GBOML: A modelling tool for structured MILPs

TB-06: Software for Optimization 2: Modelling

Bardhyl MIFTARI, Mathias BERGER, Guillaume DERVAL and Damien ERNST
University of Liège Belgium
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Examples of structured MILPs

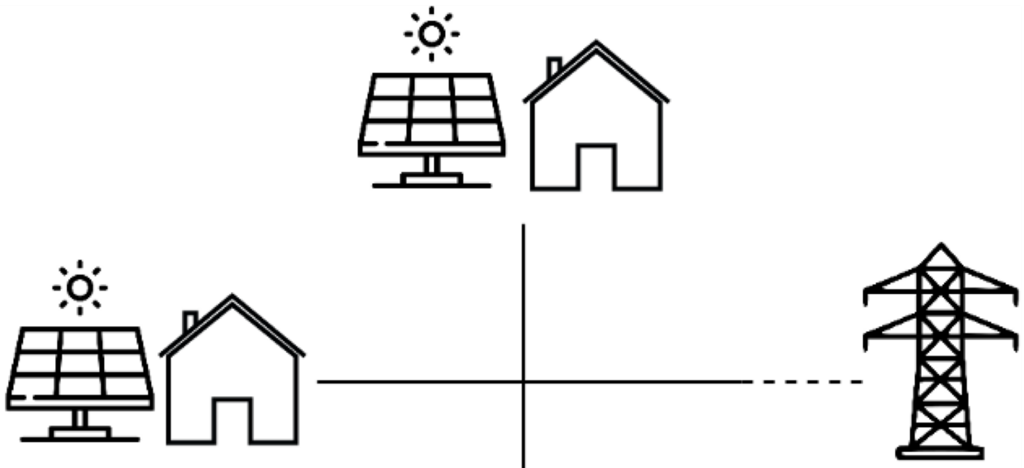

Figure 1: Renewable energy community

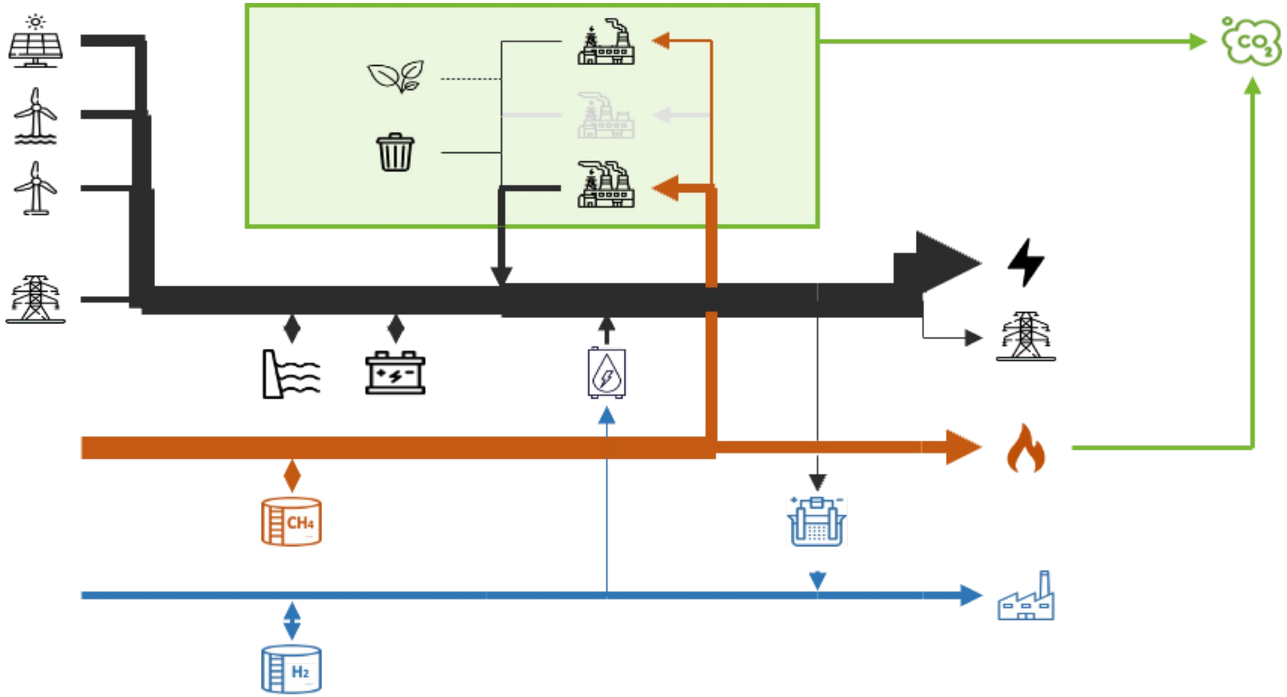

Figure 2: Belgian energy model

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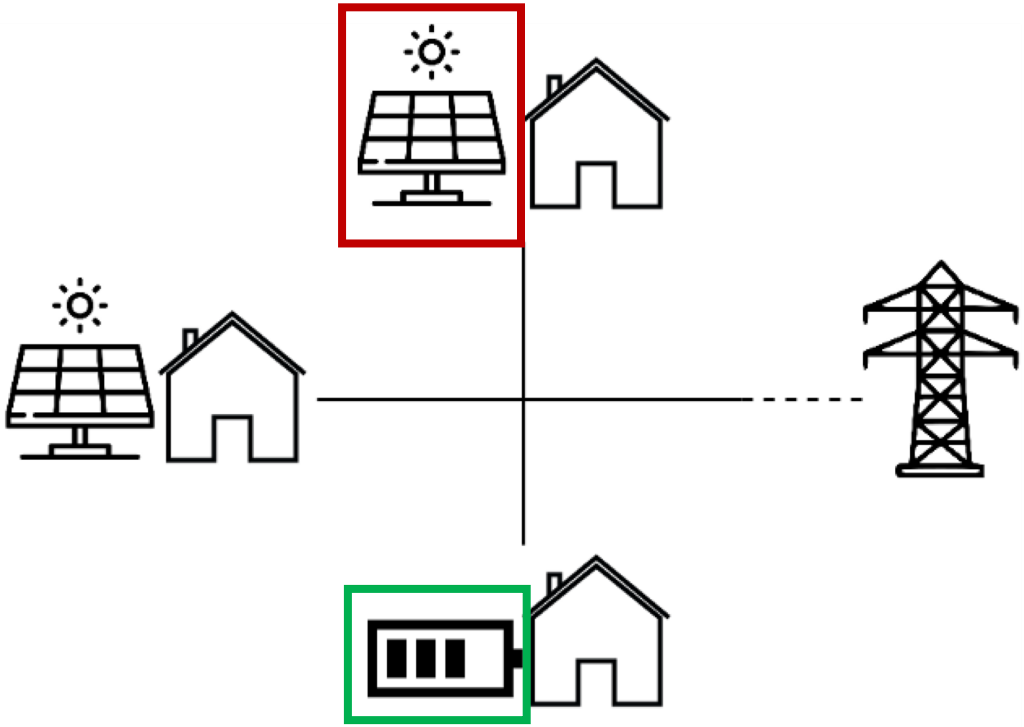

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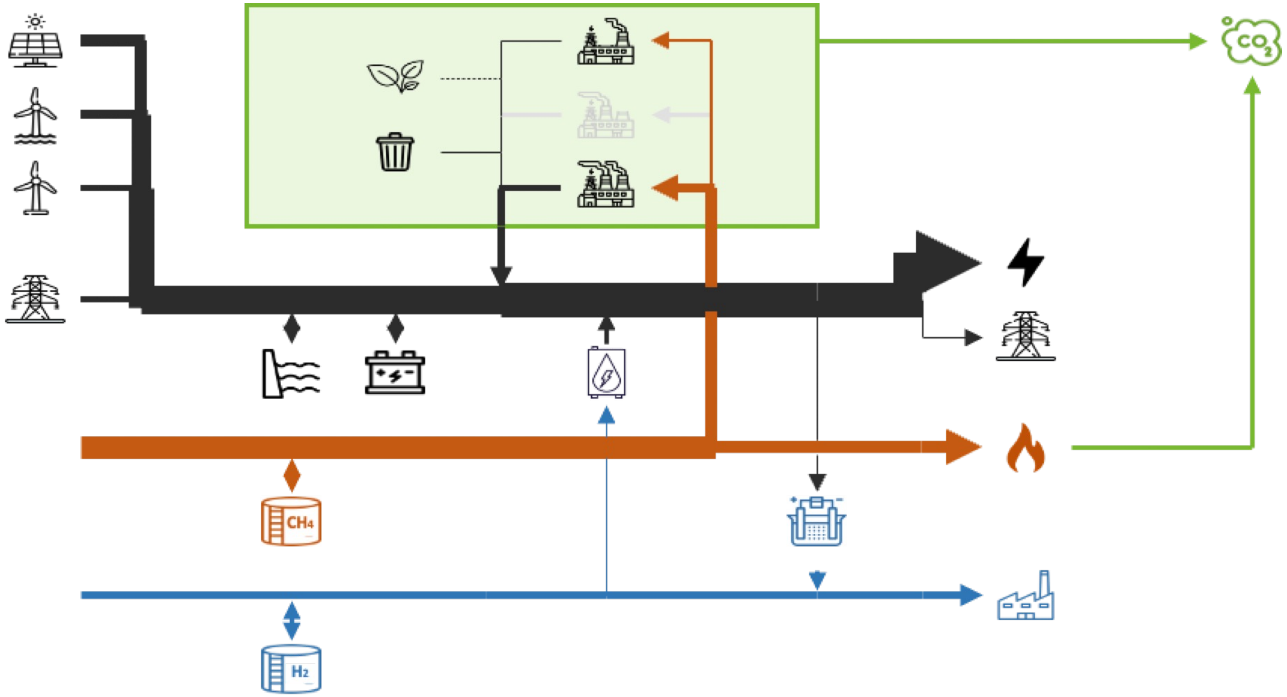

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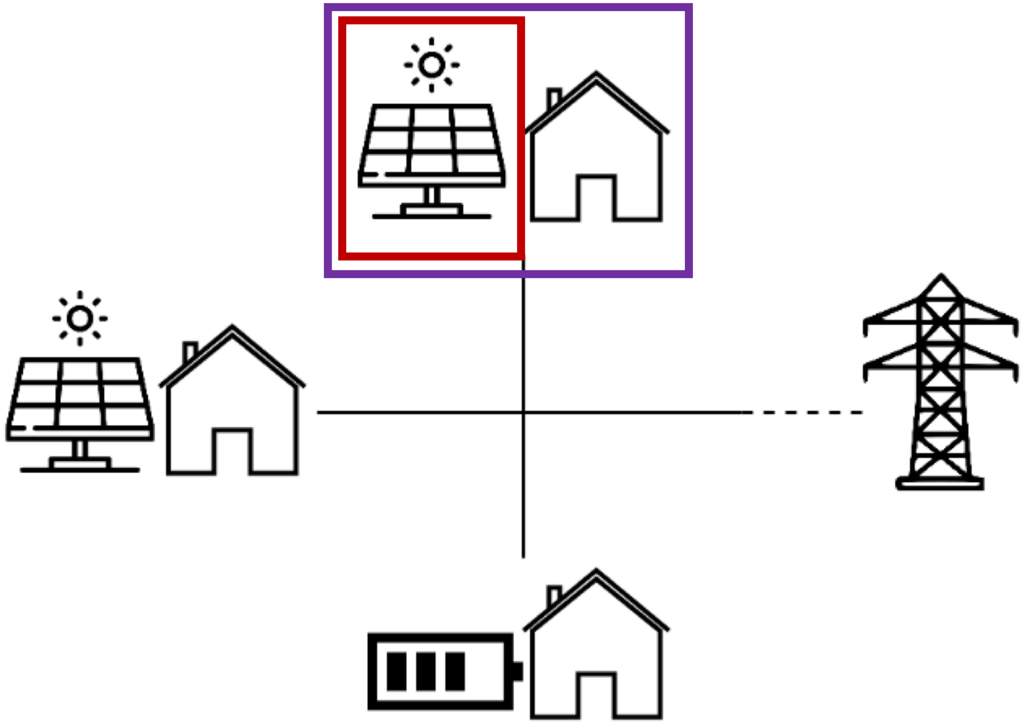

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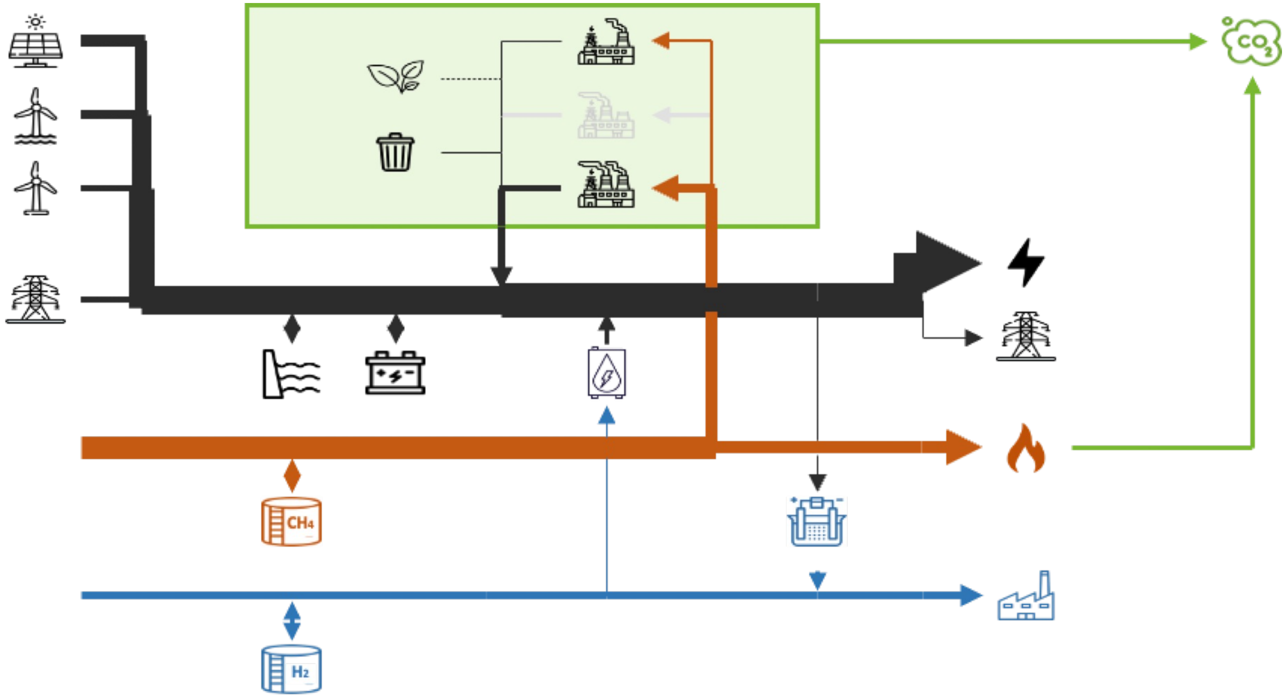

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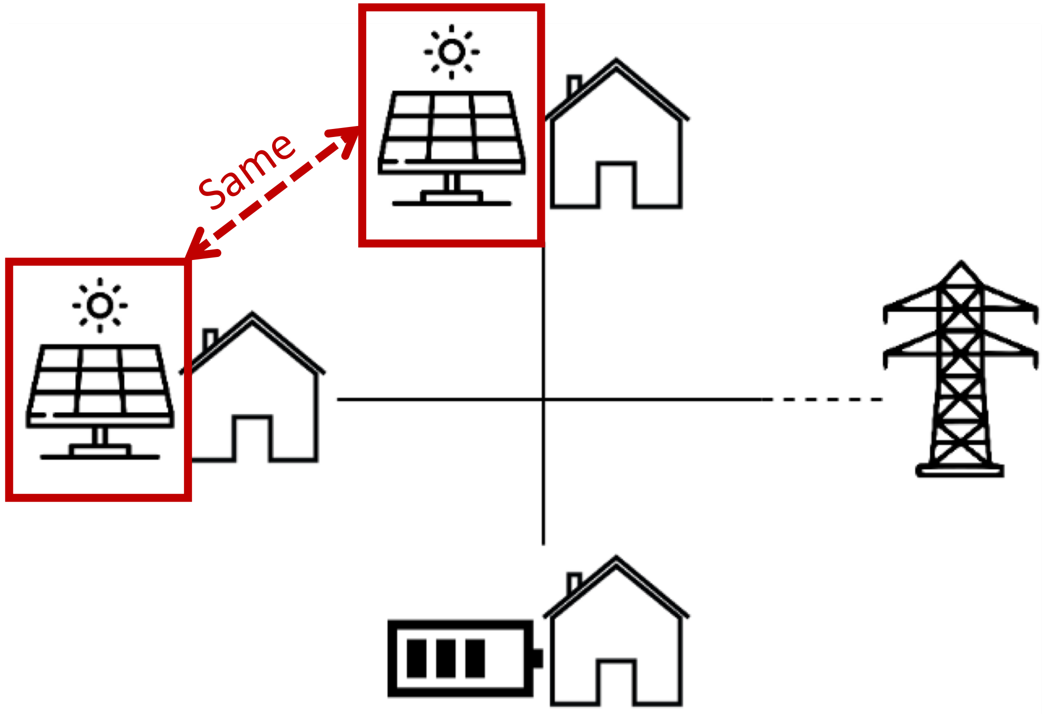

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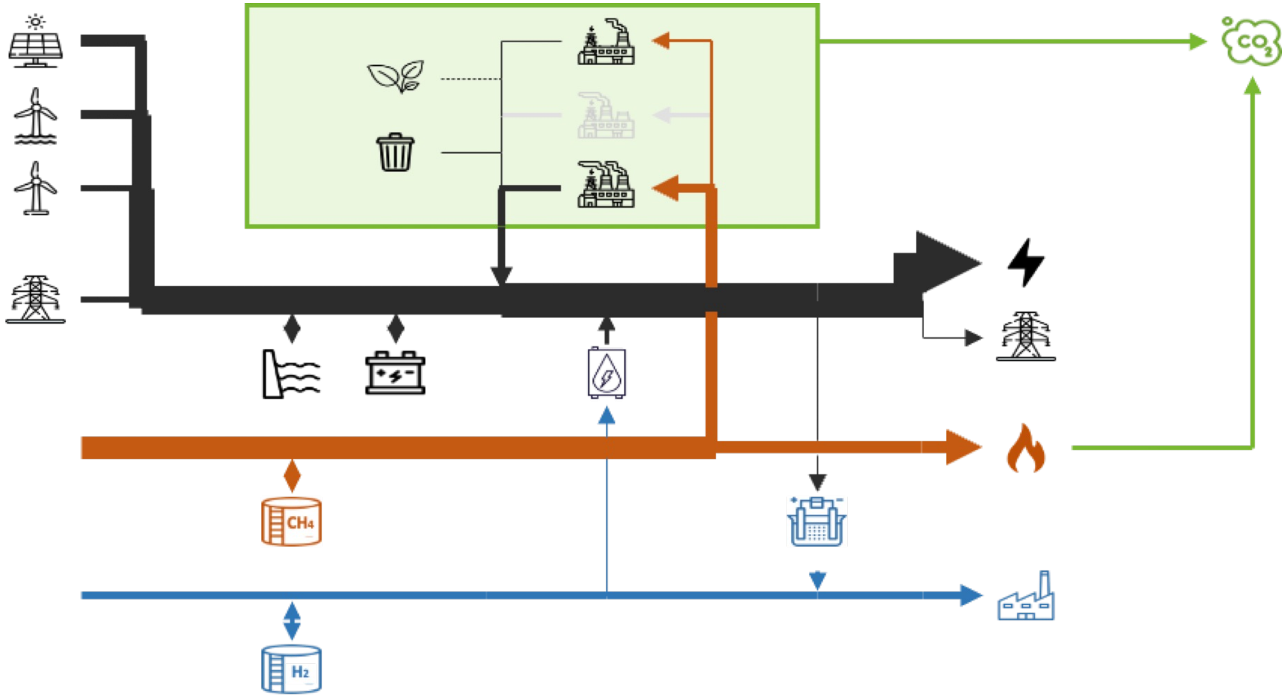

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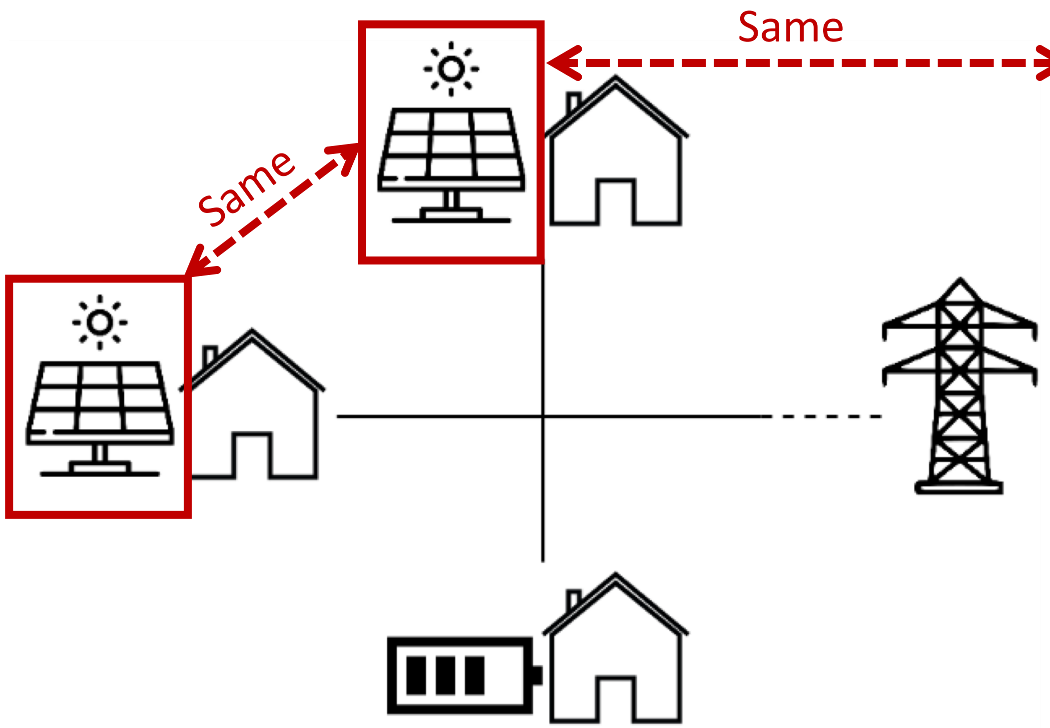

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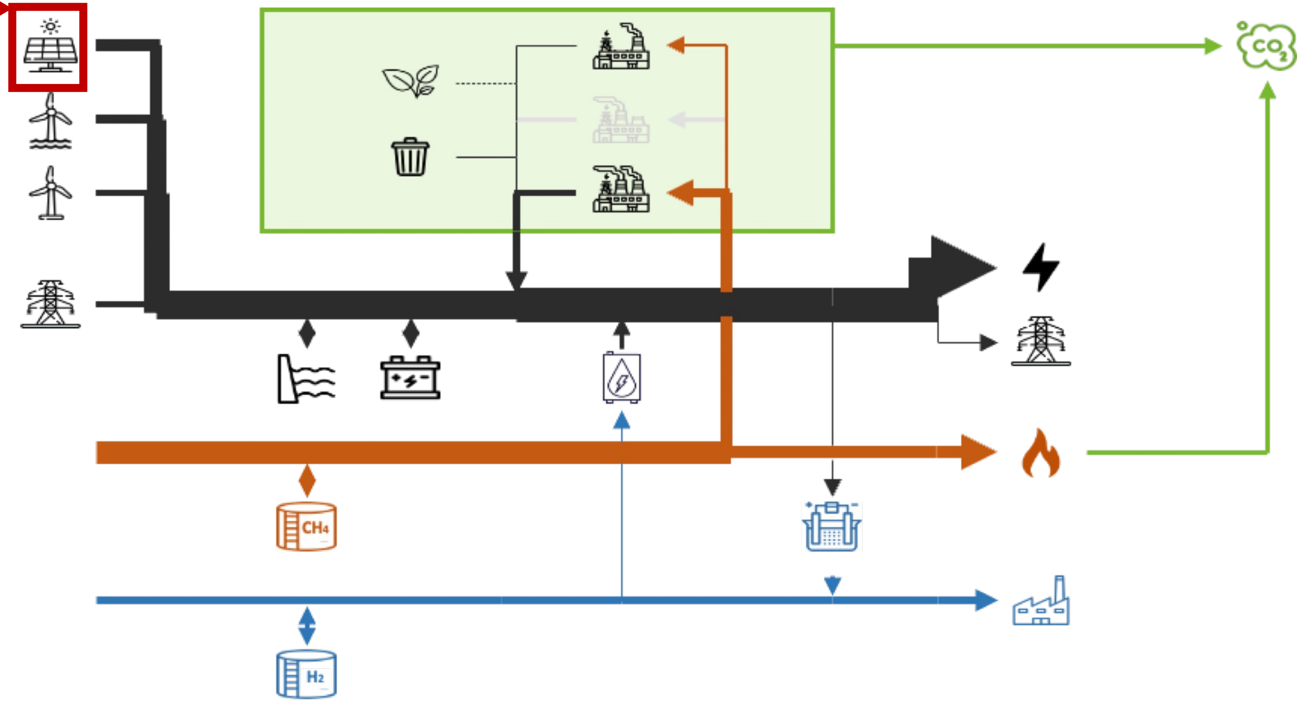

Figure 2: Belgian energy model

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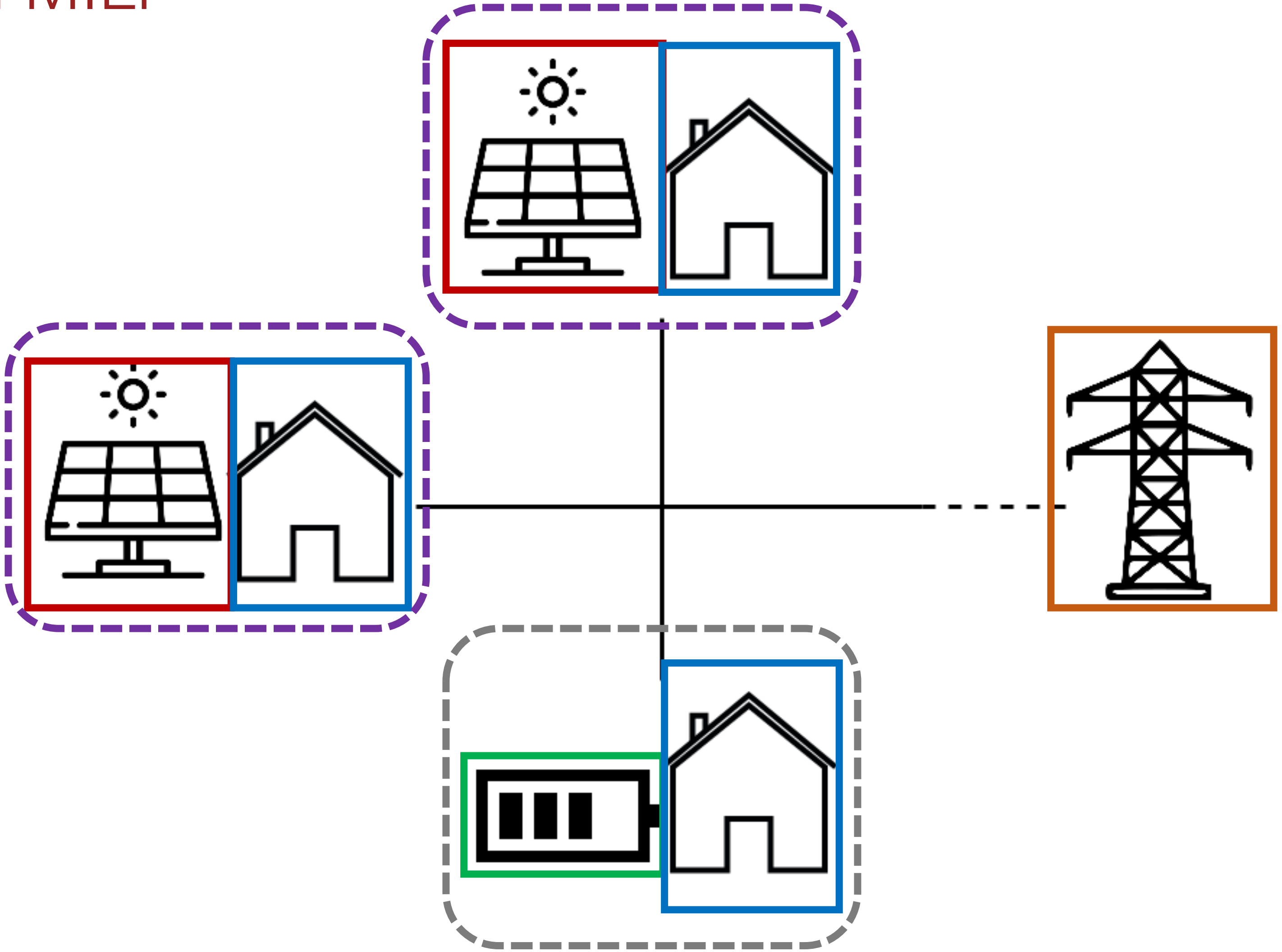
Let us formalize these problems

A structured MILP



PV Panels
House
Grid
Battery
Prosumer
Bat-consumer

Figure 1: Renewable energy community

A structured MILP

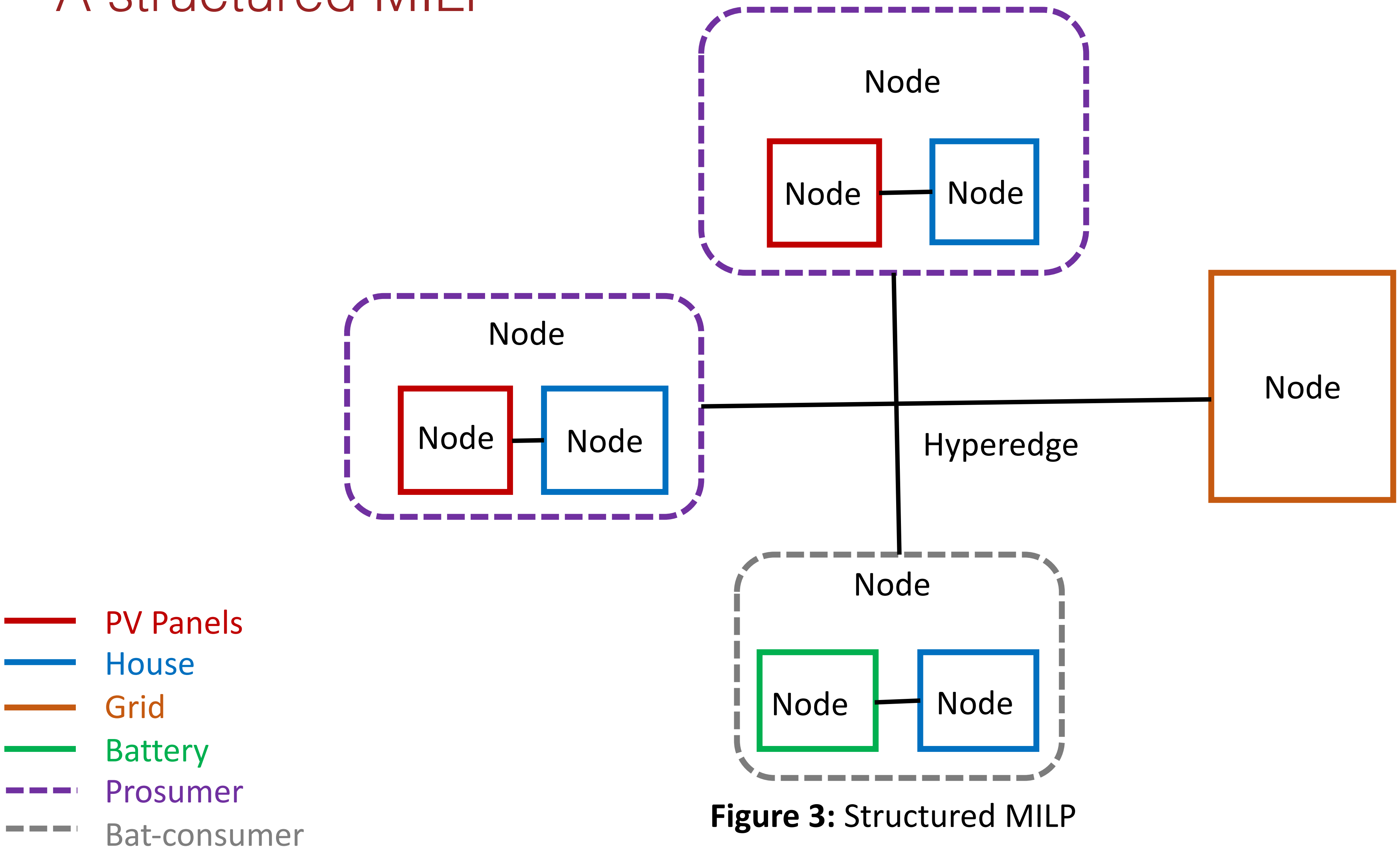


Figure 3: Structured MILP

Structured MILPs abstraction

Hierarchical hypergraph made of

- **Nodes**
- **Hyperedges**

Each **node** is itself made of

- **Parameters**
- **Variables**
- **Constraints**
- **Objectives**
- **Hierarchical hypergraph**

Each **hyperedge** is made of

- **Parameters**
- **Constraints**

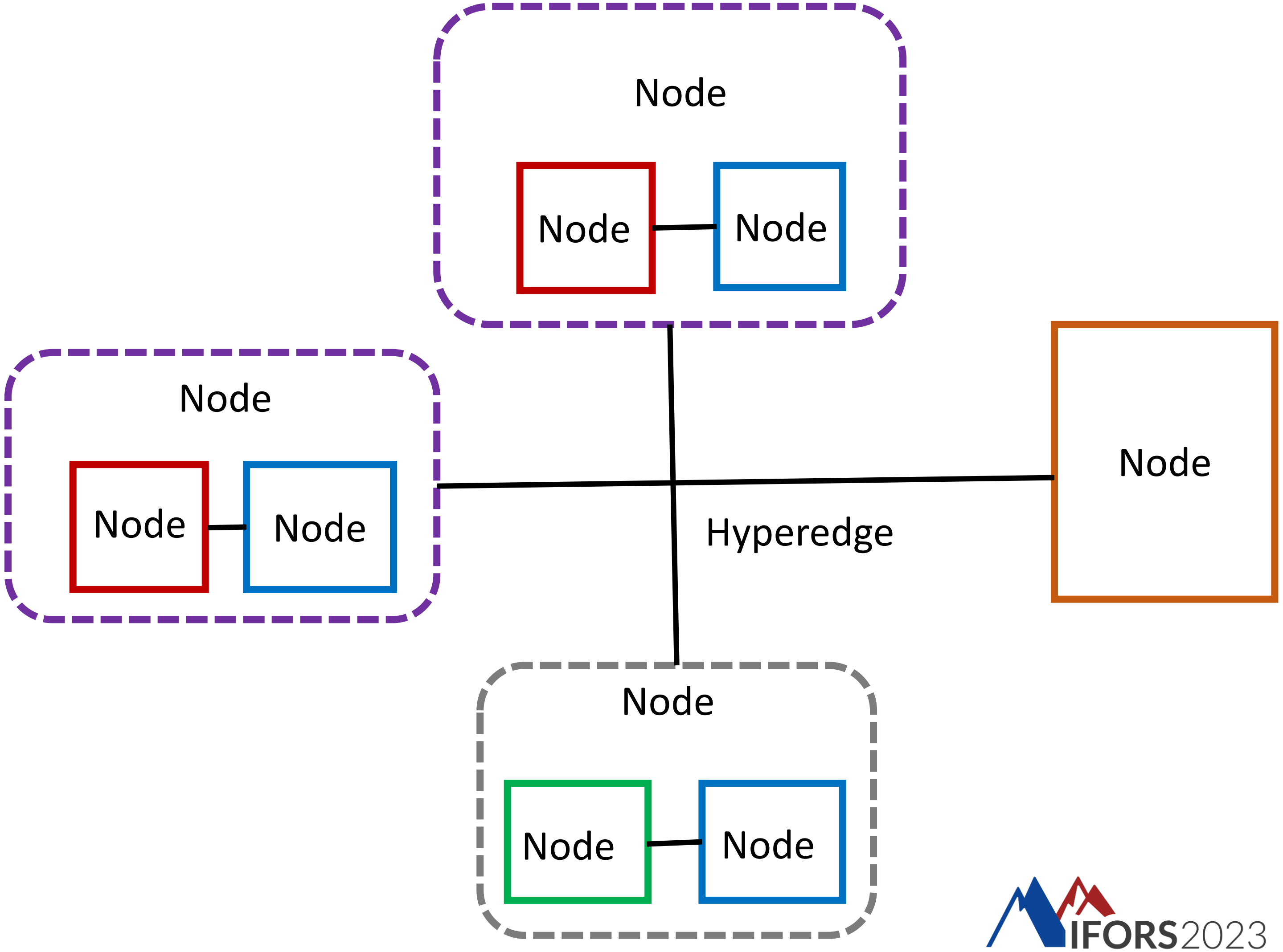


Figure 3: Structured MILP

Structured MILPs formalization

Hierarchical hypergraph $G_g = (\mathcal{N}_g, \mathcal{E}_g)$ made of

- A set of **nodes** $\mathcal{N}_n$
- A set of **hyperedges** $\mathcal{E}_n$

Each **node** $< v_n^{ext}, v_n^{int}, \boldsymbol{G_n}, \boldsymbol{H_n}, G_n, \boldsymbol{O_n} >$ is itself made of

- **External** variables v_n^{ext}
- **Internal** variables v_n^{int}

$\left.\begin{matrix} v_n^{ext} \\ v_n^{int} \end{matrix}\right] v_n$

- **Constraints** matrices $\boldsymbol{G_n}$ *and* $\boldsymbol{H_n}$
- **Objectives** matrix $\boldsymbol{O_n}$
- **Hierarchical hypergraph** G_n

Each **hyperedge** $< \mathcal{N}_e, \boldsymbol{G_e}, \boldsymbol{H_e} >$ is made of

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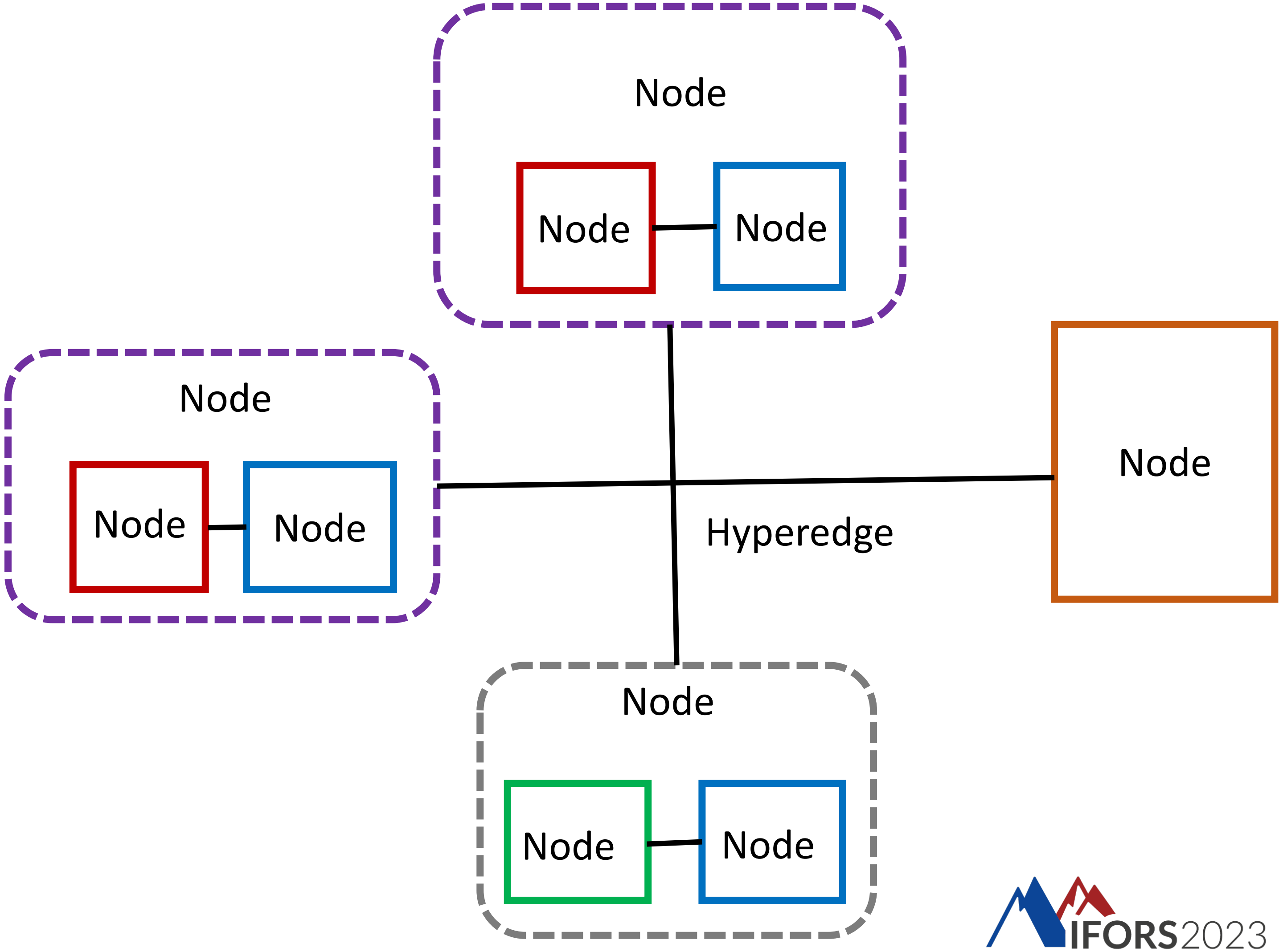
- **Constraints** matrices $\boldsymbol{G_e}$ *and* $\boldsymbol{H_e}$



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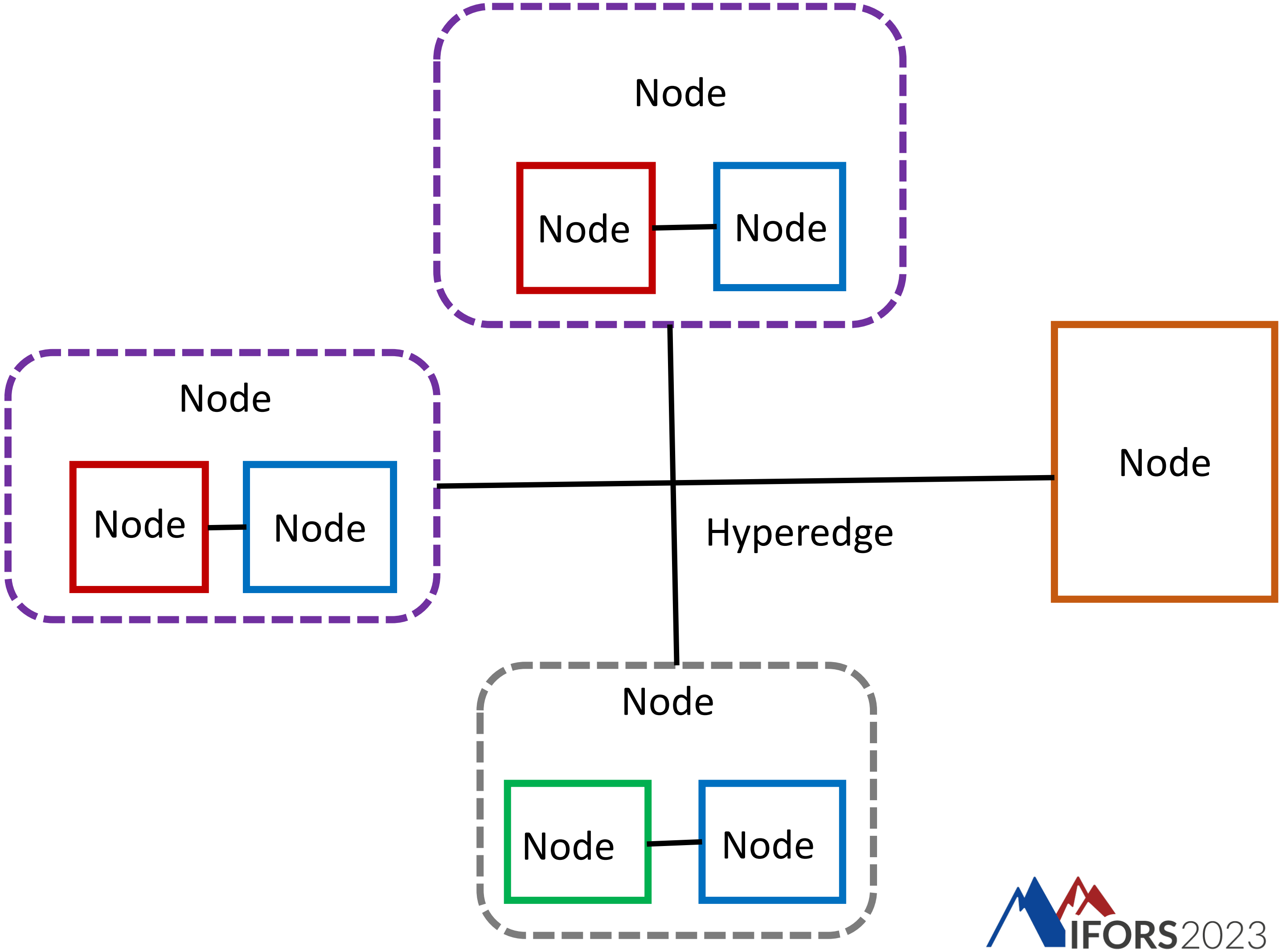

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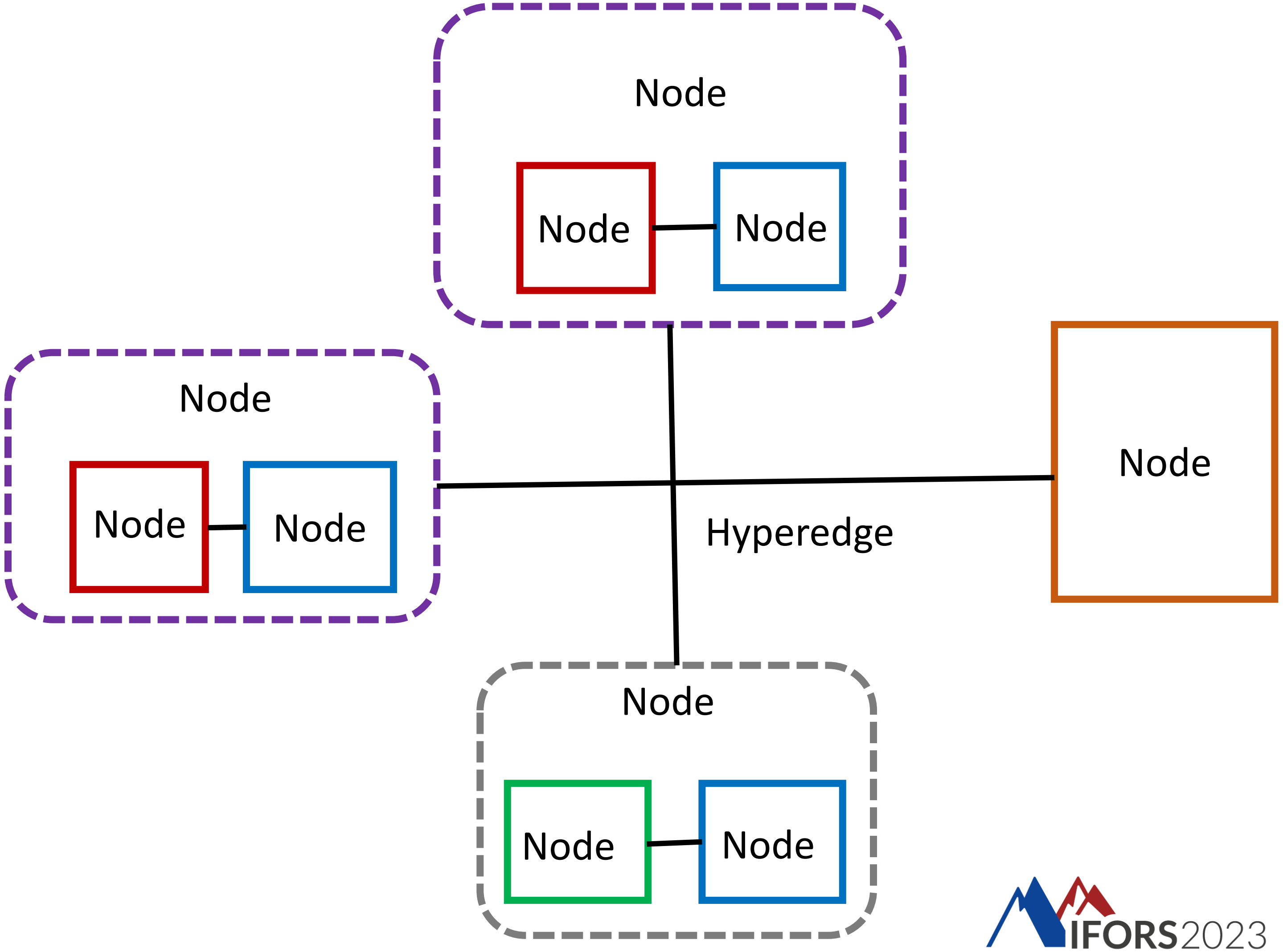

Figure 3: Structured MILP

Structured MILPs formalization

We have a **hierarchical hypergraph** $G_g = (\mathcal{N}_g, \mathcal{E}_g)$

For each node, we have

$$\begin{aligned} \min \mathbf{1}^{1\times\sigma_n}\ \boldsymbol{O_n}[1\ \boldsymbol{v_n}]^T & \\ \text{s.t.}\ \boldsymbol{G_n}[1\ \boldsymbol{v_n}]^T & \le \mathbf{0} \\ \boldsymbol{H_n}[1\ \boldsymbol{v_n}]^T & = \mathbf{0} \end{aligned}$$

For each hyperedge, we must respect the constraints

$$\begin{aligned} \boldsymbol{G_e}[1\ \boldsymbol{v_e}]^T & \le \mathbf{0} \\ \boldsymbol{H_e}[1\ \boldsymbol{v_e}]^T & = \mathbf{0} \end{aligned}$$

And so on recursively for all sub-hypergraphs.

Structured MILPs formalization

Set of nodes

We have a **hierarchical hypergraph** $G_g = (\mathcal{N}_g, \mathcal{E}_g)$ Set of hyperedges

For each node, we have

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Set of nodes

We have a **hierarchical hypergraph** $G_g = (\mathcal{N}_g, \mathcal{E}_g)$ Set of hyperedges

For each node, we have

Objective matrix

$$\min \mathbf{1}^{1\times\sigma_n} \; \boldsymbol{O_n}[1\; \boldsymbol{v_n}]^T$$

Inequality constraints

Equality constraints

$$\text{s.t.}\; \boldsymbol{G_n}[1\; \boldsymbol{v_n}]^T \leq \mathbf{0}$$
$$\boldsymbol{H_n}[1\; \boldsymbol{v_n}]^T = \mathbf{0}$$

Node variables

For each hyperedge, we must respect the constraints

$$\boldsymbol{G_e}[1\; \boldsymbol{v_e}]^T \leq \mathbf{0}$$
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And so on recursively for all sub-hypergraphs.

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Set of nodes

We have a **hierarchical hypergraph** $G_g = (\mathcal{N}_g, \mathcal{E}_g)$ Set of hyperedges

For each node, we have

Objective matrix

$$\min \mathbf{1}^{1\times\sigma_n} \ \boldsymbol{O_n}[1\ \boldsymbol{v_n}]^T$$
$$\text{s.t. } \boldsymbol{G_n}[1\ \boldsymbol{v_n}]^T \leq \mathbf{0}$$
$$\boldsymbol{H_n}[1\ \boldsymbol{v_n}]^T = \mathbf{0}$$

Inequality constraints
Equality constraints

Node variables

For each hyperedge, we must respect the constraints

$$\boldsymbol{G_e}[1\ \boldsymbol{v_e}]^T \leq \mathbf{0}$$
$$\boldsymbol{H_e}[1\ \boldsymbol{v_e}]^T = \mathbf{0}$$

Inequality constraints
Equality constraints

External variables of certain nodes

And so on recursively for all sub-hypergraphs.

Structured MILPs formalization

Let us define three recursive functions :

- the function f that takes a set of nodes $\mathcal{N}$ as input and returns the sum of the objectives of the nodes and their subnodes recursively,

$$f(\mathcal{N}) = \sum_{n \in \mathcal{N}} \left(\mathbf{1}^{1\times\sigma_n}\, \boldsymbol{O}_n [1\ \boldsymbol{v}_n]^T + f(\mathcal{N}_n) \right).$$

- the Boolean-valued function g that takes a hypergraph $G = (\mathcal{N}, \mathcal{E})$ as input and returns,

$$g(G) = [\boldsymbol{G}_e [1\ \boldsymbol{v}_e]^T \leq 0\ \forall e \in \mathcal{E}] \wedge \left[\left(\boldsymbol{G}_n [1\ \boldsymbol{v}_n]^T \leq 0 \wedge g(G_n) \right) \forall n \in \mathcal{N} \right].$$

- the Boolean-valued function h that takes a hypergraph $G = (\mathcal{N}, \mathcal{E})$ as input and returns,

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Applied recursively on its sub-nodes

- the Boolean-valued function g that takes a hypergraph $\mathrm{G} = (\mathcal{N}, \mathcal{E})$ as input and returns,

$$\mathrm{g}(\mathrm{G}) = [\boldsymbol{G_e}[1 \; \boldsymbol{v_e}]^T \leq 0 \; \forall \mathrm{e} \in \mathcal{E}] \wedge \left[\left(\boldsymbol{G_n}[1 \; \boldsymbol{v_n}]^T \leq 0 \wedge g(\mathrm{G_n}) \right) \forall \mathrm{n} \in \mathcal{N} \right].$$

- the Boolean-valued function h that takes a hypergraph $\mathrm{G} = (\mathcal{N}, \mathcal{E})$ as input and returns,

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$$\mathrm{g(G)} = \overset{\text{Hyperedge}}{\boxed{[\boldsymbol{G}_{\boldsymbol{e}}[1\ \boldsymbol{v}_{\boldsymbol{e}}]^T \le 0\ \forall \mathrm{e} \in \mathcal{E}]}} \wedge \overset{\text{Node}}{\boxed{\left[\left(\boldsymbol{G}_{\boldsymbol{n}}[1\ \boldsymbol{v}_{\boldsymbol{n}}]^T \le 0 \wedge g(\mathrm{G_n}) \right) \forall \mathrm{n} \in \mathcal{N} \right]}}.$$

- the Boolean-valued function h that takes a hypergraph $\mathrm{G} = (\mathcal{N}, \mathcal{E})$ as input and returns,

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Structured MILPs formalization

Given

- $f(\mathcal{N}) = \sum_{n\in\mathcal{N}} \left(\mathbf{1}^{1\times\sigma_n}\, \boldsymbol{O_n}[1\ \boldsymbol{v_n}]^T + f(\mathcal{N}_n)\right)$,
- $\mathrm{g(G)} = [\boldsymbol{G_e}[1\ \boldsymbol{v_e}]^T \le 0\ \forall \mathrm{e} \in \mathcal{E}] \wedge \left[\left(\boldsymbol{G_n}[1\ \boldsymbol{v_n}]^T \le 0 \wedge g(\mathrm{G_n})\right) \forall \mathrm{n} \in \mathcal{N}\right]$,
- And, $\mathrm{h(G)} = [\boldsymbol{H_e}[1\ \boldsymbol{v_e}]^\mathrm{T} = 0\ \forall \mathrm{e} \in \mathcal{E}] \wedge \left[\left(\boldsymbol{H_n}[1\ \boldsymbol{v_n}]^\mathrm{T} = 0 \wedge \mathrm{h(G_n)}\right) \forall \mathrm{n} \in \mathcal{N}\right]$.

We have that our problems can be written as,

$$\begin{aligned} &\min \mathrm{f}\left(\mathcal{N}_g\right) \\ &\text{s.t. } h\left(G_g\right) \text{ is true} \\ &\qquad \mathrm{g}\left(G_g\right) \text{ is true} \end{aligned}$$

How can we exploit this structure in a modelling tool?

Modelling tool workflow

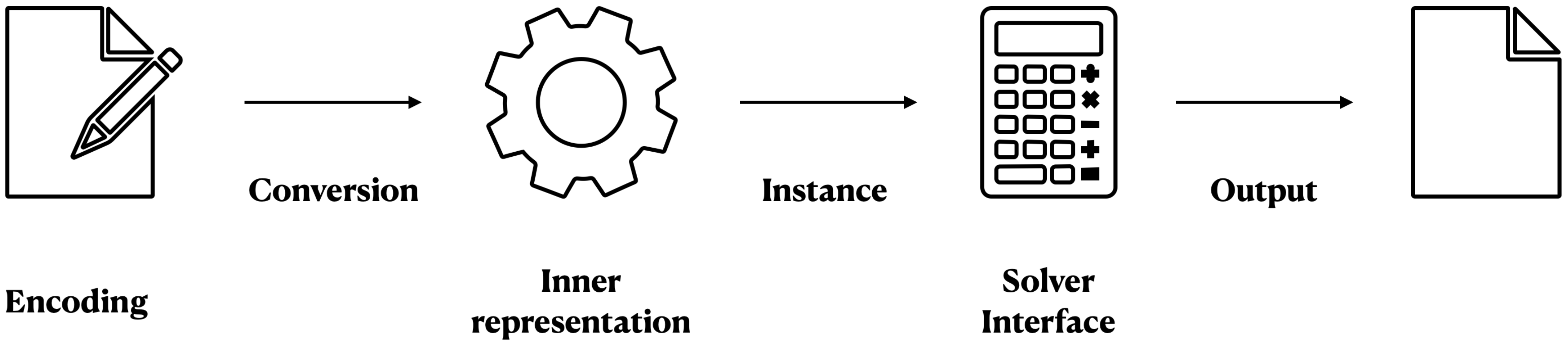

Figure 4: Modelling tool workflow

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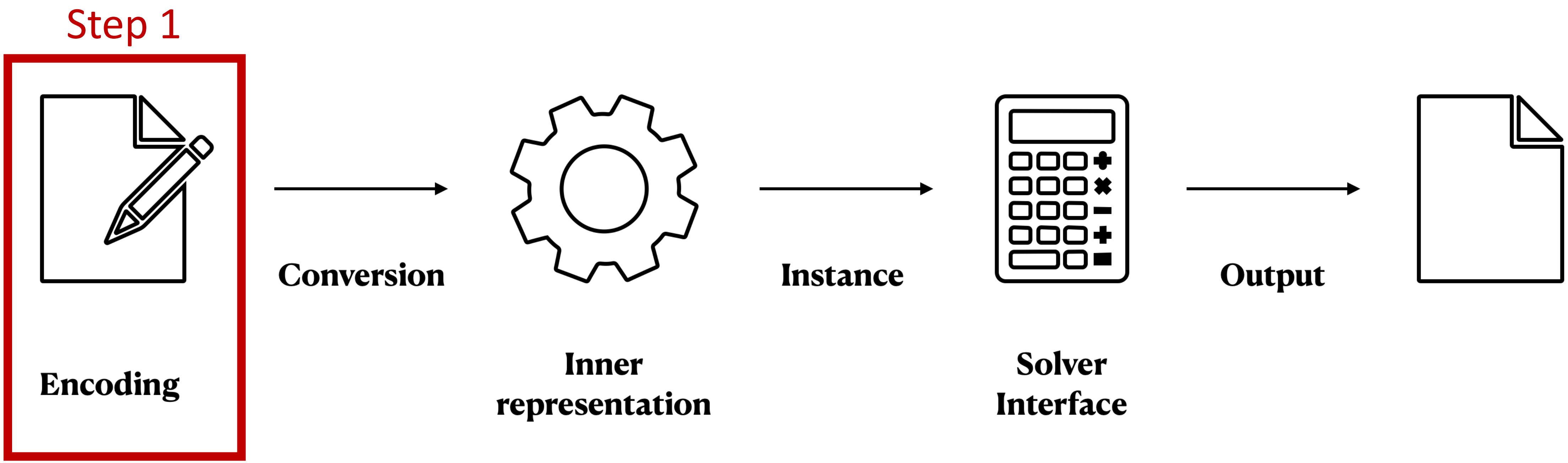
The Graph-Based Optimization Modelling Language (GBOML)



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Encoding structure [1]

```
#NODE <node_name>
#PARAMETERS
<param_def>
#VARIABLES
<var_def>
#CONSTRAINTS
<constr_def>
#OBJECTIVES
<obj_def>
```

```
#TIMEHORIZON
T = <value>;
```

```
#HYPEREDGE <edge_name>
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<param_def>
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```

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```
#HYPEREDGE <edge_name>
#PARAMETERS
<param_def>
#CONSTRAINTS
<constr_def>
```

Encoding hierarchical structure [1]

```
#NODE <node_name>
#PARAMETERS
<param_def>
[#NODE <node_name]
[#HYPEREDGE <edge_name>]
#VARIABLES
<var_def>
#CONSTRAINTS
<constr_def>
#OBJECTIVES
<obj_def>
```

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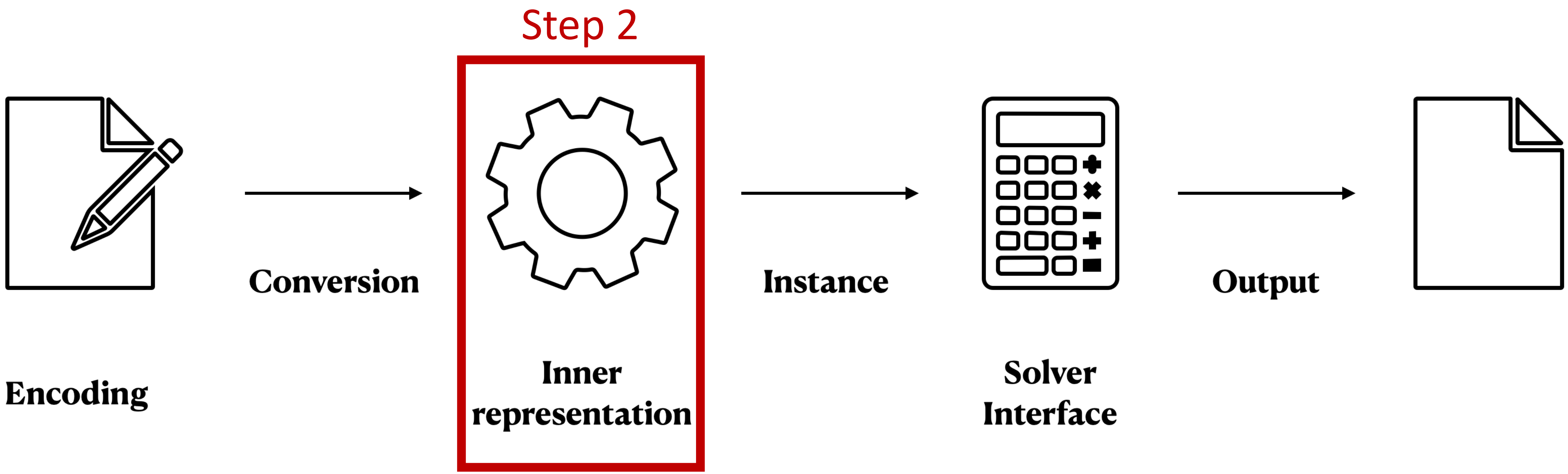

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Inner representation

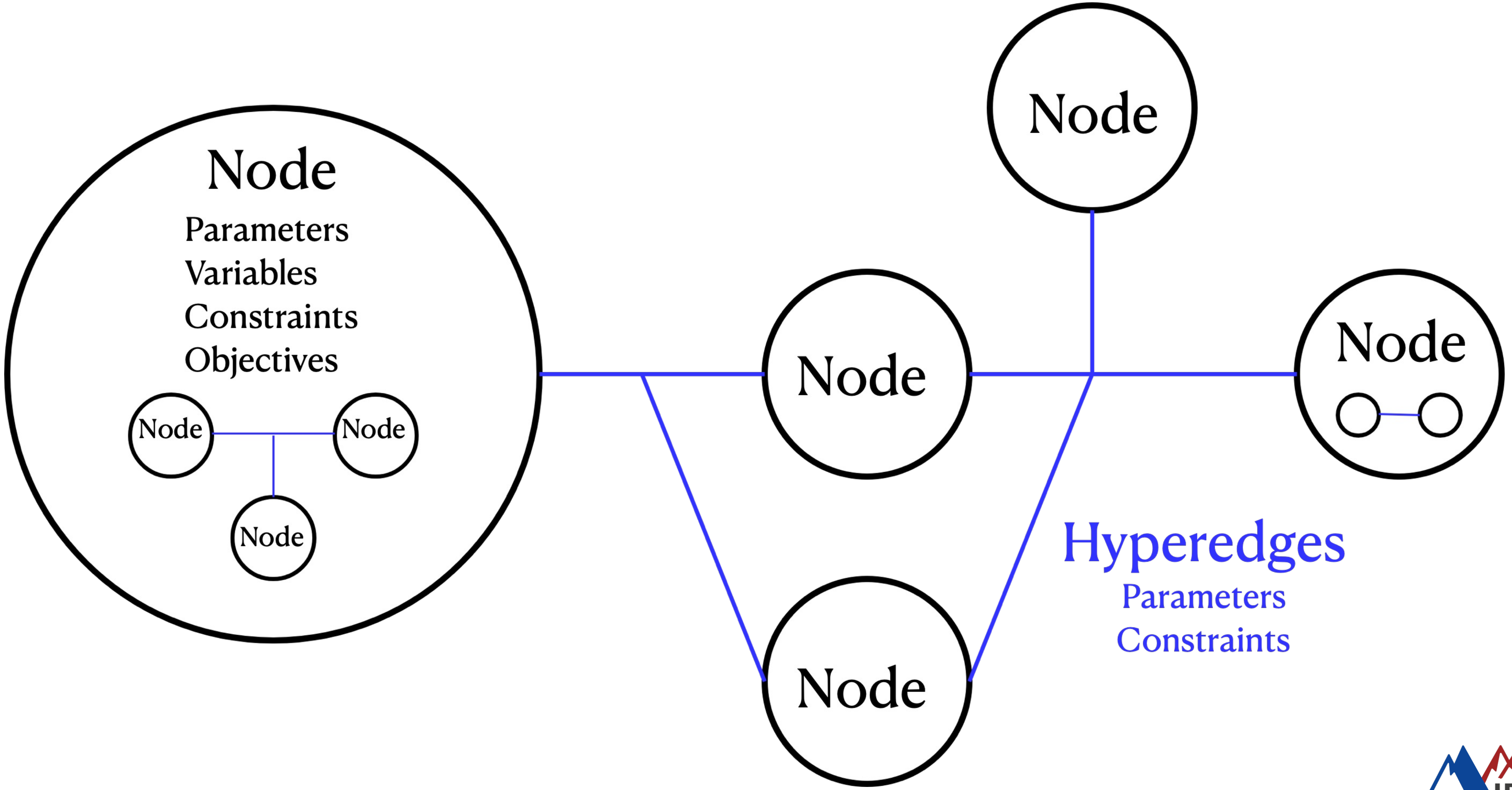

Figure 5: Hierarchical hypergraph inner representation

Inner representation

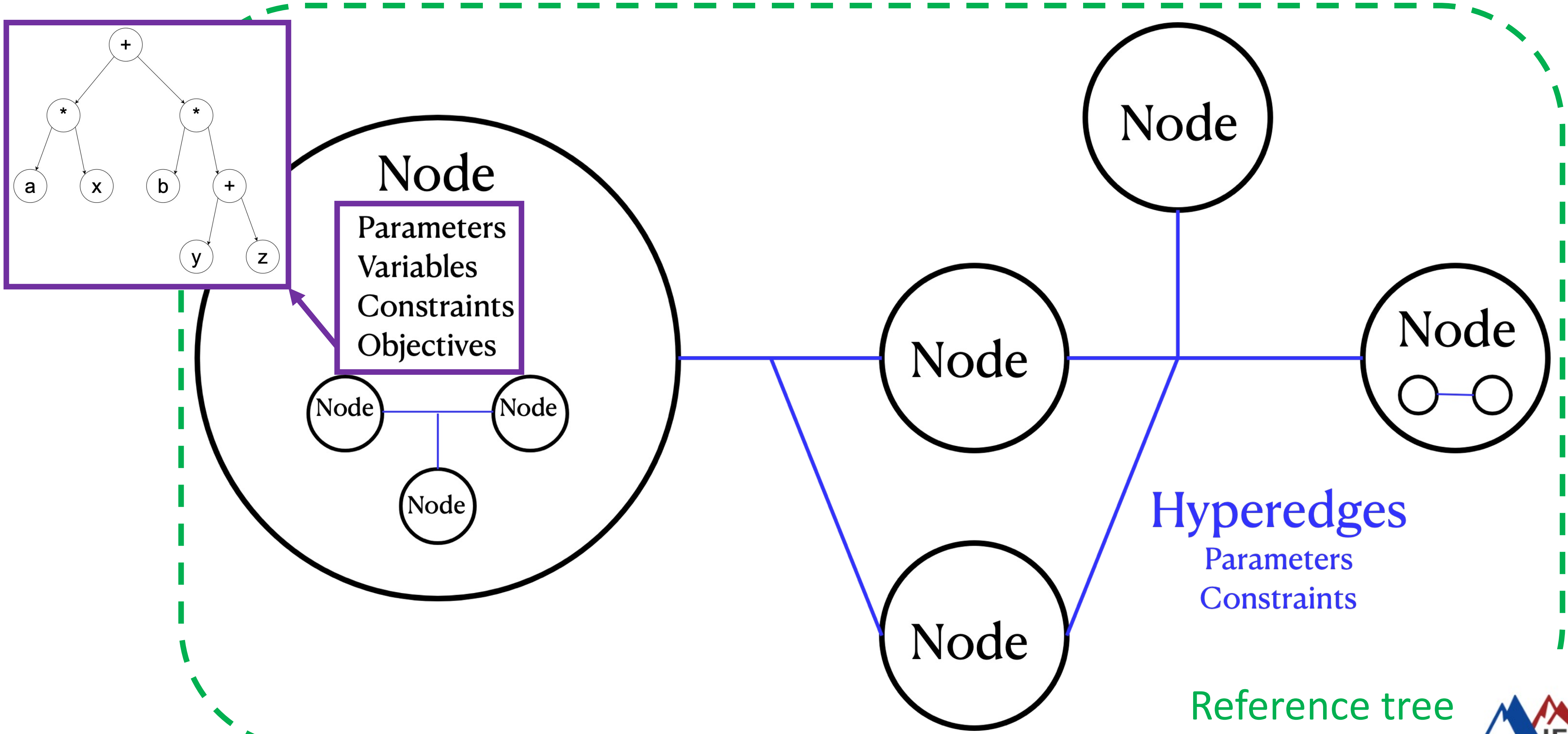

Figure 5: Hierarchical hypergraph inner representation

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Inner representation

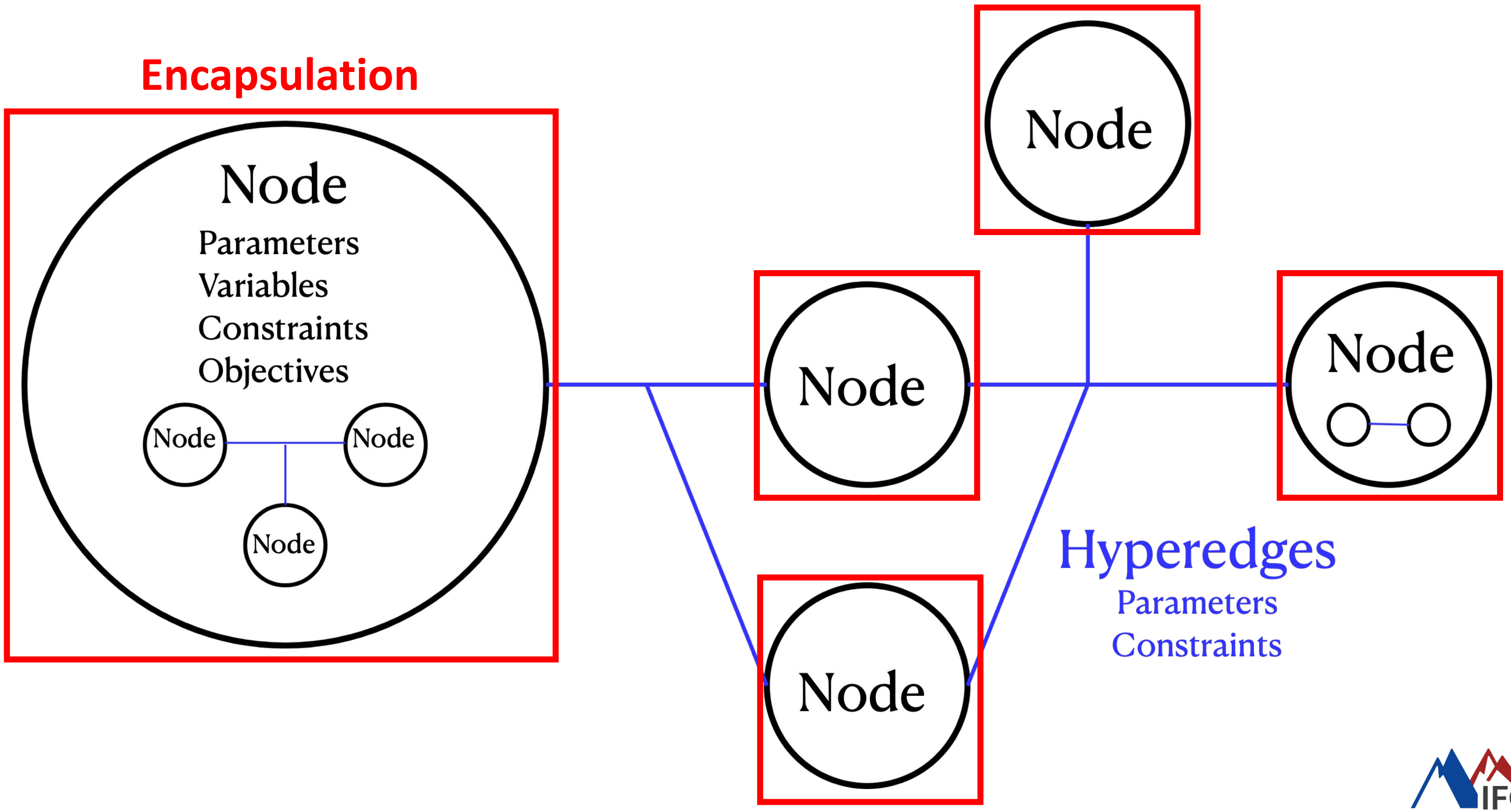

Figure 5: Hierarchical hypergraph inner representation

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Inner representation

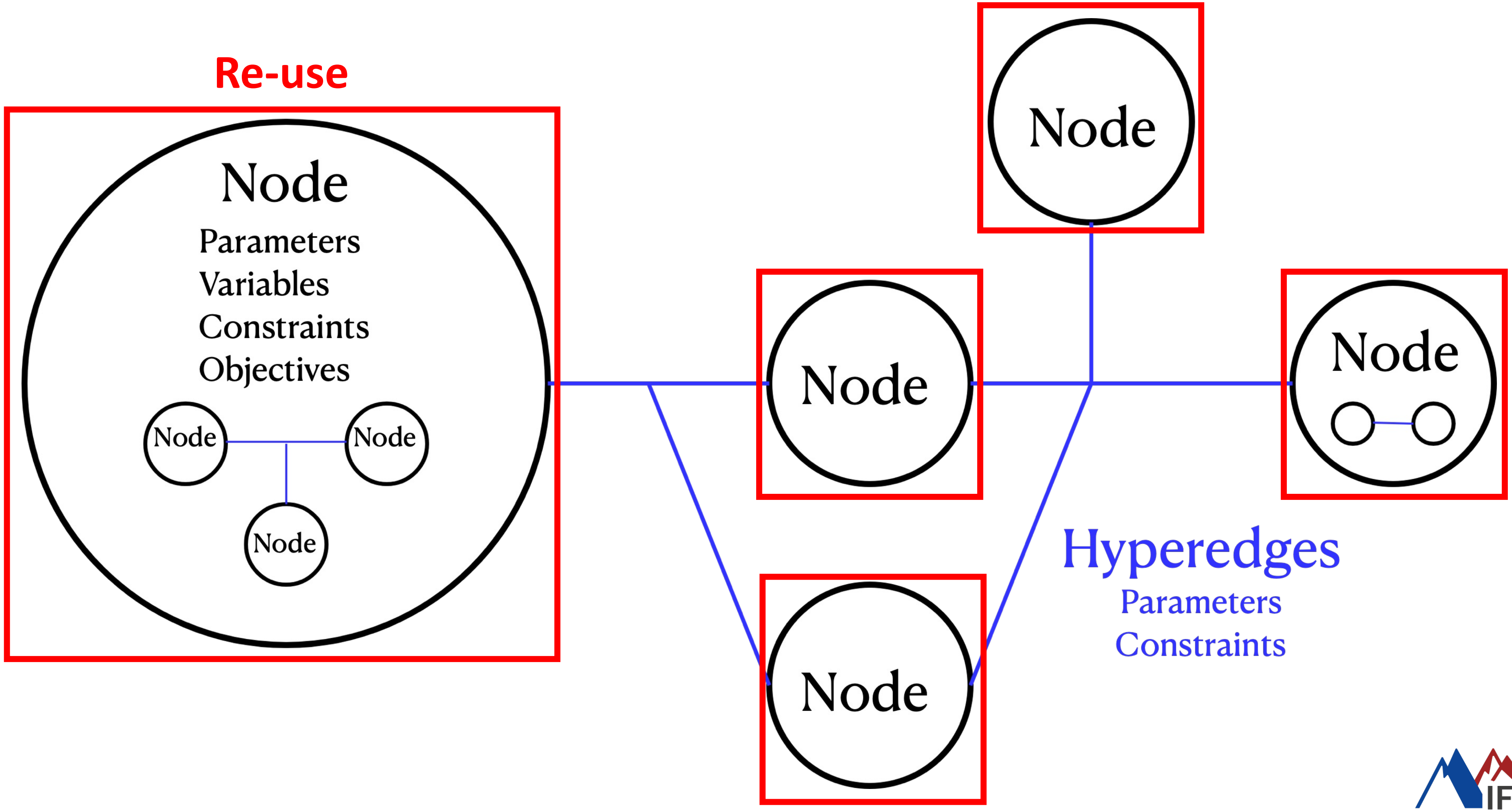

Figure 5: Hierarchical hypergraph inner representation

Inner representation

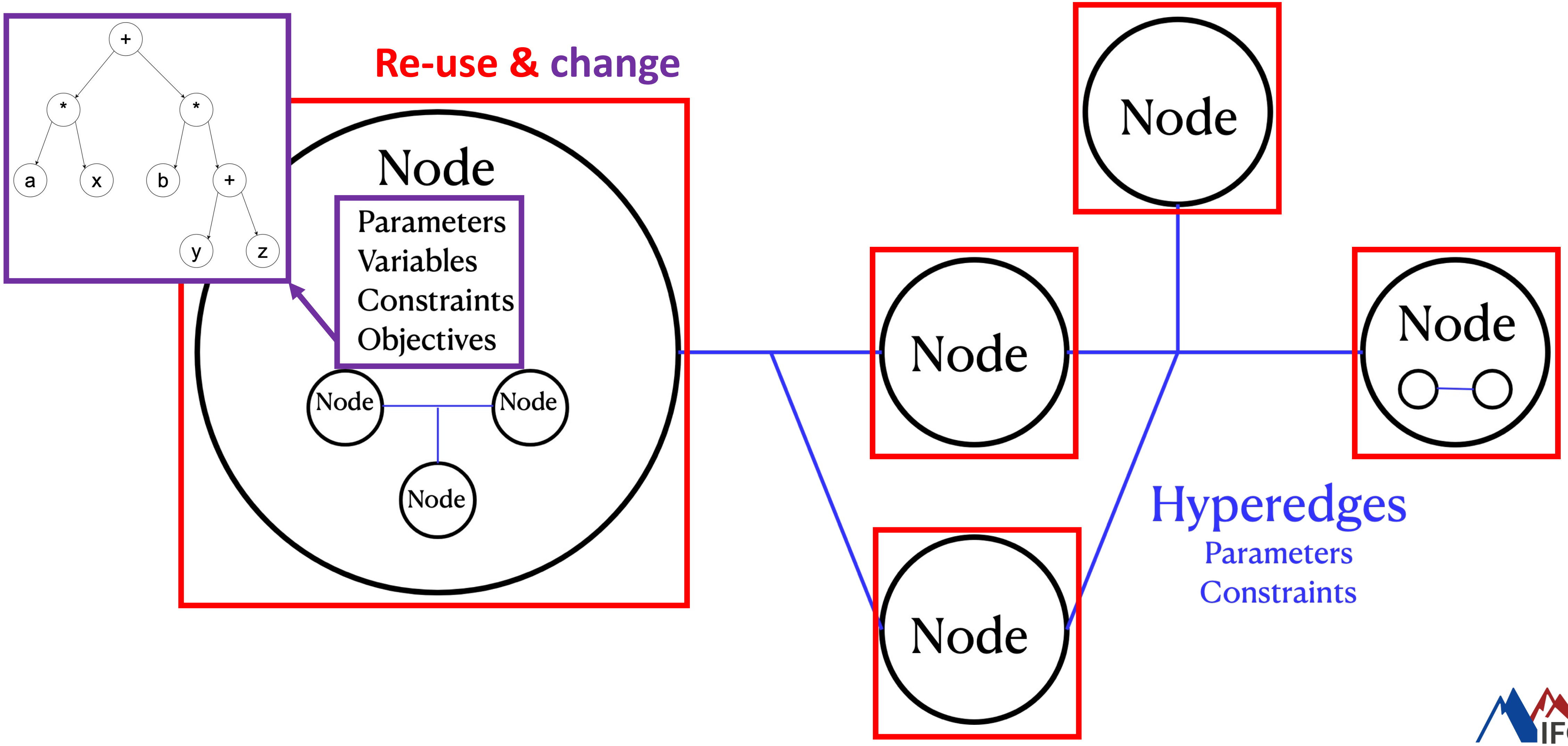

Figure 5: Hierarchical hypergraph inner representation

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Inner representation

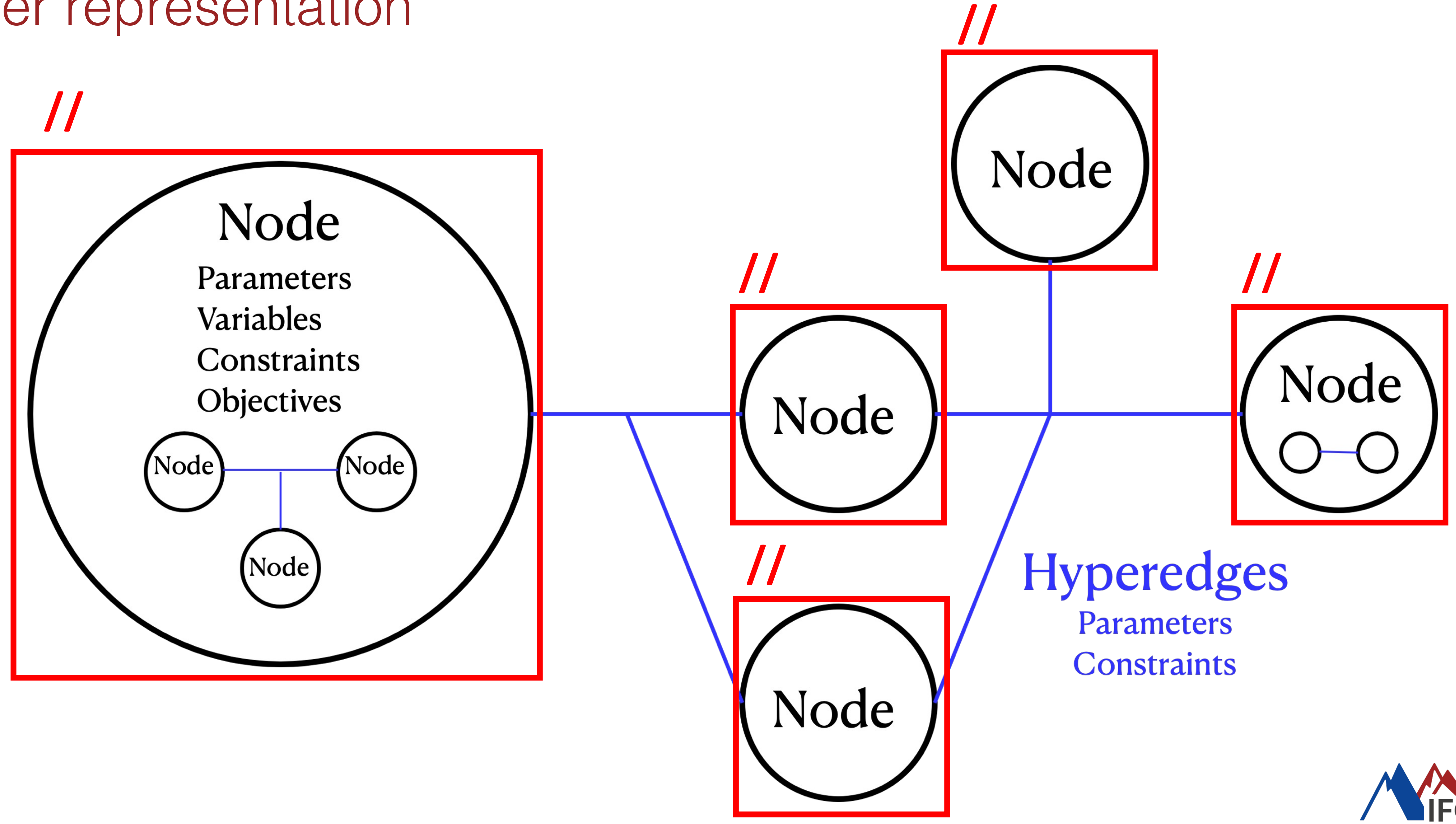

Figure 5: Hierarchical hypergraph inner representation

The Graph-Based Optimization Modelling Language (GBOML)

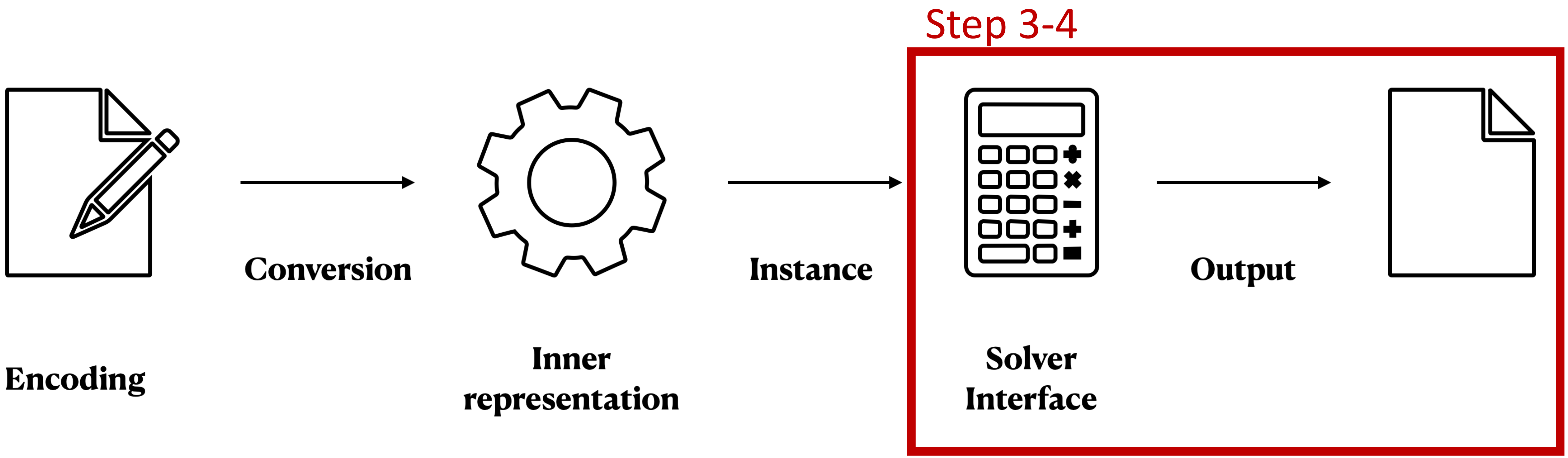

Figure 4: Modelling tool workflow

Solver interface and output

- Commercial solvers

GUROBI OPTIMIZATION [2] FICO [3] IBM [4]

- Open-source solvers

HiGHS [5] COIN|OR [6]

- Structure exploiting methods
  - DSP[7]: Dantzig-Wolfe decomposition
  - CPLEX: Benders decomposition

- Generates structure JSON and plain CSV

Benchmarking

Performances for generating an instance

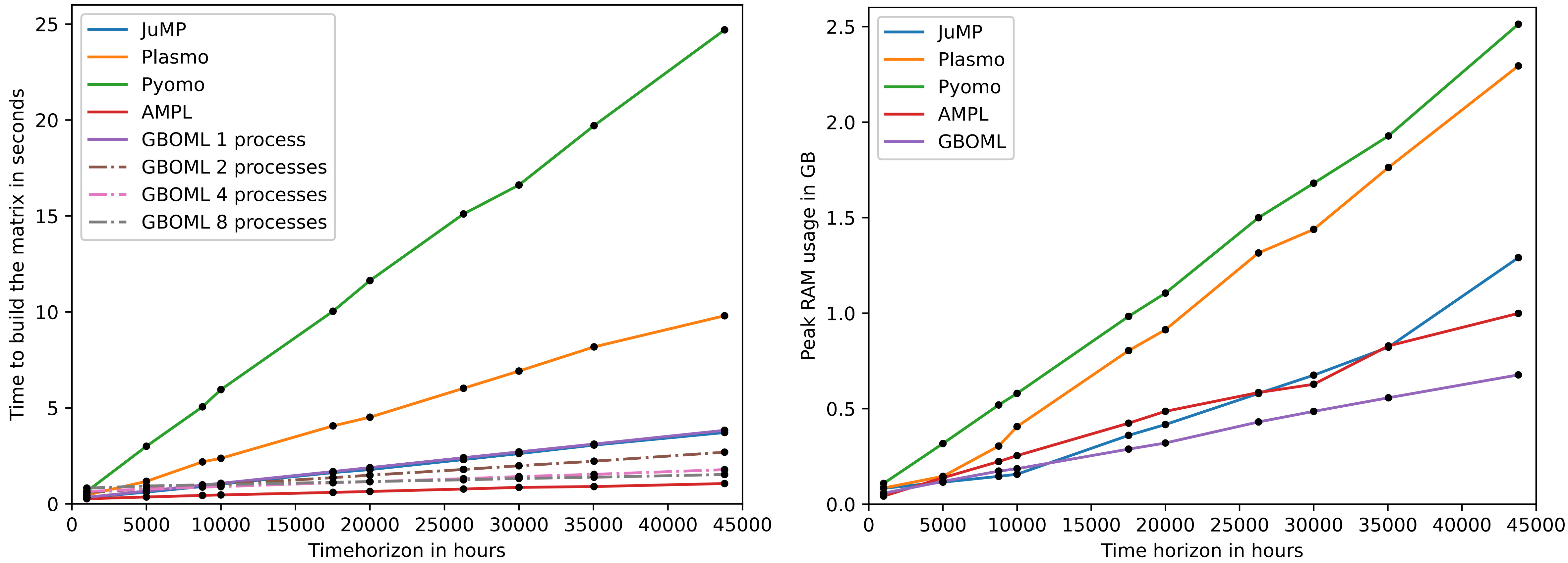

Figure 6: (Left) time taken to generate an instance (right) peak RAM usage to generate an instance – both were done on the remote renewable energy hub[8] for a growing time horizon [9]

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Structure Exploiting methods

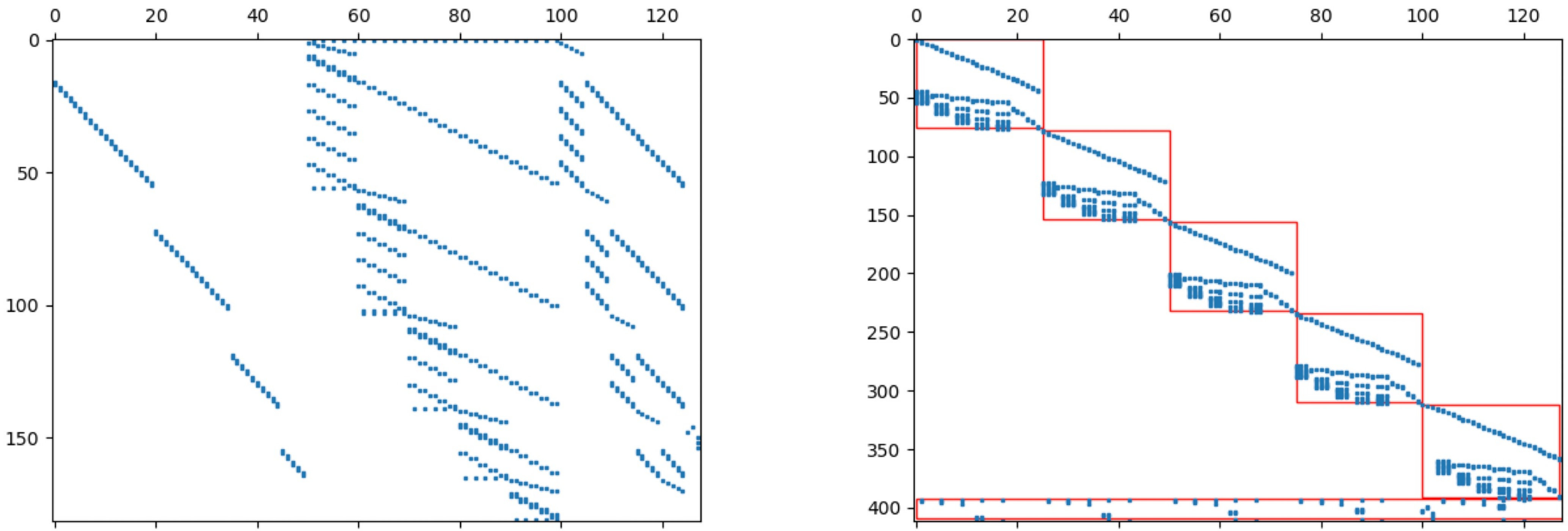

Figure 7: (Left) Plain no-swot problem problem from the MIPLIB[10] solved in 25s by Gurobi (Right) structured no-swot problem encoded in GBOML with a good decomposition solved by Dantiz-Wolfe in 2.5s.

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Conclusion

- Structure can help
  - Encode problems more naturally
  - Enable re-use and component assembling
  - Generate models faster
  - Interface with structure exploiting methods
- In terms of tool, GBOML exploits structure from model encoding to output

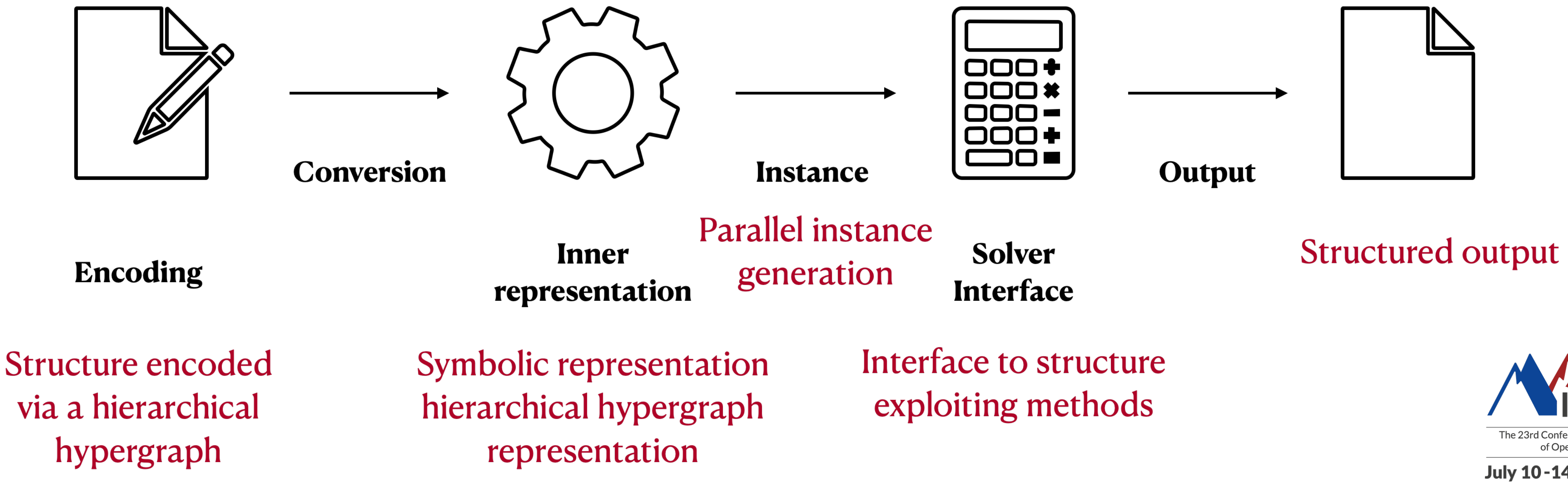

Figure 7: GBOML workflow

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Appendix : GBOML inner working