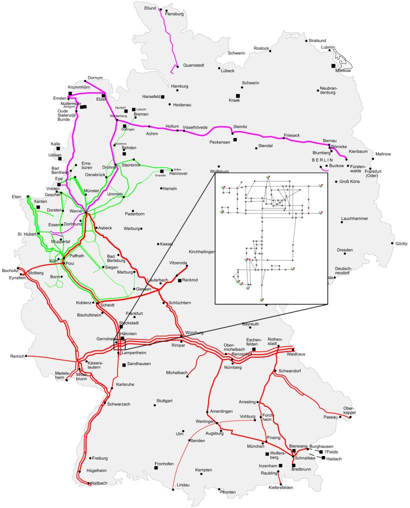
Learning Control Decisions in Gas Networks

Mark Turner

Combinatorial Optimization @ Work 2020

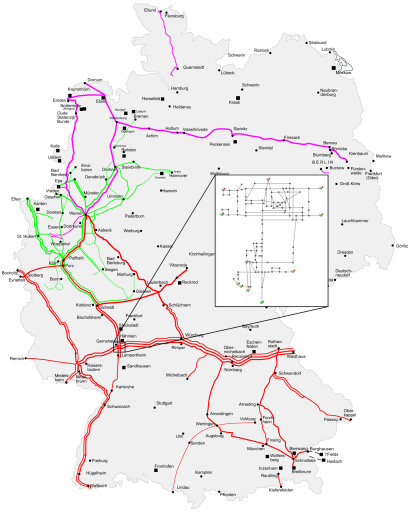
Exact control decisions of Network Stations

- Listen to previous talks
  - Provides descriptions of individual gas network elements
  - Provides background into the derivation of this problem



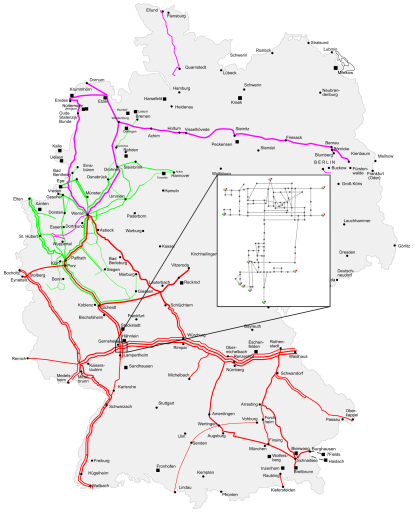
Exact control decisions of Network Stations

- Listen to previous talks
- Problem Setting (Important sub-networks inside larger network)
  - Focus on Network Stations
  - Network Stations contain all heavy machinery of the entire network
  - Network stations are commonly the intersection points between large transportation pipelines



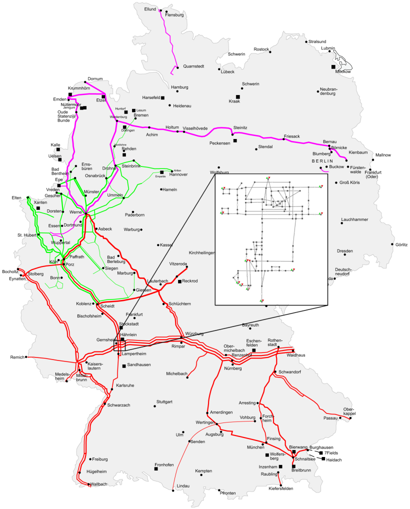
Exact control decisions of Network Stations

- Listen to previous talks
- Problem Setting (Important sub-networks inside larger network)
- Problem Aim (Control Decisions)
  - Find control decisions for all network elements
  - Ensure these control decisions are safe and realisable
  - Make these control decisions as ‘stable’ as possible
  - Control decisions are made at each time-step over a time-horizon $\{0, ..., |T|\}$.



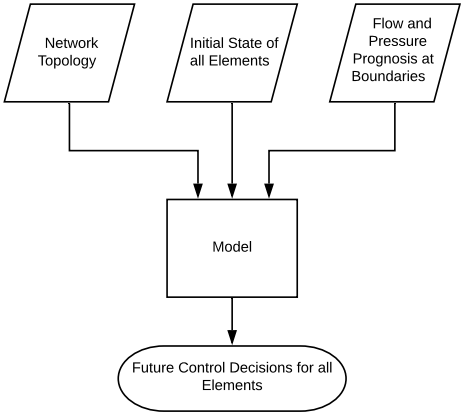
Exact control decisions of Network Stations

- Listen to previous talks
- Problem Setting (Important sub-networks inside larger network)
- Problem Aim (Control Decisions)
- Two Different Approaches:
  - (Model driven) Rolling Horizon approach
  - (Data driven) Machine Learning approach



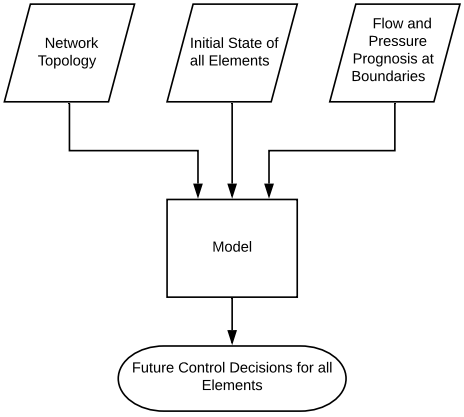
Problem Input and Output

- Input:
  - Network Topology - Complete individual element descriptions and connectedness
  - Initial State - Starting values for all elements
  - Prognosis - Set of demands we aim to meet



Problem Input and Output

- Input:
  - Network Topology - Complete individual element descriptions and connectedness
  - Initial State - Starting values for all elements
  - Prognosis - Set of demands we aim to meet
- Output (For all future time steps):
  - Valve states (Open / Closed)
  - Compressor states (Active (operating point) / Bypass / Closed)
  - Regulator states (Active (operating point) / Open / Closed)
  - Additional: Flow / Pressure levels throughout the network



Problem Uncertainties and Difficulties

- Organising priorities.

Problem Uncertainties and Difficulties

- Organising priorities.
  - Supply and Demand is met

$$\sum_u \text{flow}_{(u,v)} + \sum_u \text{flow}_{(v,u)} = v_{\text{inflow}} - v_{\text{slack}}$$

$$|v_{\text{slack}}| \leq \epsilon \quad v \in \text{Boundaries}$$

Problem Uncertainties and Difficulties

- Organising priorities.
  - Supply and Demand is met
  - Control Decisions are safe

E.g. Make sure there are well defined pressure limits for all bits of the network, and that your solution respects them:

$$\text{LB}(\text{pressure}_v) \leq \text{pressure}_v \leq \text{UB}(\text{pressure}_v)$$

Potentially less well defined requests. E.g. Avoid stressing the network

Problem Uncertainties and Difficulties

- Organising priorities.
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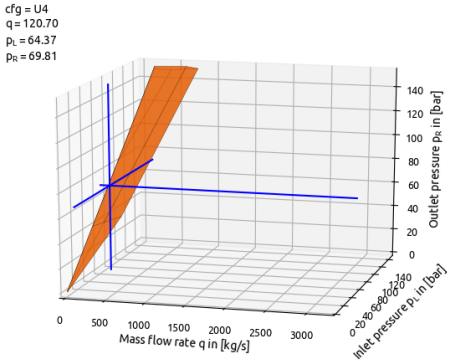
  - Control Decisions are safe
  - Control Decisions are stable

E.g. Make sure that your active point inside of a compressor polytope moves as little as possible



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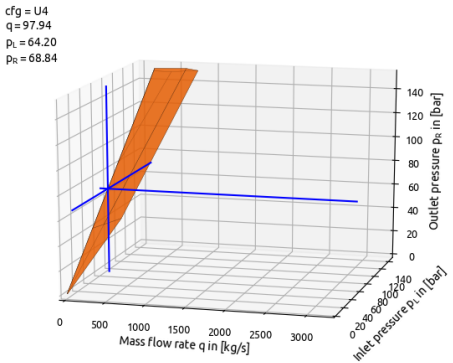

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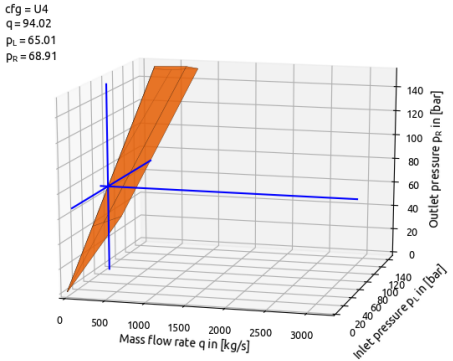

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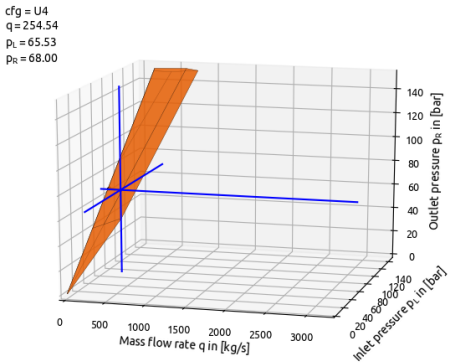

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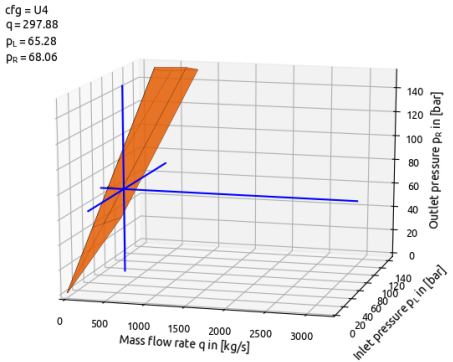

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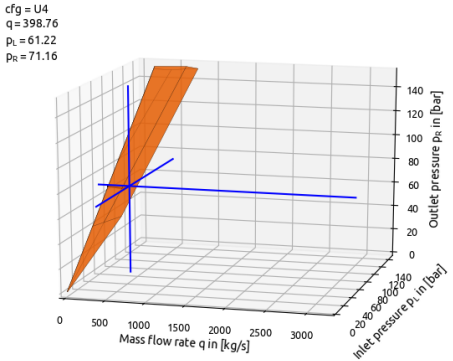

Problem Uncertainties and Difficulties

- Organising priorities.
  - Supply and Demand is met
  - Control Decisions are safe
  - Control Decisions are stable
  - Weighted Objective vs Multi Level

$$\min_{x,y} \quad Ax + By$$

vs.

$$\min_{x} \quad Ax$$
$$\text{s.t}$$
$$\min_{y} \quad By$$

Problem Uncertainties and Difficulties

- Organising priorities.
- Solution must be output in reasonable time
  - Model will be used in reality.
  - Output in time is necessary

https://xkcd.com/612/

Problem Uncertainties and Difficulties

- Organising priorities.
- Solution must be output in reasonable time
- Model exactness
  - Pipe discretisation
- What assumptions do I make? E.g. Ignore temperature
- Which discretisation technique do I use?
- Do I leave as is, convexify, or linearise my end result?
- See Kai Hoppmann's talk on more information on pipe equations. (We linearise)

Problem Uncertainties and Difficulties

- Organising priorities.
- Solution must be output in reasonable time
- Model exactness
  - Pipe discretisation
  - Compressor polytope

Compressor stations increase gas-pressure in the forward direction. We must choose which configuration of machines to use inside of the compressor station, and the operating point inside of the configuration's associated polytope.

Idea: Disjunctive Formulation

Use case: Efficiently model each compressor configuration polytope s.t we retrieve the active configuration, and the active operating point inside of the polytope.

Problem Uncertainties and Difficulties

- Organising priorities.
- Solution must be output in reasonable time
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$$
\begin{aligned}
m_c \in \{0,1\} \quad & \forall c \in \mathrm{C}: && \text{Active configuration} \\
\mathrm{pl}_c \in \mathbb{R}^+ \quad & \forall c \in \mathrm{C}: && \text{LHS pressure} \\
\mathrm{pr}_c \in \mathbb{R}^+ \quad & \forall c \in \mathrm{C}: && \text{RHS pressure} \\
q_c \in \mathbb{R}^+ \quad & \forall c \in \mathrm{C}: && \text{Flow}
\end{aligned}
$$

$$
\sum_c m_c = 1 \quad \mathrm{pl} = \sum_c \mathrm{pl}_c
$$

$$
\mathrm{pr} = \sum_c \mathrm{pr}_c \quad q = \sum_c q_c
$$

$$
LB(\mathrm{pl}_c) m_c \leq \mathrm{pl}_c \leq UB(\mathrm{pl}_c) m_c
$$

$$
LB(\mathrm{pr}_c) m_c \leq \mathrm{pr}_c \leq UB(\mathrm{pr}_c) m_c
$$

$$
LB(q_c) m_c \leq q_c \leq UB(q_c) m_c
$$

$$
w \cdot \mathrm{pl}_c + x \cdot \mathrm{pr}_c + y \cdot q_c + z \cdot m_c \leq 0 \quad \forall c \in \mathrm{C}
$$

$$
\forall (w,x,y,z) \in \mathrm{HPlanes(c)}
$$

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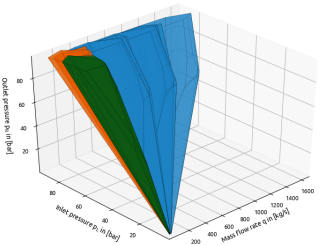
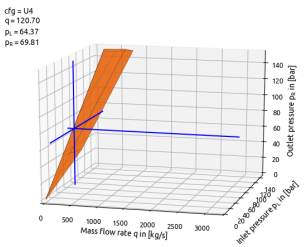




Operation Modes (Example Constraint Set)

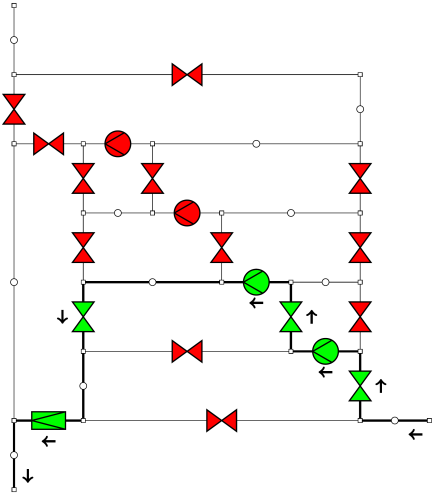
Operation Modes:

- Determines modes and configurations (binary decisions) for all valves and compressors

$M(o, a) := x$ where x is the mode / configuration of arc a in operation mode o $\forall o \in \mathrm{O}$

with $x \in \{\text{open}, \text{closed}\}$ if $a \in \text{Valves}$

$x \in \{\text{bypass}, \text{closed}, \text{cfgs}\}$ if $a \in \text{Compressors}$

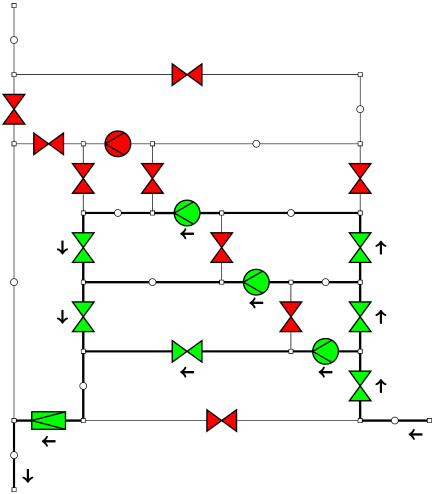


Operation Modes (Example Constraint Set)

Operation Modes:

- Determines modes and configurations (binary decisions) for all valves and compressors
- Limits these mode combinations to a set of size $|\mathrm{O}|$

$$|\mathrm{O}| \quad << \quad 2^{|\text{valves}|} \cdot \prod_{a \in \text{compressors}} (2 + |\text{cfgs}_a|)$$



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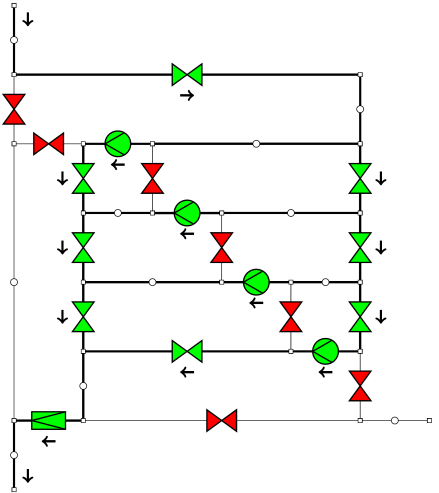
Operation Modes:

- Determines modes and configurations (binary decisions) for all valves and compressors
- Limits these mode combinations to a set of size $|\mathrm{O}|$
- Determines the polytope choice for each compressor (Not the active point within)

$$m_{c_1} = 0 \quad m_{c_2} = 1 \quad m_{c_3} = 0$$
$$\mathrm{pl}_{c_1} = \mathrm{pl}_{c_3} = \mathrm{pr}_{c_1} = \mathrm{pr}_{c_3} = q_{c_1} = q_{c_3} = 0$$
$$w \cdot \mathrm{pl}_{c_2} + x \cdot \mathrm{pr}_{c_2} + y \cdot q_{c_2} + z \leq 0$$
$$\forall (w, x, y, z) \in \mathrm{HPlanes}(c_2)$$



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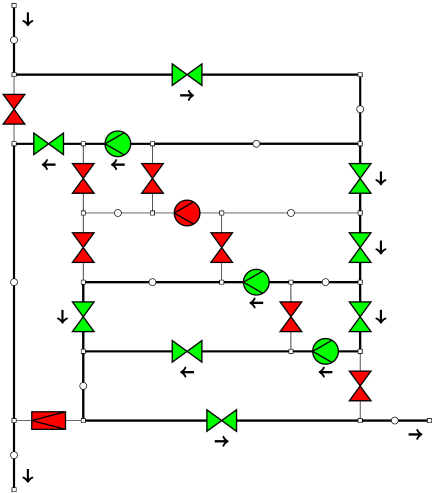
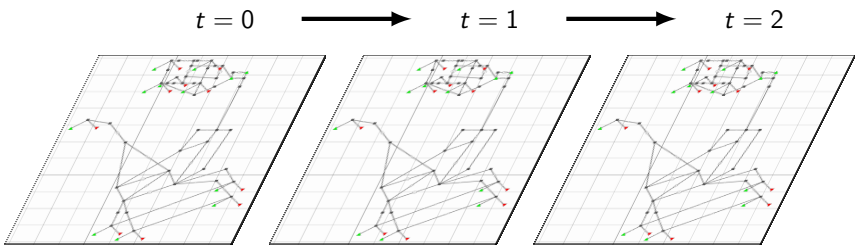
- Determines modes and configurations (binary decisions) for all valves and compressors
- Limits these mode combinations to a set of size $|\mathrm{O}|$
- Determines the polytope choice for each compressor (Not the active point within)
- Has an allowed set of flow directions with each choice. For example, the four choices shown never allowed east to north flow.



Model Driven Rolling Horizon Approach

- Single large MIP is too unreliable. Solve times can take days to even find a primal solution.



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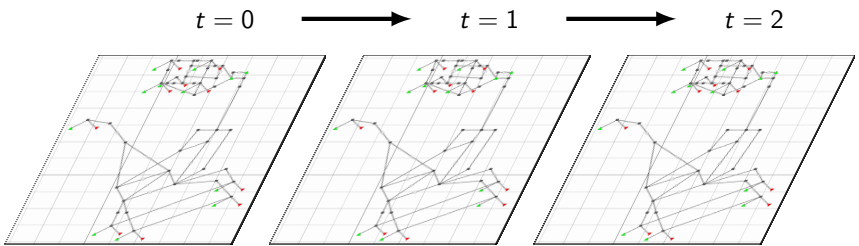
- Idea: Break up by timesteps. Create greedy heuristic for determining best binary decisions



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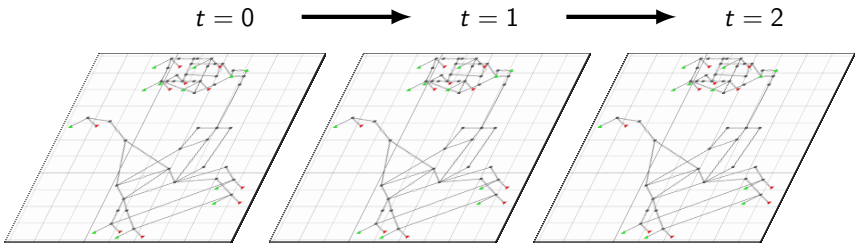
- Introduce a penalty for changing operation modes (set of binary control decisions)



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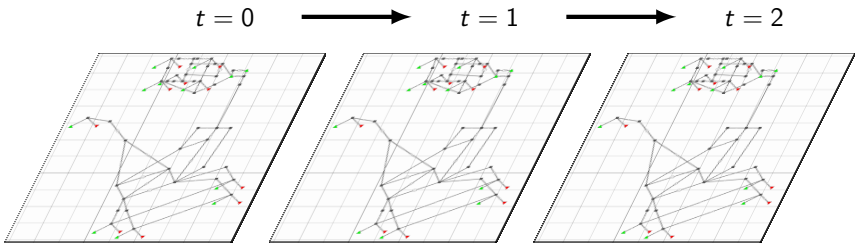

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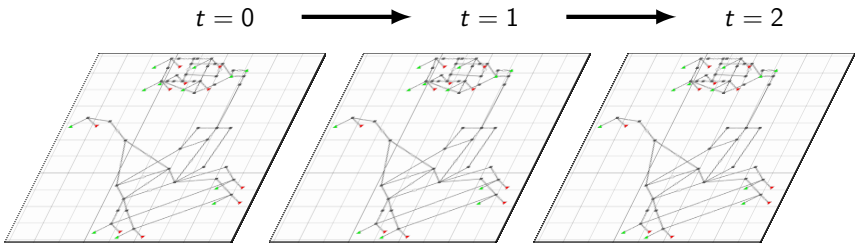
- Create process where series of operation modes can be re-combined if continuity leads to better objective value
- Smooth solution and make it feasible w.r.t the larger impractical MIP



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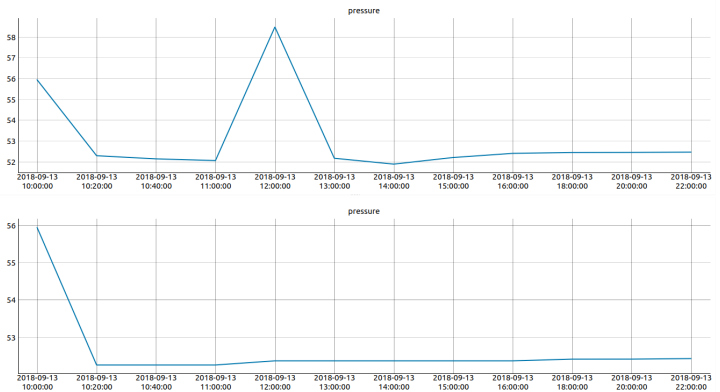
- Solution: Rolling Horizon Approach with fixed binary variables to smooth solution



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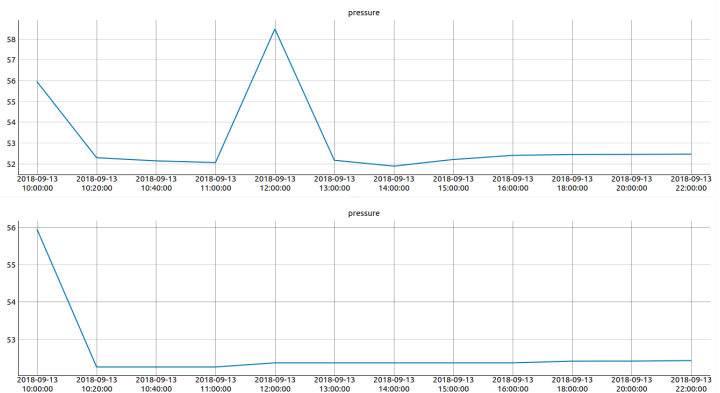
- Downside of greedy approach: Time steps continuous variables are largely independent
- Upside of greedy approach: Quick to solve and end-result scales linearly w.r.t number of time-steps.
- Solution: Rolling Horizon Approach with fixed binary variables to smooth solution
- Guarantees primal feasibility to original MIP



Data Driven Dual Neural Network Approach

- Do I have enough data?
  - Substantial amount of data needed for complex tasks
  - Never ending amount of new features and interfaces
  - The first step of a project is often simply creating data readers and ensuring data quality

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Data Driven Dual Neural Network Approach

- Do I have enough data?
- What technique is best for my purpose?
  - More complex techniques aren't always better!
  - There is no universal method (Free Lunch Theorem)
  - Choose method that best fits the problem. Can be from a theoretic approach or preliminary trial and error.

https://xkcd.com/1838/

Data Driven Dual Neural Network Approach

- Do I have enough data?
- What technique is best for my purpose?
- Will a simple heuristic suffice?
  - As seen in this series of lectures, non data-driven heuristics can be very effective
  - Do I need to worry about proven optimality?

https://xkcd.com/1838/

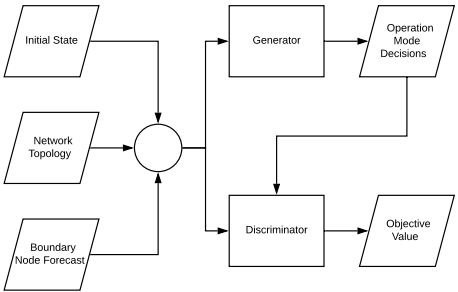
Data Driven Dual Neural Network Approach

- Do I have enough data?
- What technique is best for my purpose?
- Will a simple heuristic suffice?
- How do I model my input?
  - Heavily depends on your method choice
  - Does your data already have intrinsic patterns? E.g. Time repeated values

https://xkcd.com/1838/

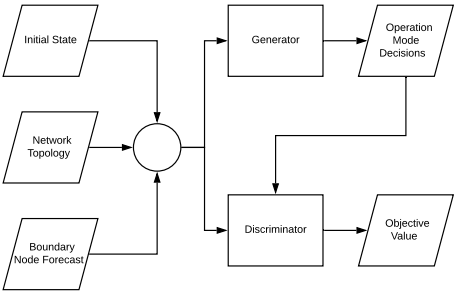
Dual Neural Network Design

- Inspiration
  - Generative Adversarial Networks (GANs) (Learn by having two networks compete against each other)
  - Actor-Critic Methods (Learn with feedback from an environment with an introduced variability in downstream decisions)



Dual Neural Network Design

- Properties of our design:
  - Uses a Generator and Discriminator Design
  - Generator produces binary decisions
  - Disicriminator predicts the induced optimal objective value of a problem with these variables fixed
  - Our MIP/LP solver is the environment
  - Discriminator and Generator are trained at different times, never simultaneously



Pros and Cons of design and implementation

- Pros:
  - Can generate our own data. As we learn our MIP formulation instead of reality itself, data generation is much simpler.
- Cons:
  - Our MIP must accurately represent reality. This may be a problem in extreme scenarios due to simplifications such as our linearisation.

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  - Definition of objective function may change. No bound guarantees on solution.
  - The Generator requires on-line training to ensure that the Discriminator is returning accurate induced optimal objective values.

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  - Learn on a gradient of objective values. This means that our non-optimal decisions are much more likely to be near optimal.
  - Can move a substantial amount of training off-line. Specifically the Discriminator's early training.
  - Reduced problem complexity and is used as primal heuristic
- Cons:
  - Our MIP must accurately represent reality. This may be a problem in extreme scenarios due to simplifications such as our linearisation.
  - Definition of objective function may change. No bound guarantees on solution.
  - The Generator requires on-line training to ensure that the Discriminator is returning accurate induced optimal objective values.
  - Output is only binary variables, and the continuous variable values must be found by a MIP/LP solver.

The Last Slide

Thanks for watching!

Combinatorial Optimization @ Work 2020