

Fault Diagnosability Analysis of Multi-Mode Systems

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Overview and Goal

Model-based fault diagnostics

Goal

Reuse design models to optimize system exploitation: detect component aging and failure early to minimize down time

Model, faults, sensors & data

- **System model** : autonomous dynamical system, eg. ODEs
- **Component fault** : system behavior does not match one or several equations capturing the physics of the component
- **Sensors** : direct or indirect measurement of some of the system state variables
- **Measurement data** : additional equations rendering the model overdetermined

$$\dot{x} = f(x, t)$$

$$y = g(x)$$

$$y = Y(t)$$

Structural method

- ODEs \rightarrow DAEs
- Exploit the structural redundancies
- **Syndrome** : minimal set of of structurally overdetermined equations
- **Alarm** : syndrome residuals can not be zero

Overview and Goal

Structural fault diagnostics for multi-mode systems

Li-ion batteries are keys for the sustainable electrification of vehicles.

Challenges

- Multi-mode systems (switched systems) with frequent mode changes
- Complex systems with many components
- Direct diagnosis --> Exponential explosion of analysis complexity

- Tools extension and development
- Overcome the complexity of diagnostics
- New fault modeling approach

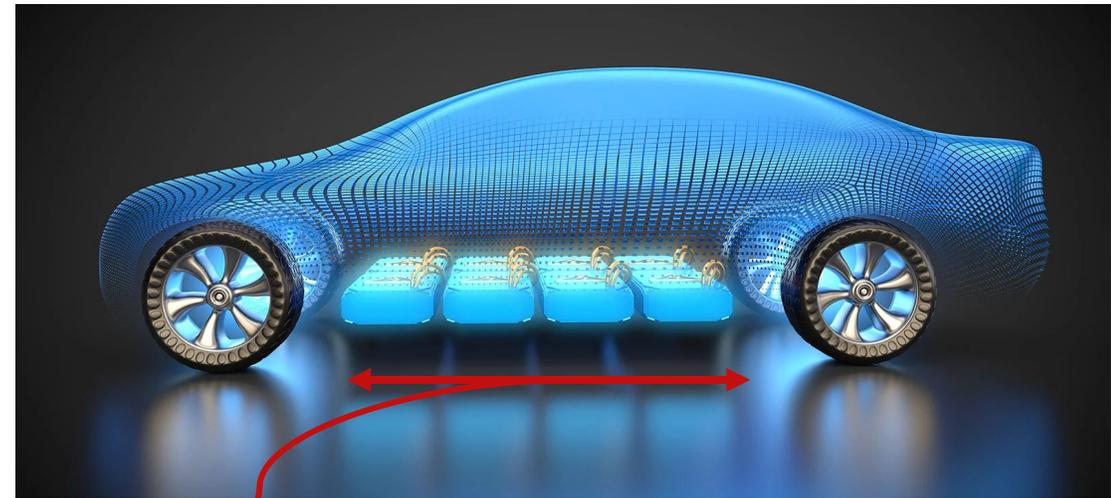
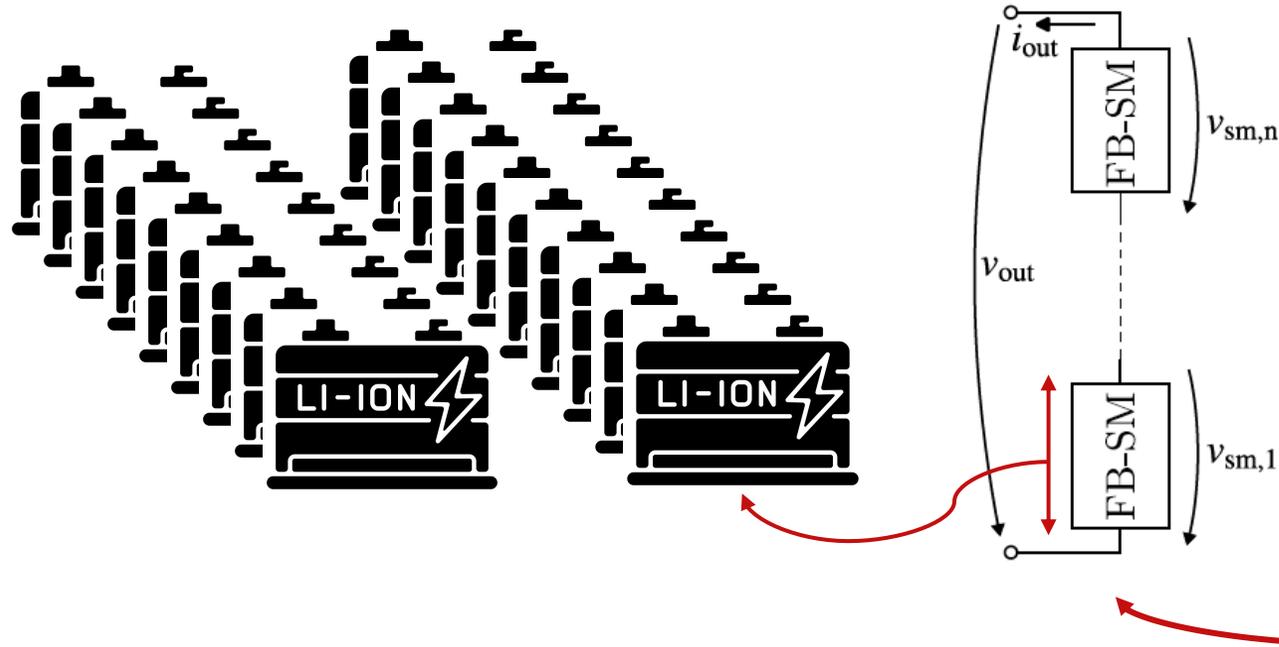
G@AL:



Multi- Mode System

(motivation)

Reconfigurable battery system is an example of multi-mode systems.

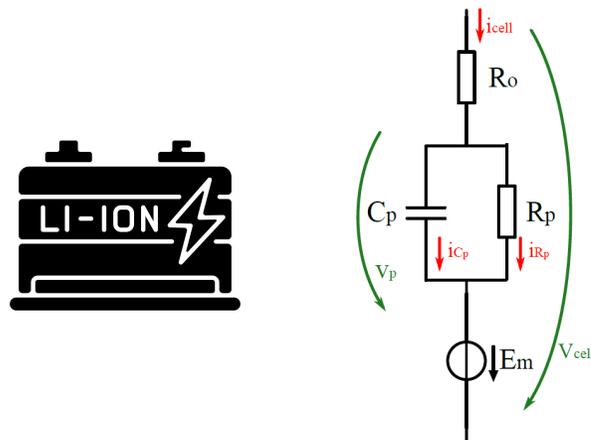


Multi- Mode Battery System

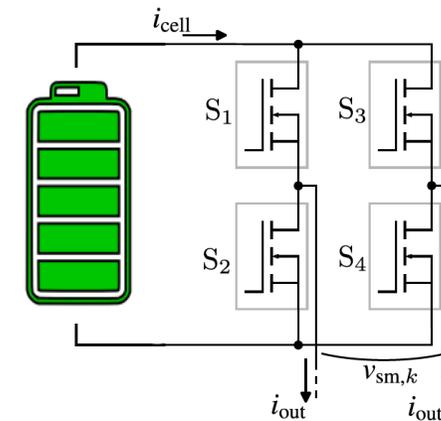
(simplified Battery example)

Based on the switch positions, there are 4 valid modes!

A Li-ion cell is modeled by an equivalent circuit model.



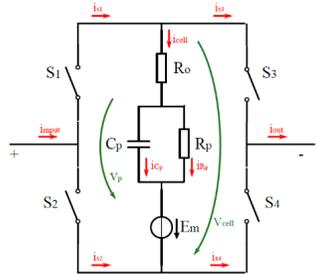
Full bridge modular multilevel converter (MMC) to produce AC.



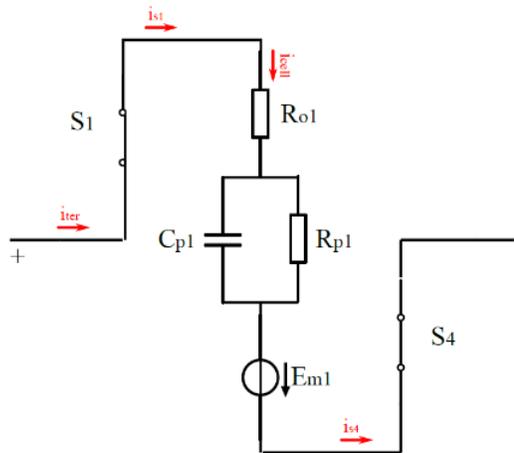
Multi- Mode Battery System

(Different modes)

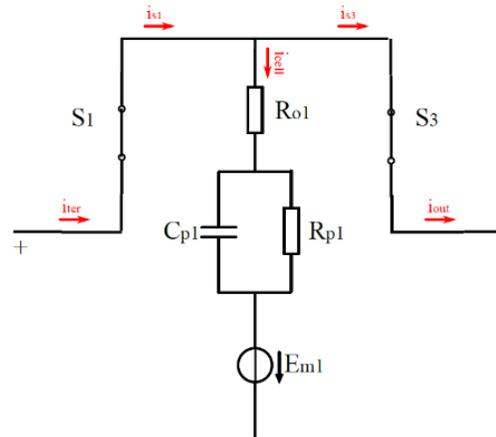
Based on the switch positions, the system works in different modes!



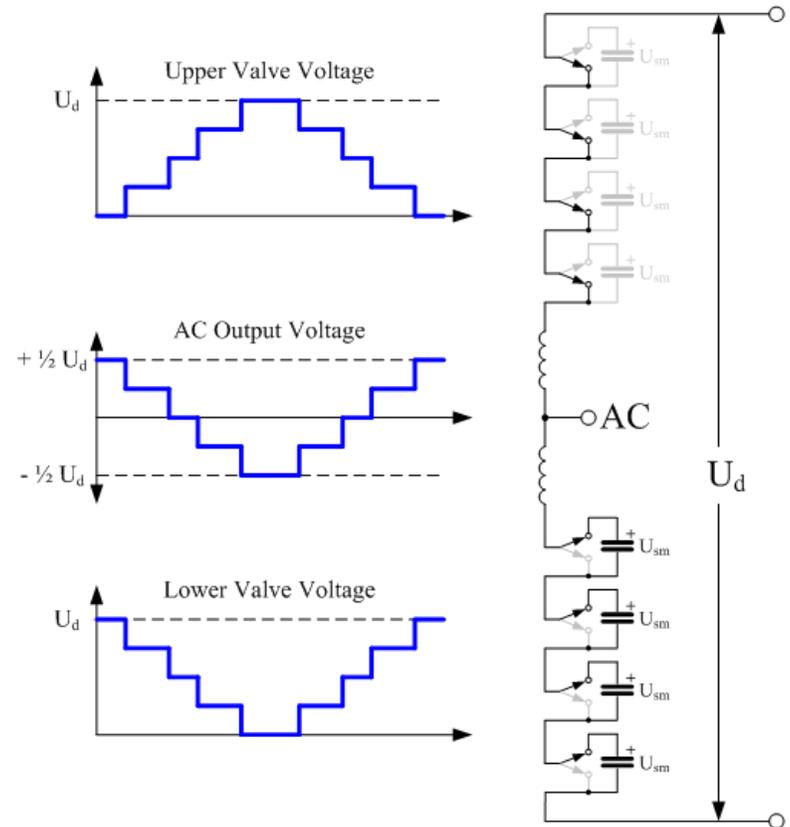
There are 16 possible modes, but only 4 modes are valid. Others are not feasible.



Connected



Bypassed



Operating principle of Modular Multi-Level Converter (MMC). Source: Wikipedia

Multi- Mode DAE*

Equations valid for **all** modes:

$$\dot{v}_p = \frac{i}{C_p} - \frac{v_p}{R_p C_p} \quad (1)$$

$$v_{cell} = v_p + R_0 i + E_m + f_{cell} \quad (2)$$

$$y_i = i + f_i \quad (3)$$

$$y_v = v_{cell} + f_v \quad (4)$$

$$\dot{v}_p = \frac{dv_p}{dt} \quad (5)$$

Measured data

Same

Switch dependent equations:

Forward/ Backward mode:

$$v_{sm} = \pm v_{cell} \quad (6)$$

$$i = \pm i_{pack} \quad (7)$$

Bypass 1&2 mode:

$$v_{sm} = 0 \quad (6)$$

$$i = 0 \quad (7)$$

Different

The system structure changes when the mode changes!

Equations valid for a **special** mode:

$$v_{sm} = \begin{cases} v & \text{if (Forward)} \\ -v & \text{if (Backward)} \\ 0 & \text{else} \end{cases} \quad (6)$$

$$i = \begin{cases} i_{pack} & \text{if (Forward)} \\ -i_{pack} & \text{if (Backward)} \\ 0 & \text{else} \end{cases} \quad (7)$$

*Benoît Caillaud, Mathias Malandain, Joan Thibault. Implicit structural analysis of multimode DAE systems. HSCC 2020 - 23rd ACM International Conference on Hybrid Systems: Computation and Control, Apr 2020, Sydney New South Wales Australia, France. pp.1-11, (10.1145/3365365.3382201).



Problem Formulation/Challenges

Even for a small system:

6 battery cells in one pack → Each cell has 4 modes → $4^6 = 4096$ combinations for switch configuration.

- 1. How to do diagnosis analysis for multi-mode systems with high number of components and configurations? (contribution 1)

A general solution

- 2. How to model faults? Pros and cons? (contribution 2)



Direct Fault Isolability Analysis

Classic Dulmage-Mendelsohn Decomposition

M^- : underdetermined part

M^0 : just determined part

M^+ : overdetermined part

M^- : underdetermined part

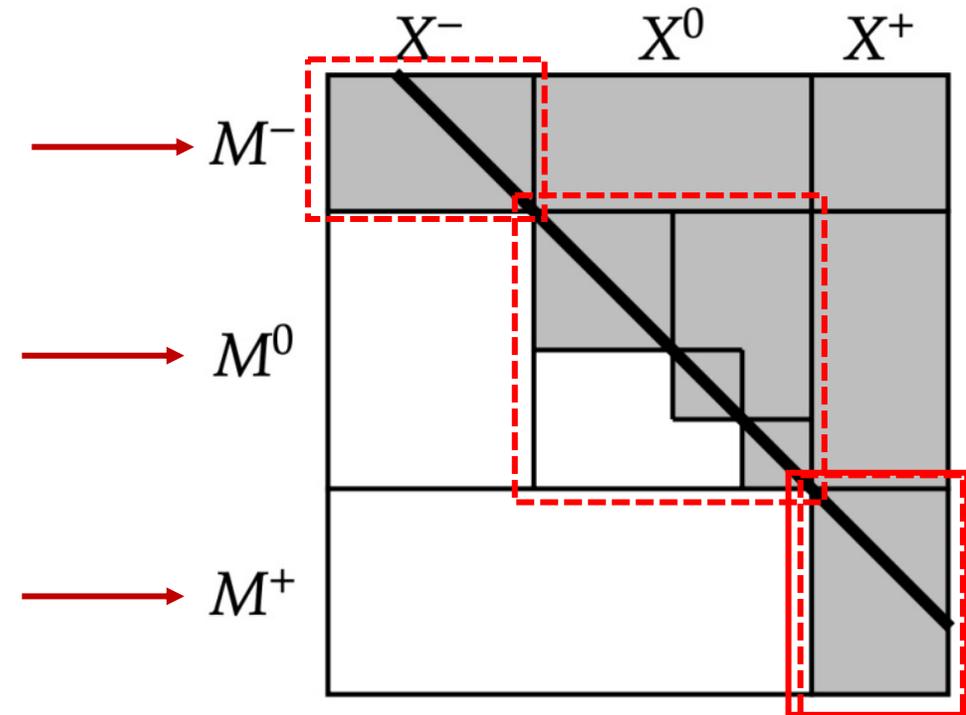
M^+ : Number of equations is **more** than unknown variables

M^0 : just determined part

Here, there is **redundancy** that will be used for diagnosis and residual generation.

M^+ : overdetermined part

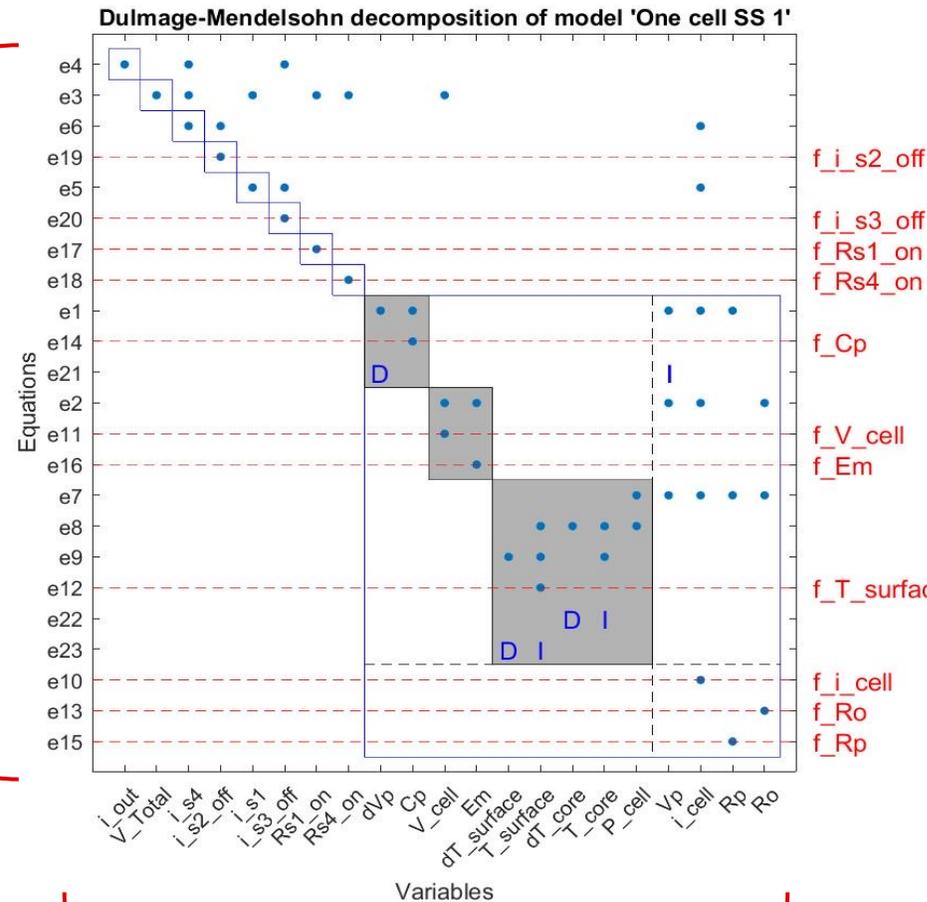
M: Set of equations
X: Set of unknown variables



Extended DM Decomposition

Extended DM:
Toolbox (Matlab and Python)*

Equations



Unknown variables



Extended DM Decomposition

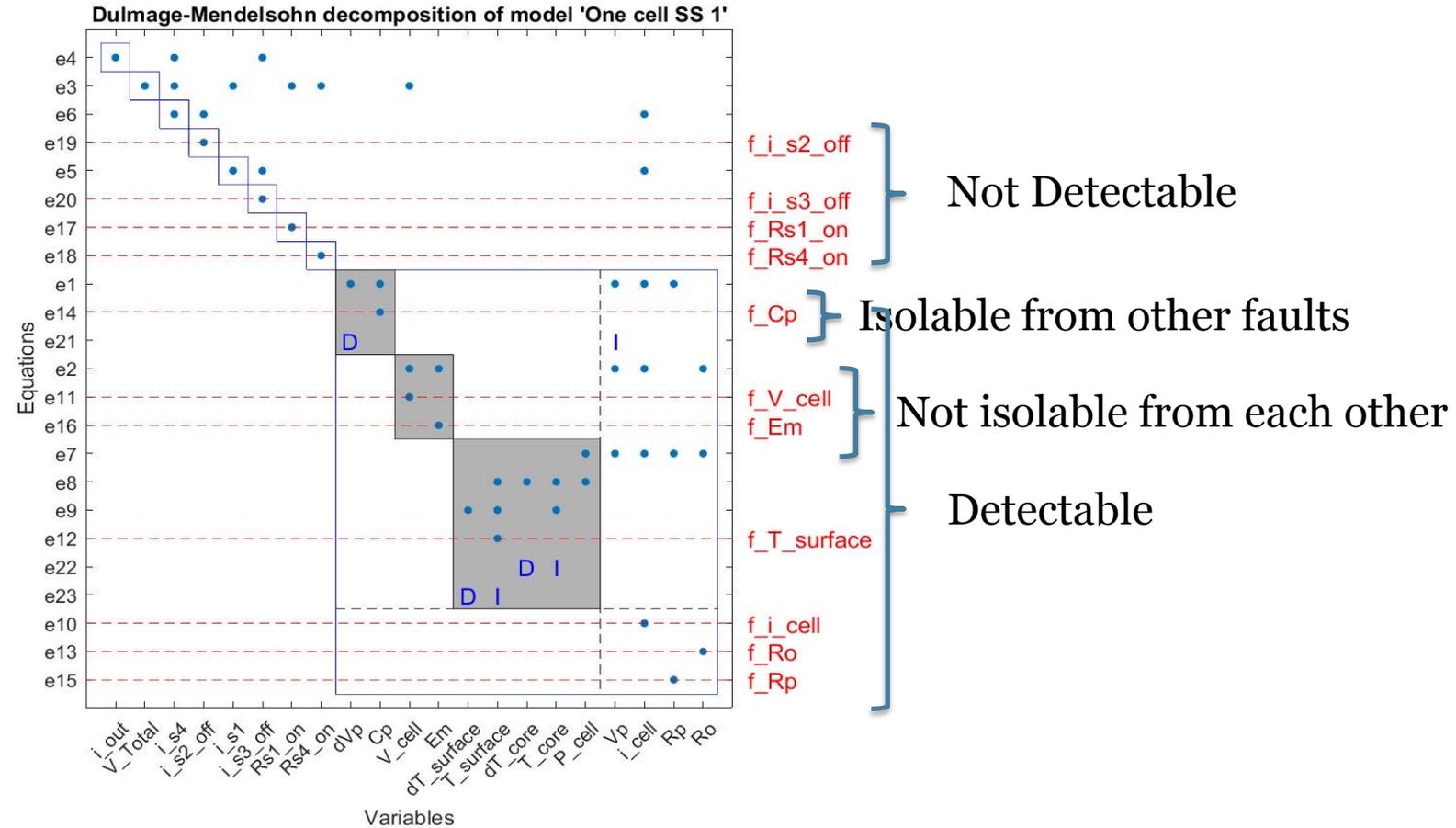
Extended DM: Diagnosability

Detectability:

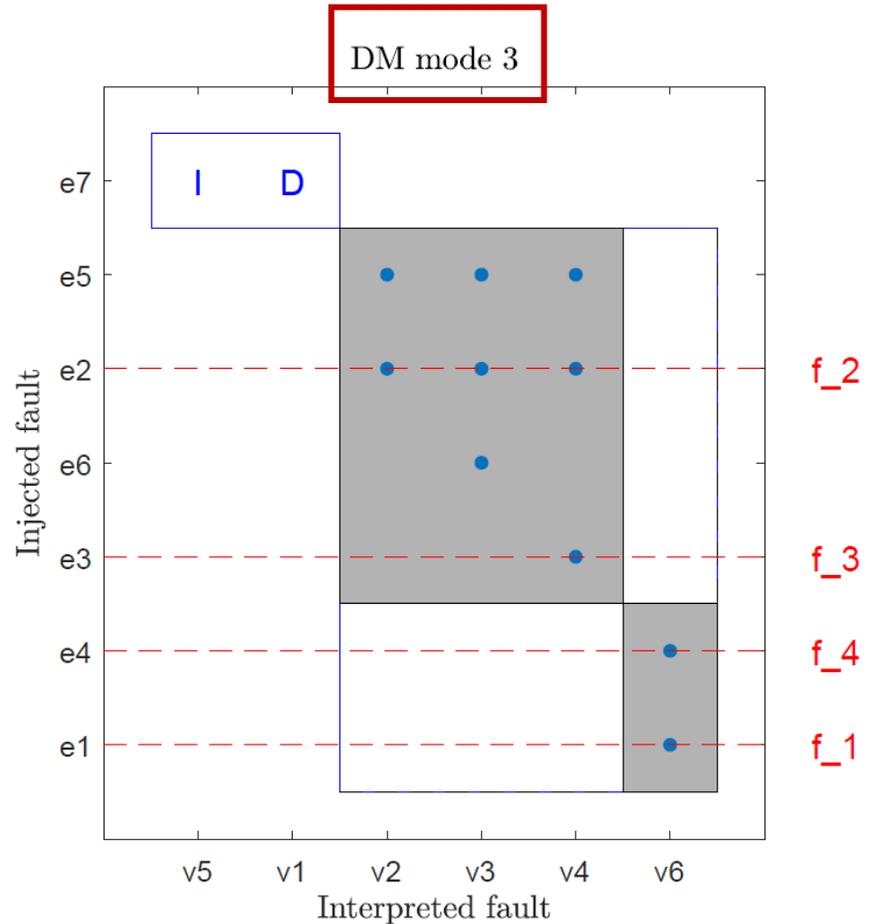
Fault f is detectable if it is in the overdetermined part.

Isolability:

A fault f_i is structurally isolable from f_j in a model M if $e_{f_i} \in (M \setminus \{e_{f_j}\})^+$.



Multi-mode DM Decomposition

f₁

e1_under: mode2

f₄

e1_det: mode1

e1_over: mode3

f₂

e4_under: False

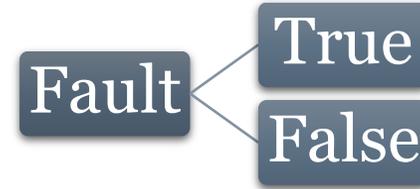
f₃

e4_det: mode2

e4_over: mode1 ^ mode3



Fault Modeling



Fault as Signal

`e_1:` $x_1 = x_2$

`e_f1:` $x_3 = 5x_2 + f1$

`e_f1_under:` False

`e_f1_det:` $\text{mode1} \wedge \text{mode2}$

`e_f1_over:` $\neg \text{mode3}$

Fault as Boolean mode variables

`e_1:` $x_1 = x_2$

If $\neg F1$ then `e_f1:` $x_3 = 5x_2$

`e_f1_under:` False

`e_f1_det:` $\text{mode1} \wedge \text{mode2} \wedge \neg F1$

`e_f1_over:` $\neg \text{mode3} \wedge \neg F1 \wedge \neg F3$

Multi-mode Isolability Matrix

Single – mode Fault Isolability Matrix

	f_{cell}	f_v	f_i
f_{cell}	0	0	0
f_v	0	0	0
f_i	0	0	0

Mode 1

	f_{cell}	f_v	f_i
f_{cell}	0	0	1
f_v	0	0	1
f_i	1	1	0

Mode 2

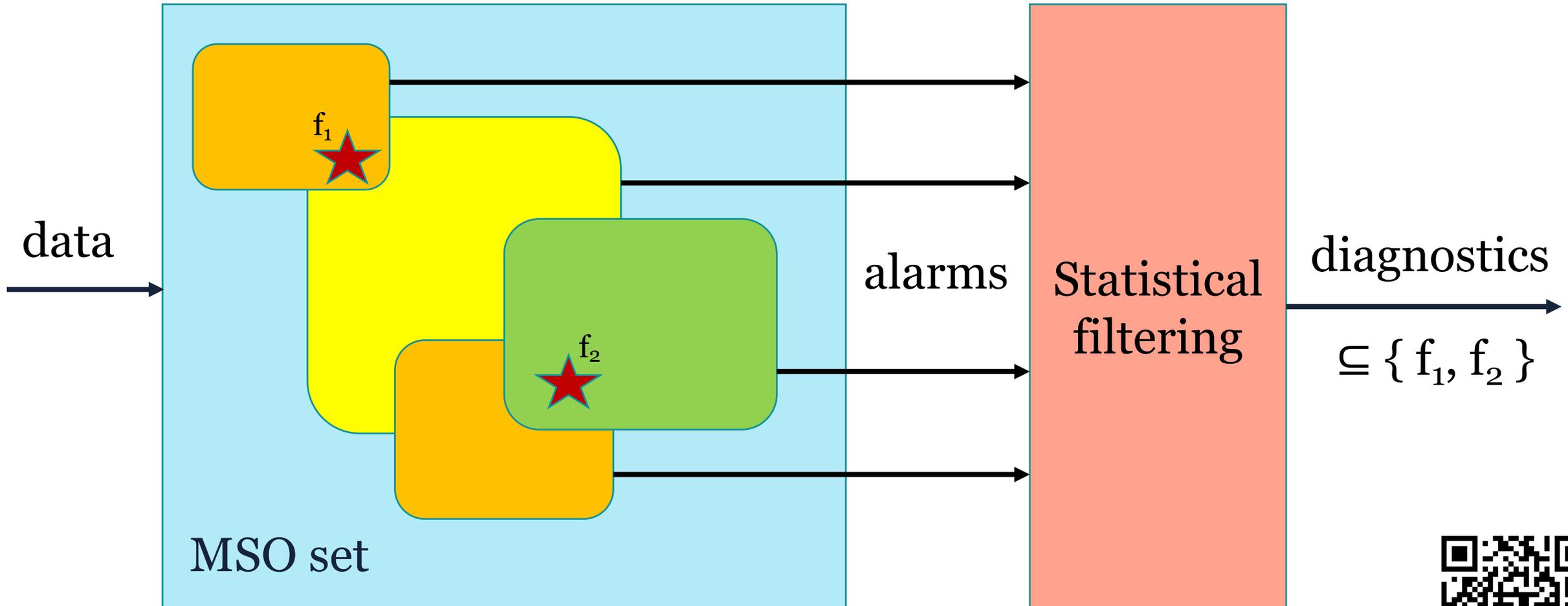
Multi – mode \Rightarrow for *All modes**

	NF	f_{cell}	f_v	f_i
f_{cell}	1	0	0	$m \in \{2, 4\}$
f_v	1	0	0	$m \in \{2, 4\}$
f_i	1	$m \in \{2, 4\}$	$m \in \{2, 4\}$	0

Table 3. Multi-mode fault diagnosability.

	NF	$f_{cell,k}$	$f_{v_{cell,k}}$	$f_{i_{cell,k}}$	$f_{i_{pack}}$	$f_{v_{pack}}$
$f_{cell,k}$	T	F	$\neg bypass_k$	T	T	T
$f_{v_{cell,k}}$	T	$\neg bypass_k$	F	T	T	T
$f_{i_{cell,k}}$	T	T	T	F	T	T
$f_{i_{pack}}$	$\neg bypass_{all}$	$\neg bypass_{all}$	$\neg bypass_{all}$	$\neg bypass_{all}$	F	$\neg bypass_{all}$
$f_{v_{pack}}$	T	T	T	T	T	F

Alarm filtering & correlation at runtime



Conclusion and Future Work

- A methodology for conducting structural fault diagnostics for multi-mode systems
 - Using a **multi-mode** extension of the Dulmage-Mendelsohn decomposition
- **2** types of **fault modeling** with diagnosability definitions
 - **Signal**: better for large systems, but small number of faults
 - **Boolean variable**: relevant for higher number of faults and multiple simultaneous faults
- Complexity study on a battery pack with n SMs in series
 - Scales up to about 10 cells ; definitely does not scale up to a full pack

Future Work

- Generalizing our approach to more complex multi-mode models
 - Some faults can only occur in some modes
- Algorithmic improvements of mmDM
 - **Improve computation time** : modular algorithm, based on message passing principles †





Thank You!



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A Multimode Dulmage-Mendelsohn Decomposition Algorithm

Benoît Caillaud Mathias Malandain

November 18th, 2024



Implicit representation of the structure of a multimode DAE system

A multimode Dulmage-Mendelsohn decomposition algorithm

A compositional approach: the CoSTreD method

Focus on the ArgMax algorithm

Encoding a model (in a nutshell)

- Everything is encoded as **functions** of the mode variables
- BDDs (Binary Decision Diagrams) are an appropriate framework:
 - Compact and canonical representation of Boolean functions as DAGs
 - Efficient computations on such functions
 - Integer functions: variable-length little-endian binary encoding (list of BDDs)
- Negation \neg and equality check in $\mathcal{O}(1)$, other operations include:
 - Conjunction/disjunction: \wedge/\vee
 - Existential quantification: $\exists a. f(a, b)$
 - Universal quantification: $\forall a. f(a, b)$
- However: very sensitive to variable and computation **ordering**

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- M encodes the modes (model-dependent encoding)
- $I = \bigcup_{m \in M} I_m$ encodes the equations (unary representation)
- $J = \bigcup_{m \in M} J_m$ encodes the variables (unary representation)
- $E = \bigcup_{m \in M} E_m$ encodes the equation-variable edges (unary representation)

(Unary encoding of a set S provides access to $\mathcal{P}(S)$.)

Encoding the problem data

The following data can be obtained by parsing the original model:

Name	Type	Meaning
χ_M	$M \rightarrow \mathbb{B}$	Set of possible modes
χ_I	$M \times I \rightarrow \mathbb{B}$	Mode dependency of equations
χ_J	$M \times J \rightarrow \mathbb{B}$	Mode dependency of variables
χ_E	$M \times E \rightarrow \mathbb{B}$	Mode dependency of edges
σ	$M \times E \rightarrow \mathbb{N}$	Values of the $\sigma_{m,i,j}$'s

Implicit representation of the structure of a multimode DAE system

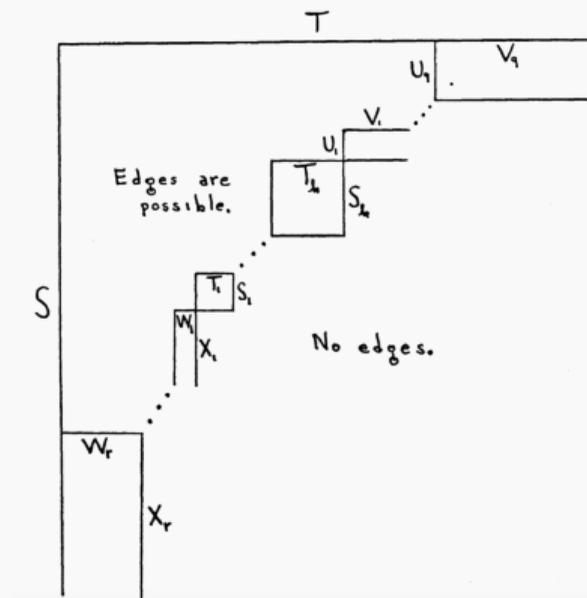
A multimode Dulmage-Mendelsohn decomposition algorithm

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The Dulmage-Mendelsohn decomposition

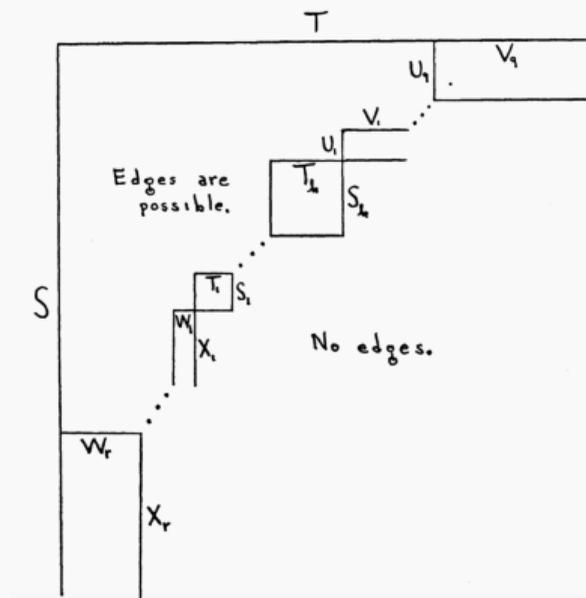
- Canonical decomposition of a bipartite graph $(S \cup T, E)$
- Applied to a system of algebraic equations, yields a partition into three subsystems:
 - I_u : **underdetermined part** (variables in J_u)
 - I_c : **'enabled' (square) part** (variables in J_c)
 - I_o : **overdetermined part** (variables in J_o)
- Uses: over-/underdetermination diagnostics (model debugging), **health monitoring**



Matrix representation [Dulmage & Mendelsohn, 'Two Algorithms for Bipartite Graphs', 1963]

The Dulmage-Mendelsohn decomposition

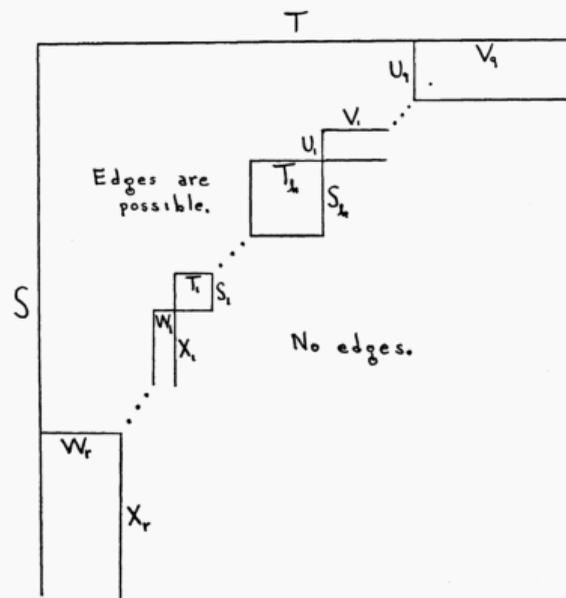
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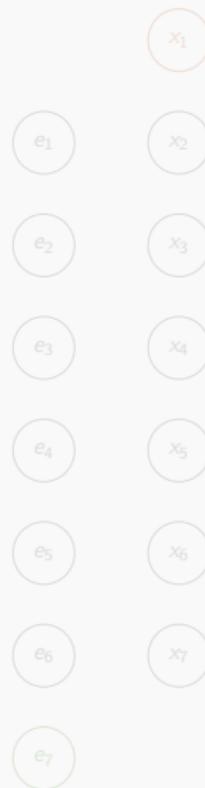
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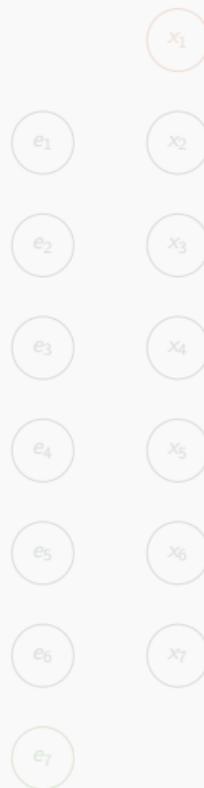
A graph-based algorithm for DM

- Requires a maximum matching \mathcal{M} of the system's adjacency graph
- Define I^u (resp. J^u): set of unmatched equations $i \in I$ (resp. variables $j \in J$); then:
 - I_o, J_o : reachable via an alternating path from I^u
 - I_u, J_u : reachable via an alternating path from J^u
 - I_c, J_c : remaining equations and variables
- The decomposition does **not** depend on the choice of a maximal matching.



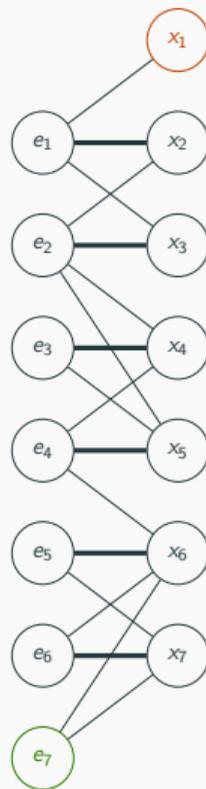
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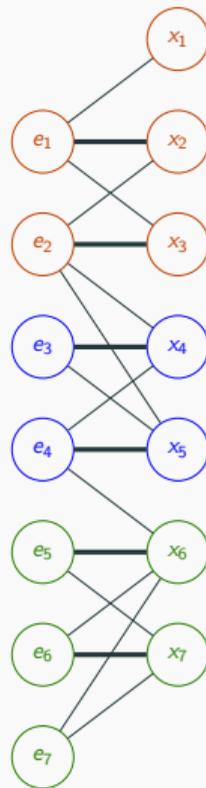
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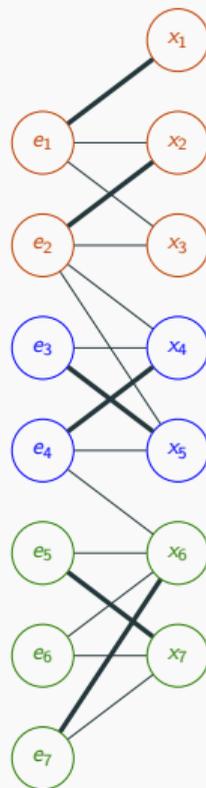
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Multimode adaptation: computing all partial matchings

Already existing: description of all perfect matchings

Modified: description of all matchings

$\mu : M \times \mathcal{P}(E) \rightarrow \mathbb{B}$ (each equation is connected to one and only one variable)

$\nu : M \times \mathcal{P}(E) \rightarrow \mathbb{B}$ (each variable is connected to one and only one equation)

$\Upsilon : M \times \mathcal{P}(E) \rightarrow \mathbb{B}$ (an edge must be active to be part of a matching)

$X := \mu \wedge \nu \wedge \Upsilon$ (all perfect matchings)

Multimode adaptation: computing all partial matchings

Already existing: description of all perfect matchings

Modified: description of all matchings

$\mu : M \times \mathcal{P}(E) \rightarrow \mathbb{B}$ (each equation is connected to **at most one** variable)

$\nu : M \times \mathcal{P}(E) \rightarrow \mathbb{B}$ (each variable is connected to **at most one** equation)

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Multimode adaptation: picking one maximum matching per mode

- **ArgMax and choice algorithms** already implemented (by induction on the BDD structure)
 - ArgMax needs a weight function $\omega : M \times \mathcal{P}(E) \rightarrow \mathbb{N}$ as input
- Create ω such that every edge has weight 1
 - Results in the choice of one maximum matching per mode
- Finally: compute one characteristic function $T_e : M \rightarrow \mathbb{B}$ per edge (in which modes is this edge in the chosen matching?)
 - Already implemented specialized inductive algorithm

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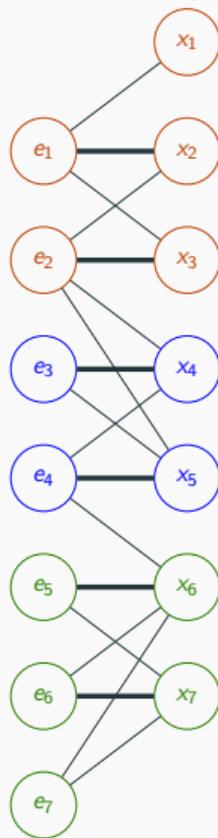
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Multimode adaptation: the Dulmage-Mendelsohn algorithm

- Important observation: in a given 'propagation step', either only edges in \mathcal{M} are followed, or only edges outside \mathcal{M}
- Easy to translate in the multimode setting:
 - Three functions $\sigma_i, \mu_i, \varepsilon_i : M \rightarrow \mathbb{B}$ for every equation i ; for instance, initial value of μ_i (unmatched eqs):

$$\mu_i = \bigvee_{e \in \mathcal{I}^{-1}(i)} T_e$$

- Same idea for every variable j
- Simple iterations until the over- and under- determined parts are known (fixpoint)

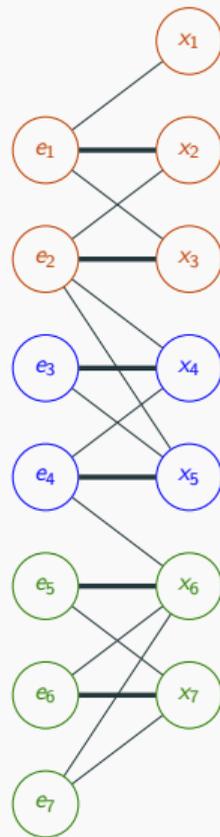


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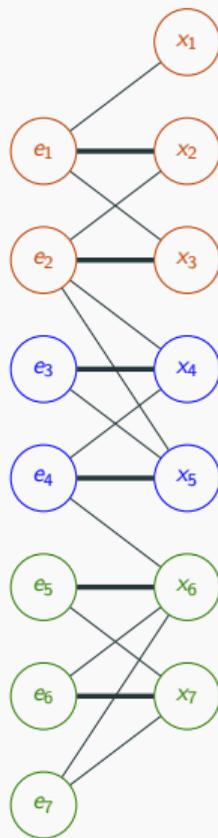


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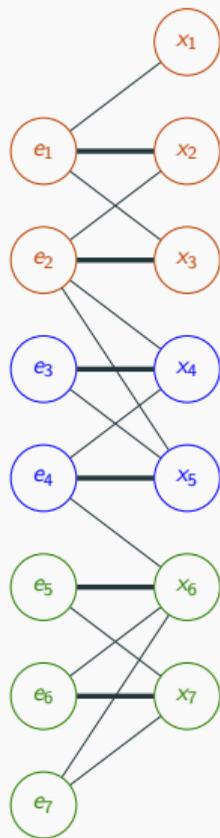


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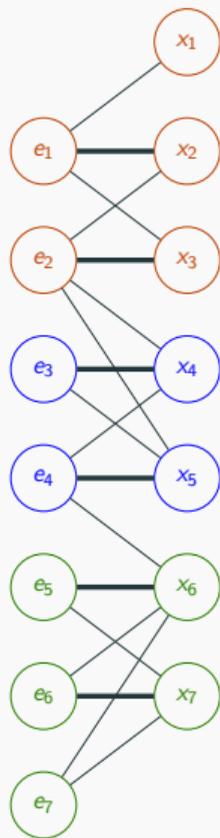


Multimode adaptation: the Dulmage-Mendelsohn algorithm

- Important observation: in a given 'propagation step', either only edges in \mathcal{M} are followed, or only edges outside \mathcal{M}
- Easy to translate in the multimode setting:
 - Three functions $\sigma_i, \mu_i, \epsilon_i : M \rightarrow \mathbb{B}$ for every equation i ; for instance, initial value of σ_i (unmatched eqs):

$$\neg \left(\bigvee_{e \in \mathcal{I}^{-1}(i)} T_e \right) \wedge \chi_I(\cdot, i)$$

- Same idea for every variable j
- Simple iterations until the over- and under- determined parts are known (fixpoint)



Implicit representation of the structure of a multimode DAE system

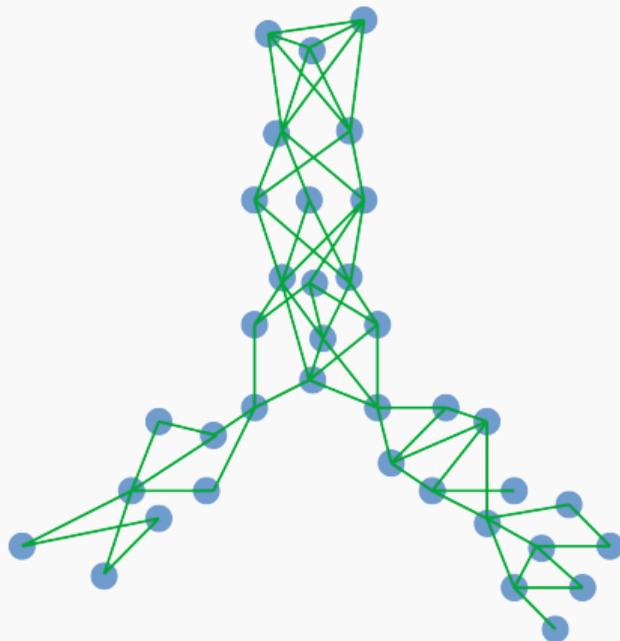
A multimode Dulmage-Mendelsohn decomposition algorithm

A compositional approach: the CoSTreD method

Focus on the ArgMax algorithm

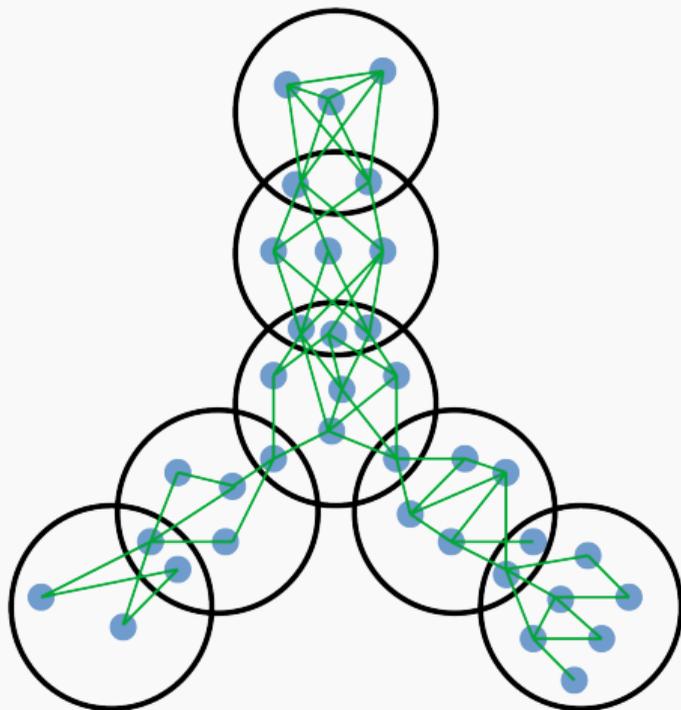
Principle of CoSTreD: Decomposing a constraint problem

Primal graph of the constraint system



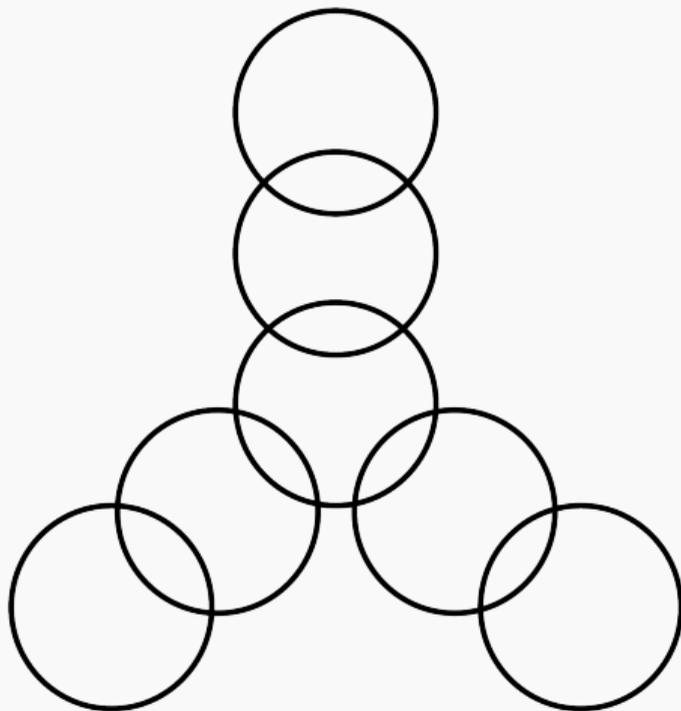
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Use **sparsity** and low **tree width** to compute a decomposition



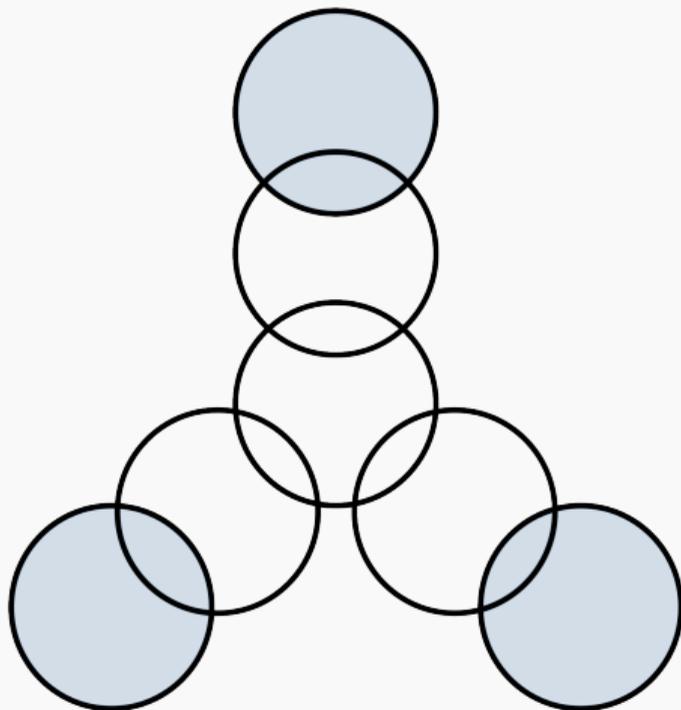
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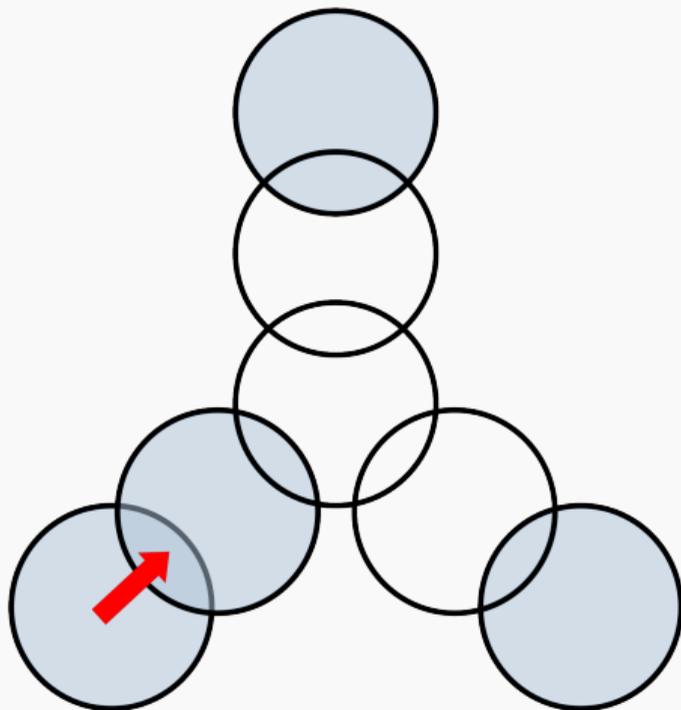
Principle of CoSTreD: Forward Reduction Process

project **local** constraints on **shared** variables



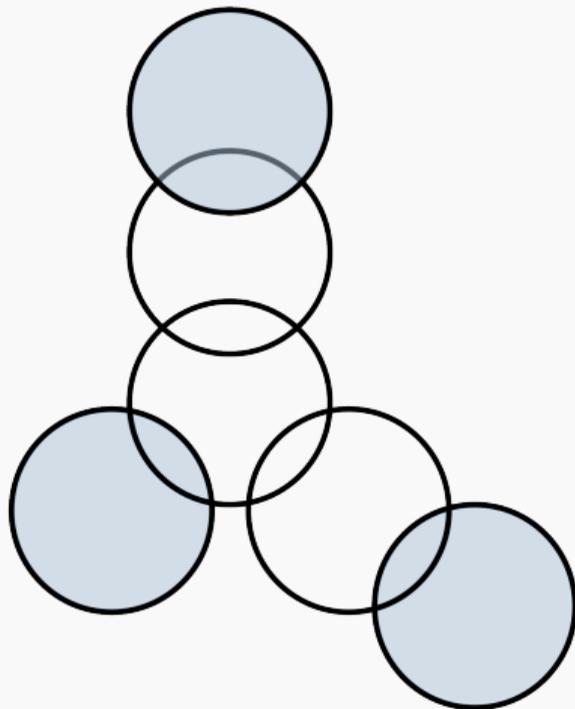
Principle of CoSTreD: Forward Reduction Process

Pass to **parent** and combine with **local** constraints



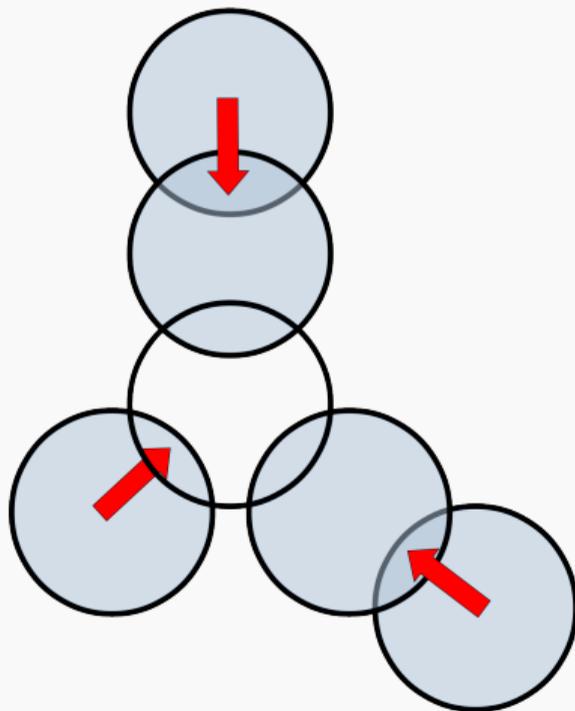
Principle of CoSTreD: Forward Reduction Process

project **resulting** constraints on **shared** variables



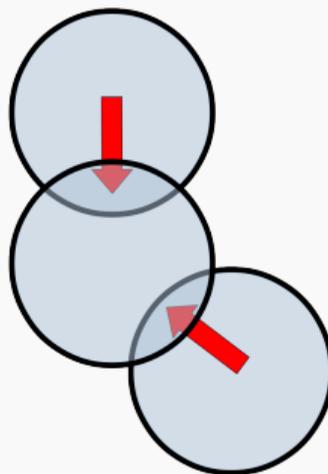
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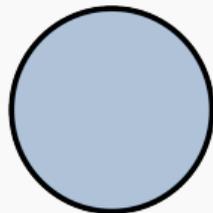
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... and so on, up to the tree **root**



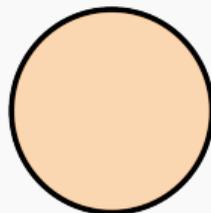
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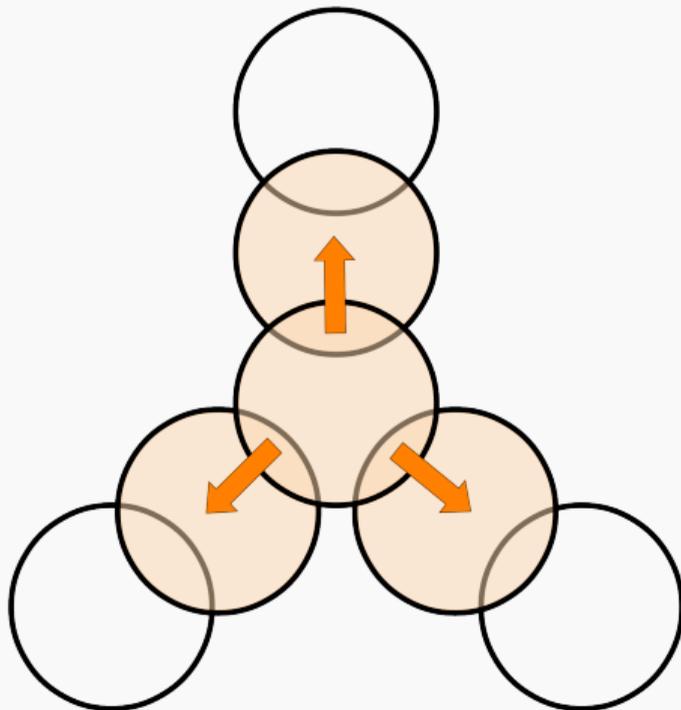
Principle of CoSTreD: Backward Propagation Process

Compute **partial** solution at the **root**



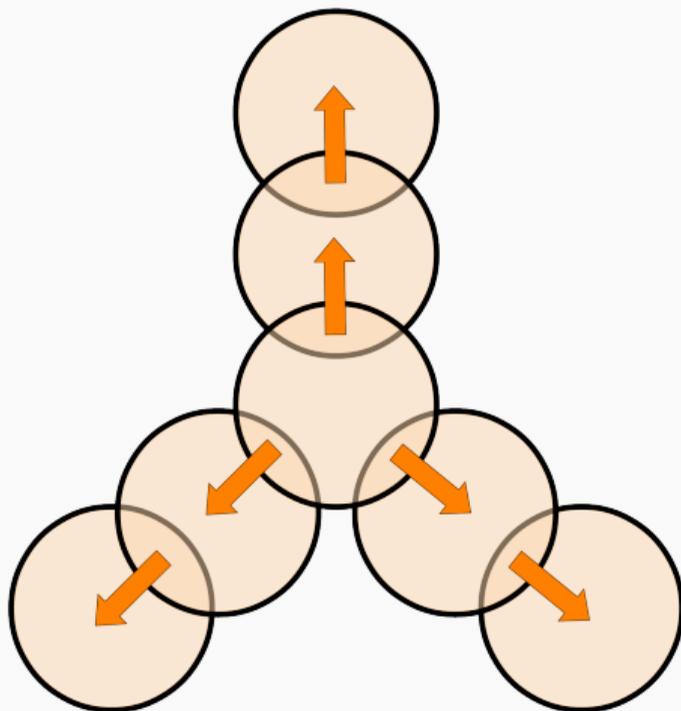
Principle of CoSTreD: Backward Propagation Process

Pass solution **down** the tree, **combine** with local constraints and compute **partial** solution

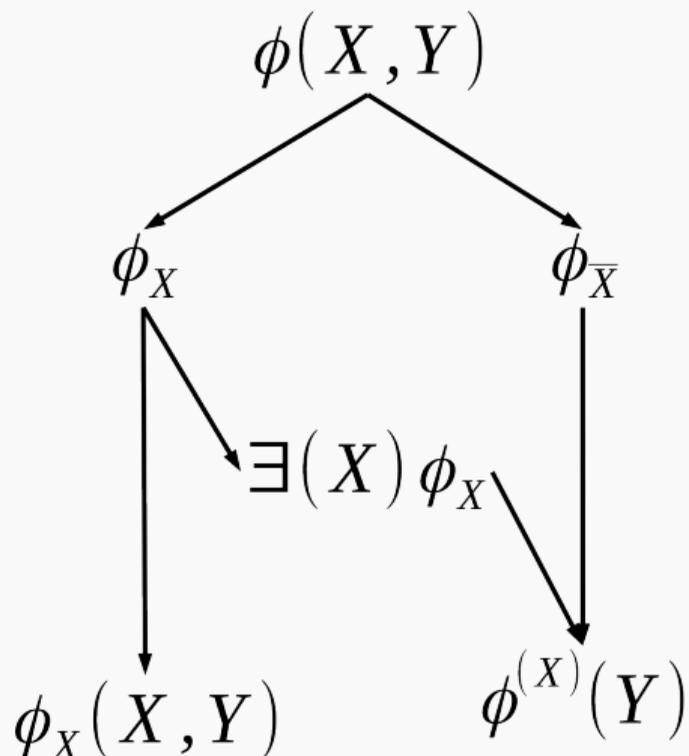


Principle of CoSTreD: Backward Propagation Process

... and so on, **down** to the leaves

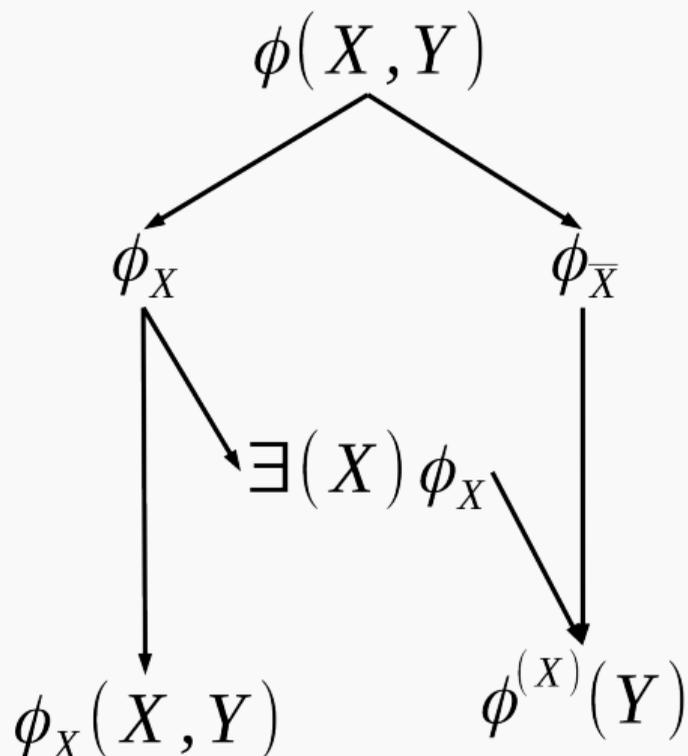


Application to mmDM: ArgMax(Boolean constraints *wedge* weight function)



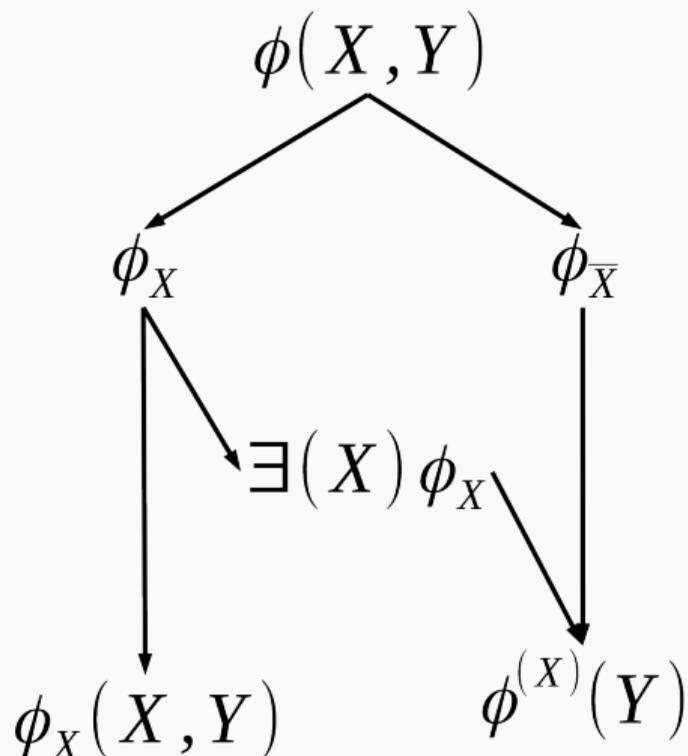
- CoSTreD exploits the **sparsity** and low **tree width** of physical models
- Cost model for computation time and memory consumption
 - \Rightarrow graphical optimization problem WAP
 - \Rightarrow strongly related to treewidth (NP-complete)
- Naive but effective solving: **greedy heuristics** (min-degree)
- CoSTreD can also be used for MaxSAT and QBF problems

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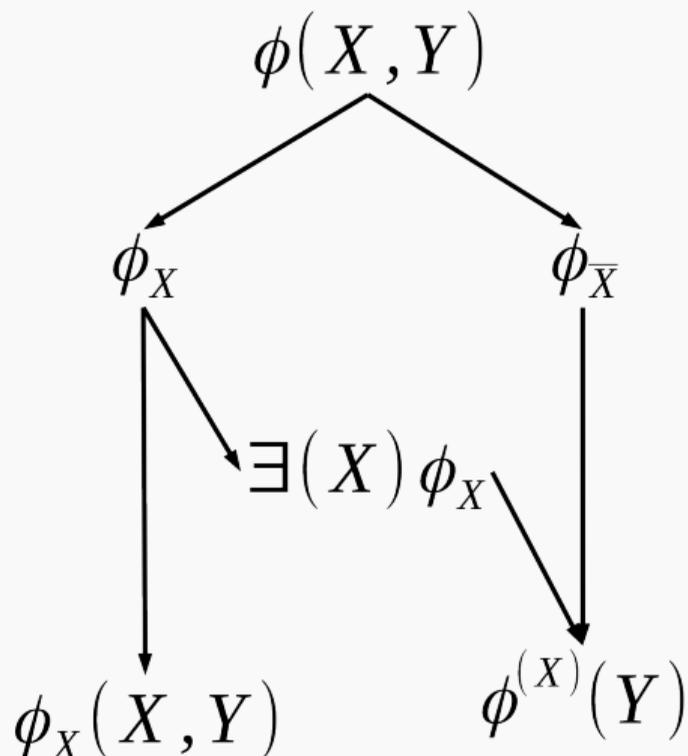
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The ArgMax algorithm for maximum-weight matchings

- **Input:**
 - $X : M \times E \rightarrow \mathbb{B}$ (all perfect matchings)
 - $(\omega_k : M \times E \rightarrow \mathbb{B})_{k=0 \dots N-1}$ (matching weights in little-endian representation)
- Let $S_N \equiv X$; for $k = N - 1$ down to 0:
 - $\omega_k^{\max} \equiv \exists \vec{E}. (S_{k+1} \wedge \omega_k)$ ($\omega_k^{\max} : M \rightarrow \mathbb{B}$)
 - $S_k \equiv S_{k+1} \wedge (\omega_k \Leftrightarrow \omega_k^{\max})$
- **Output:**
 - $S_0 : M \times E \rightarrow \mathbb{B}$ represents all maximum-weight perfect matchings
- ArgMax may also be used for selecting one matching in every mode from S_0 : replace $(\omega_k)_{k=0 \dots N-1}$ with $(\chi_E(e))_{e \in E}$ to get a lexicographical order

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