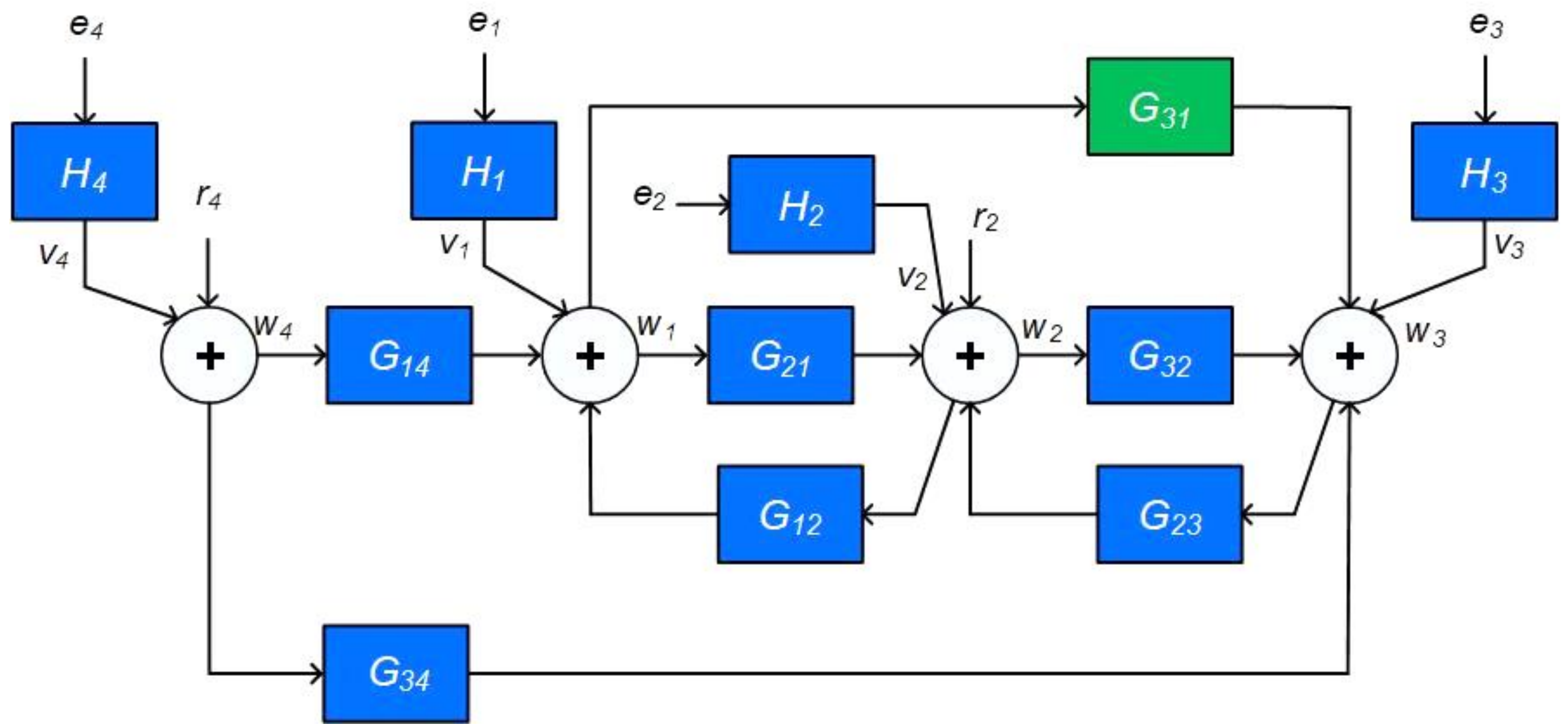
$$\eta := [\theta \quad \lambda_j \quad \lambda_{k_1} \quad \dots \quad \lambda_{k_p} \quad \beta_j \quad \beta_{k_1} \quad \dots \quad \beta_{k_p} \quad \sigma_j^2]^\top$$

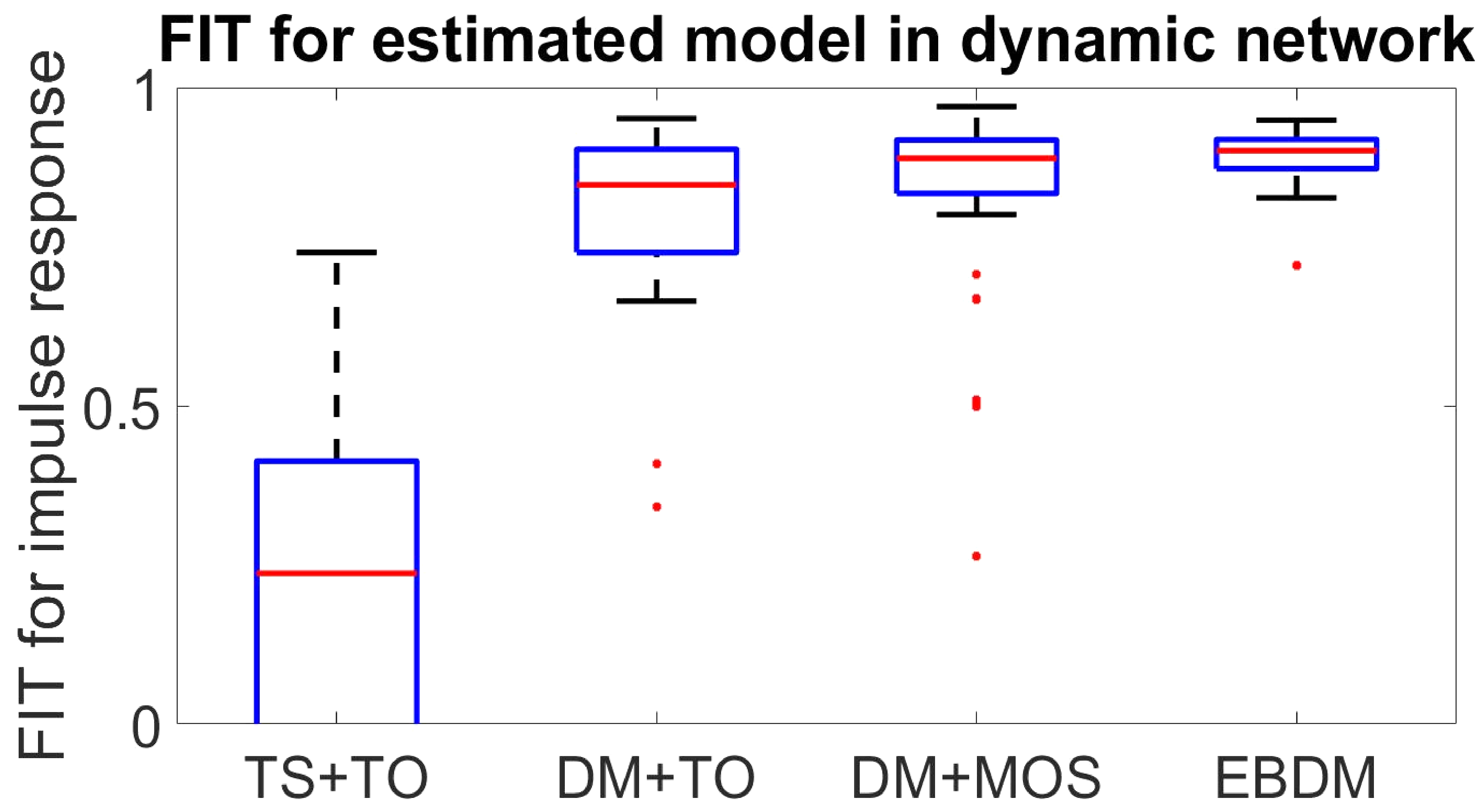
[1] Everitt et al., Automatica 2017.

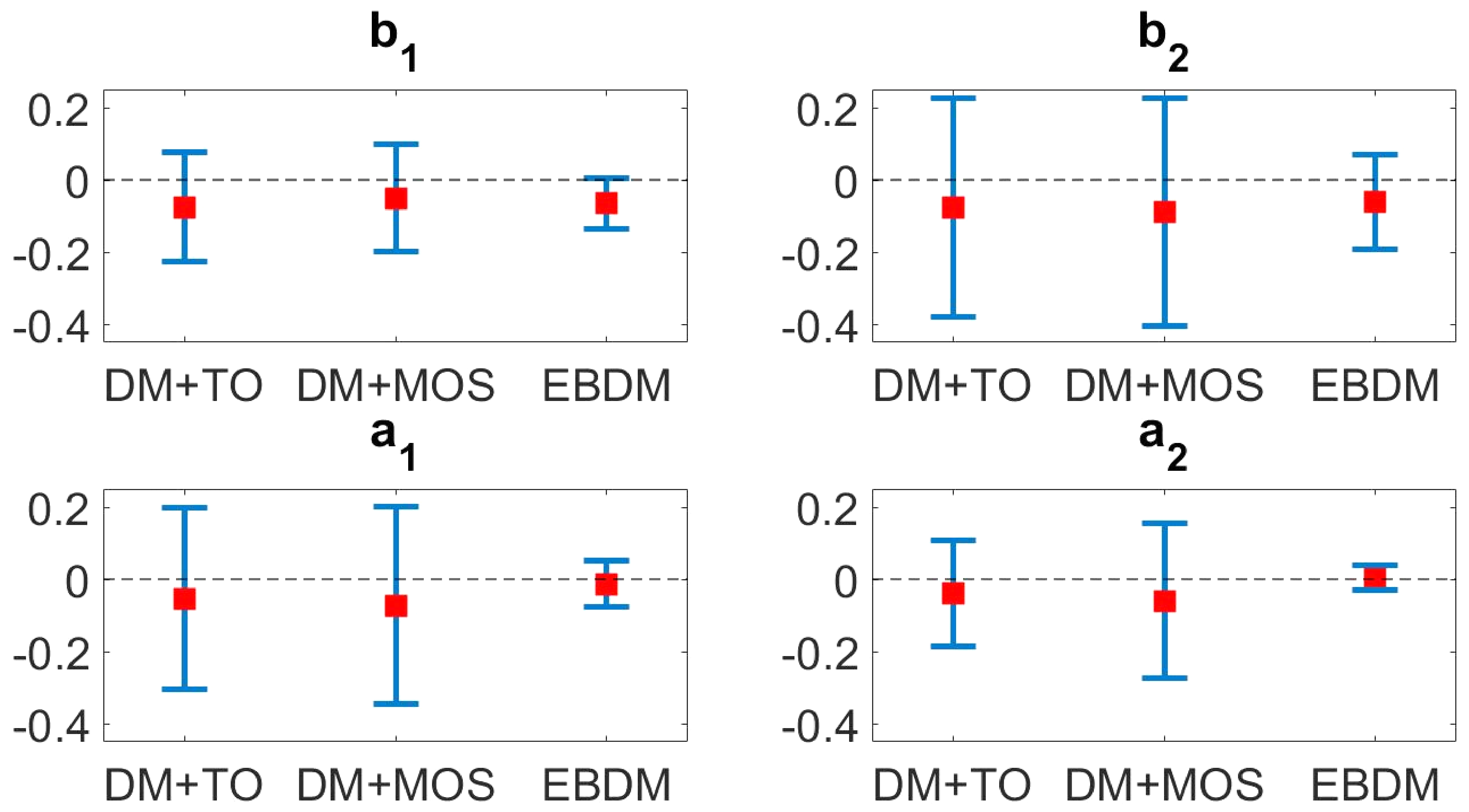
[2] K.R. Ramaswamy et al., CDC 2018; Automatica 2021.

Numerical simulation

- Identify G_{31} given data
- 50 independent MC simulation
- Data = 500







Multi-step least squares method[1][2]

Step 1: Select the nodes to construct a predictor model

Step 2: High order ARX modeling to reconstruct the innovation

Step 3: Parametric target module estimate using Weighted Null Space Fitting[3]

- ➢ No non-convex optimization problems
- ➢ Identification with analytical solutions → scalable and effective

[1] S. Fonken, et al., Automatica, 2022

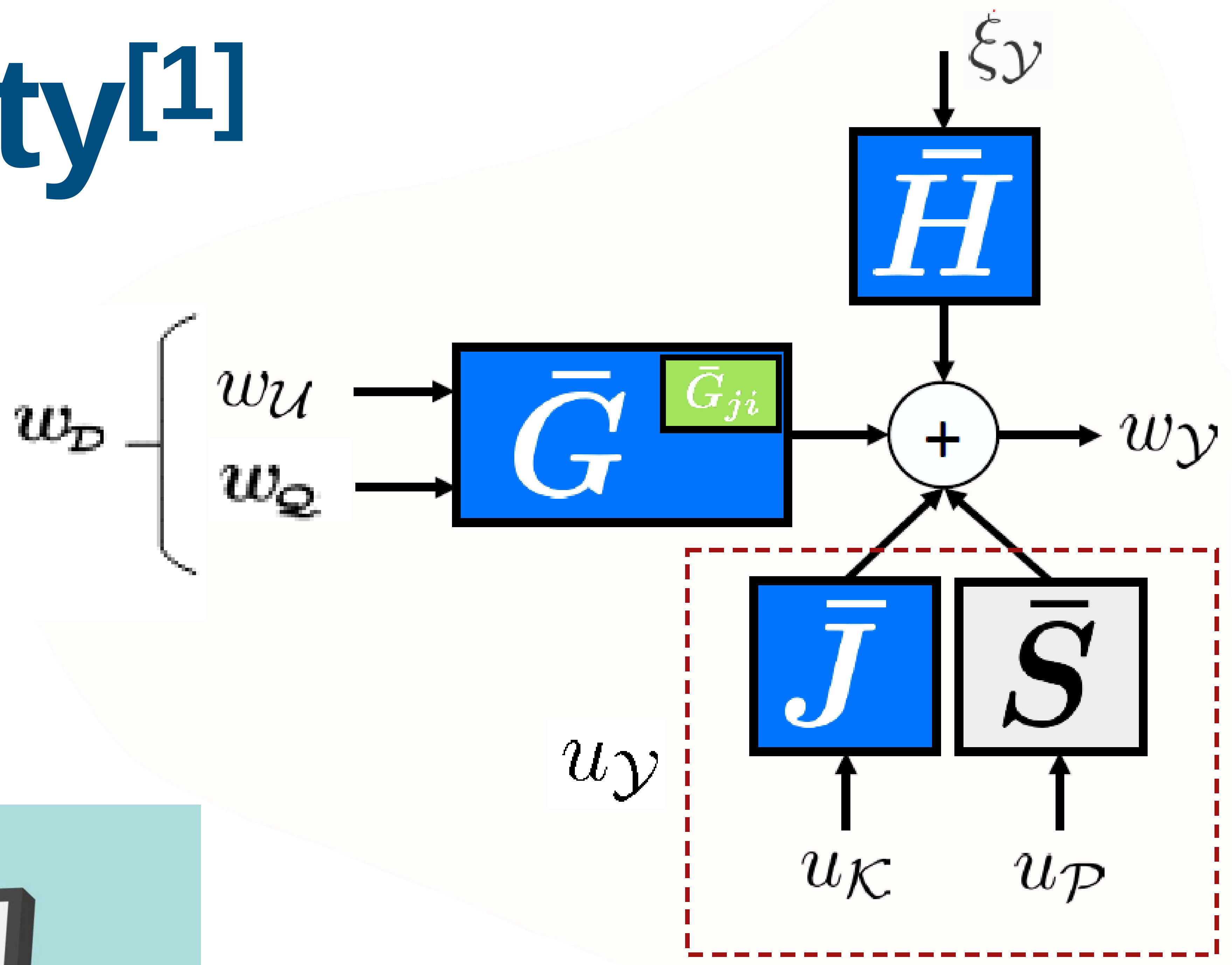
[2] S. Fonken, et al., CDC, 2023

[3] M. Galrinho, et al., TAC, 2019

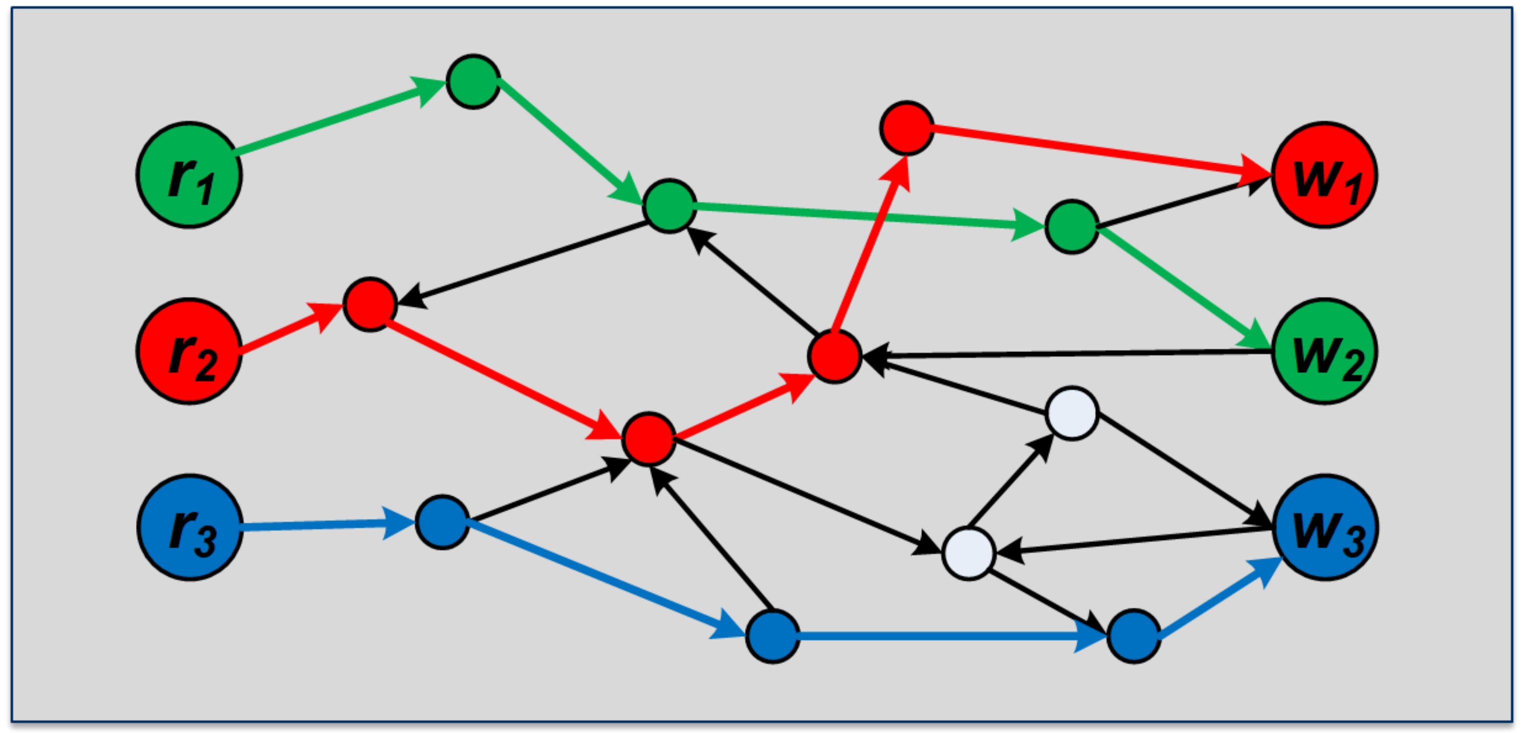
Path-based data informativity[1]

➢ Data informativity[1][2] :

$$\Phi_\kappa(\omega) > 0, \quad \kappa = \begin{bmatrix} w_D \\ \xi_Y \\ u_K \end{bmatrix}$$



This is satisfied generically if there are dim(w_D) vertex disjoint paths from all external network signals except (ξ_Y, u_K) to w_D



$b_{\mathcal{R}\to\mathcal{W}} = 3$

Simple sufficient condition that can be easily checked

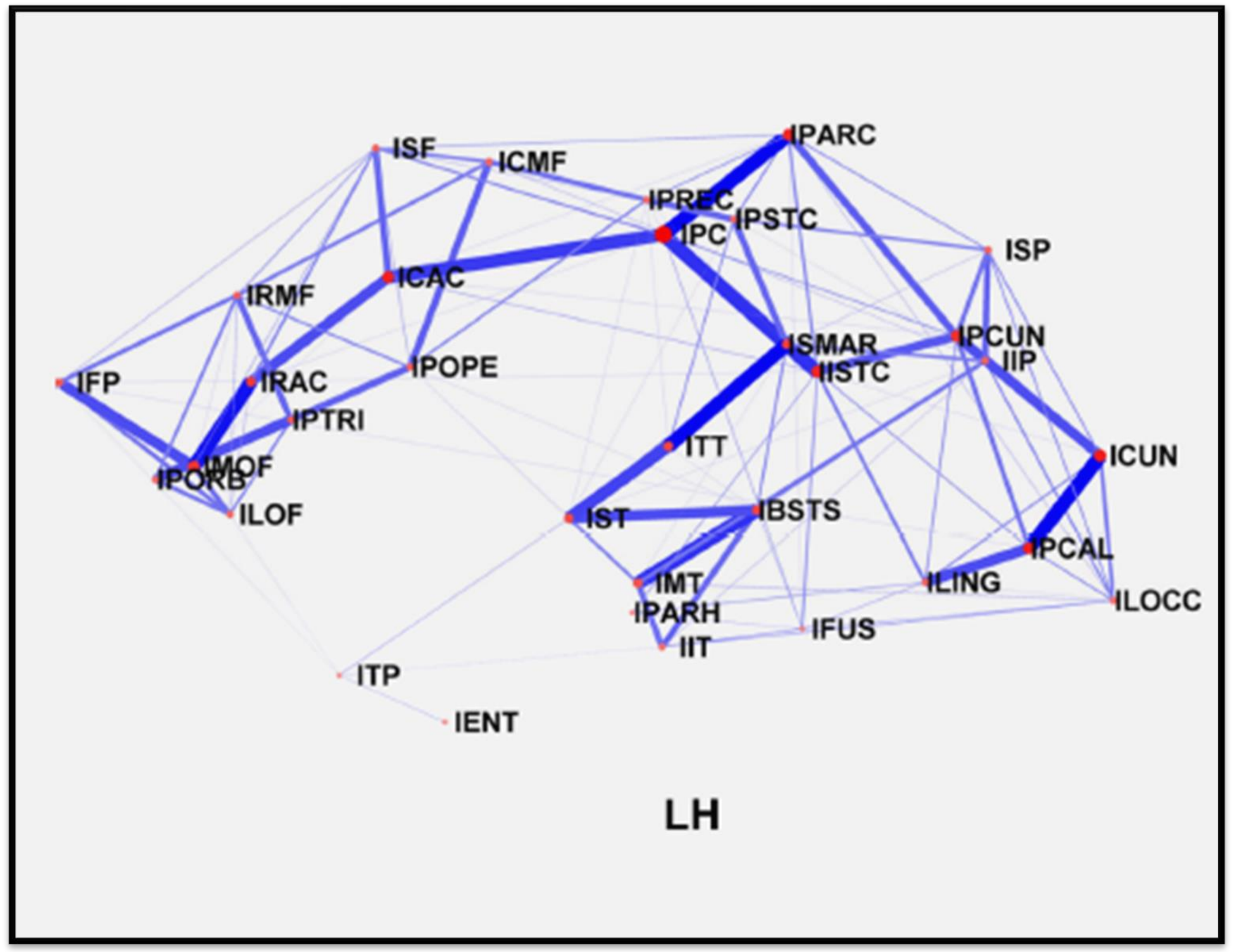
[1] P.M.J. Van den Hof and K.R. Ramaswamy, CDC 2020

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

[3] X. Bombois, et al., Automatica, 2023 (Move from genericity and move towards optimal experiment design)

[4] A. Bazanella, CDC2017; J. Hendrickx et al., IEEE-TAC, 2019.

Topology identification



- Interconnection structure of the full network
- Lots of approaches available in literature
  - Wiener filter based[1][2]
  - Bayesian based[3][4] – connection with kernel-based method
- Local topology identification for networks with correlated noise is introduced in [5]

Problem

Approach

No prior topology

1. Identify locality of output node
2. Reduce the network size
3. Estimate noise innovation
4. Cleverly search for the topology

Predictor model

Local direct method [6]

Module estimation

Regularized kernel based methods

[1] D. Materassi & Innocenti, TAC 2010

[2] D. Materassi et al ., TAC, 2012

[3] A. Chiuso & G. Pillonetto, Automatica, 2012

[4] S. Shi et al ., ECC 2019

[5] V. C. Rajagopal et al ., CDC 2021

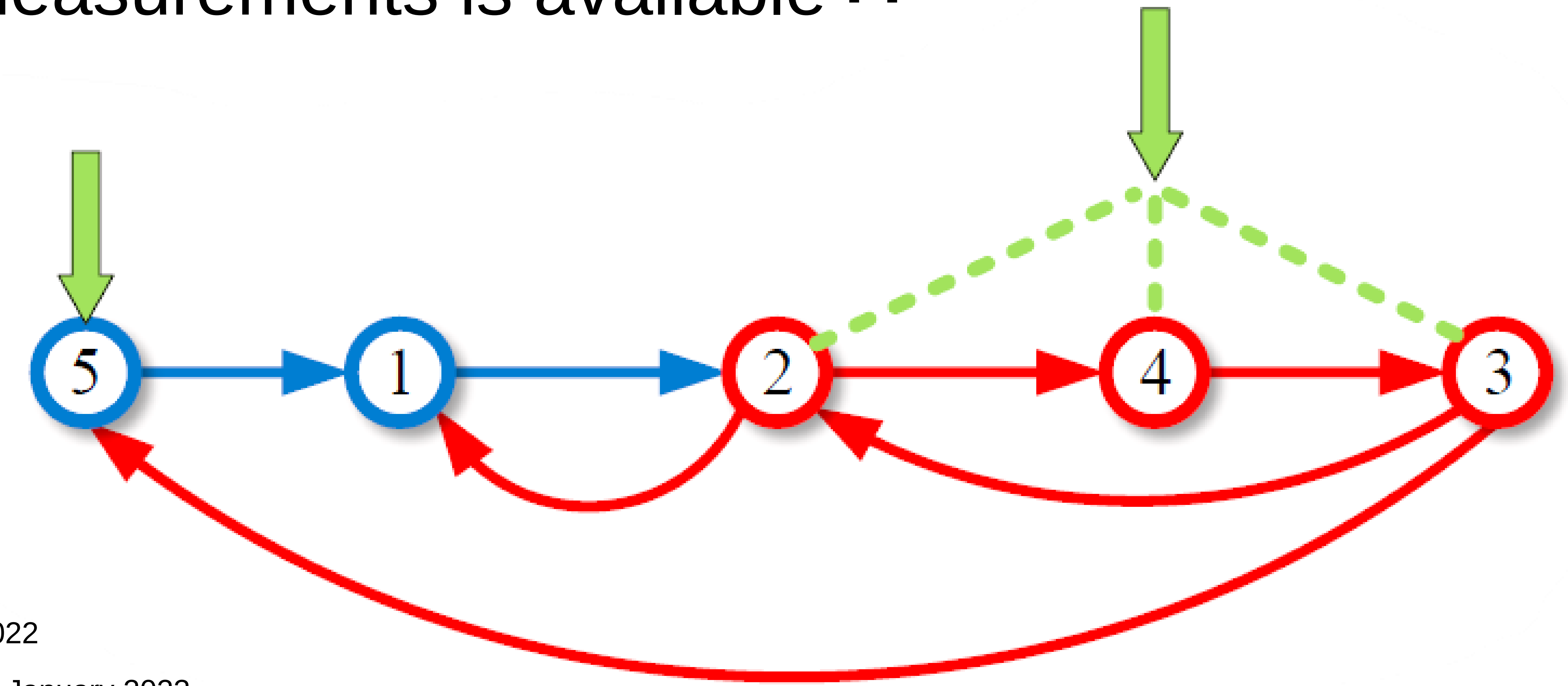
[6] K.R. Ramaswamy et al., IEEE-TAC, 2021.

Identifiability

- ➢ Under which conditions can we uniquely estimate the topology and/or dynamics of the full/local network?
- ➢ Ability to distinguish between network models from measured signals – not dependent on identification method

- ➢ Boils down to excitation and sensor allocation in the network
- ➢ Attractive synthesis algorithm for allocation of external signals that guarantee generic identifiability for a network with all node measurements is available [3]

- Cover network with minimum number of pseudo-trees
- Excite one of the roots of each pseudo-trees

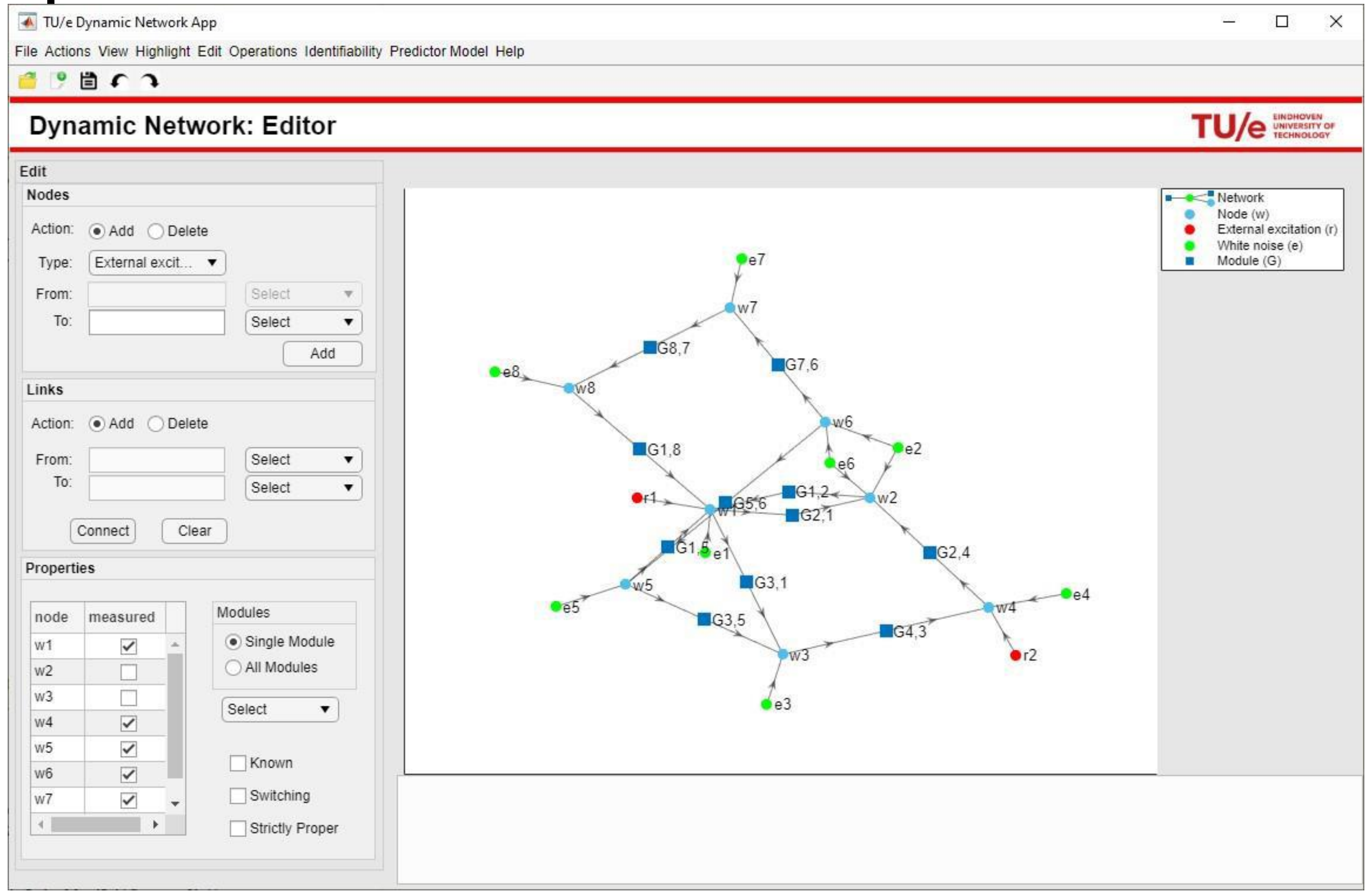


[1] Bazanella, CDC2017; Hendrickx et al., IEEE-TAC, 2019.
[2] Weerts et al., Automatica, March2018
[3] X. Cheng et al., TAC, 2022
[4] S, Shi et al., IEEE-TAC, January 2023

Some more info..

- MATLAB toolbox – GUI with all the structural analysis and operations we discussed so far. Extensions with estimation algorithms planned.[1]

- Least costly experiment design [2][3]



- Applications are in swing (leak detection in pipelines, fault detection analysis, analysis with brain functions, vehicle platooning)

- Extension of auto-correlation and cross-correlation tests to dynamics networks has been recenty explored. The correlaion tests are used for fault detection (narrowing to a module) in local subnetwork [4]

[1] www.sysdynet.net

[2] M. Gevers and A. Bazanella, CDC 2015.

[3] F. Morelli, et al., ECC 2019

[4] Y, Shi et al., SYSID, 2024

A look through the  of industry

The grass is always green in dynamic networks

How can we go from here?

- Low hanging fruits:
  - Networks with sensor noise
  - Extension of all theory of module dynamic networks to physical networks
- Through the lens of industry:
  - Dynamic network with non-linear elements
  - Finding source of non-linearity from data[1][2]
  - Fault detection or error-localization
  - Model validation and uncertainty quantification
  - Experiment design

[1] M. Schoukens and P.M.J. Van den Hof, SYSID 2018

[2] J.P. Noel, M. Schoukens and P.M.J. Van den Hof, IMAC 2019

Thank you Paul and best wishes !!

The evolving landscape of data-driven modeling in dynamic networks

Retrospect and Prospect

Dr. Ir. Karthik Raghavan Ramaswamy

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