CO@Work 2020

Optimized Execution of Dispatching

Algorithmic Intelligence over Steel

The ZIB/TUB/OGE MODAL GasLab Team

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Algorithmic Intelligence over Steel

Your mission, should you choose to accept it:

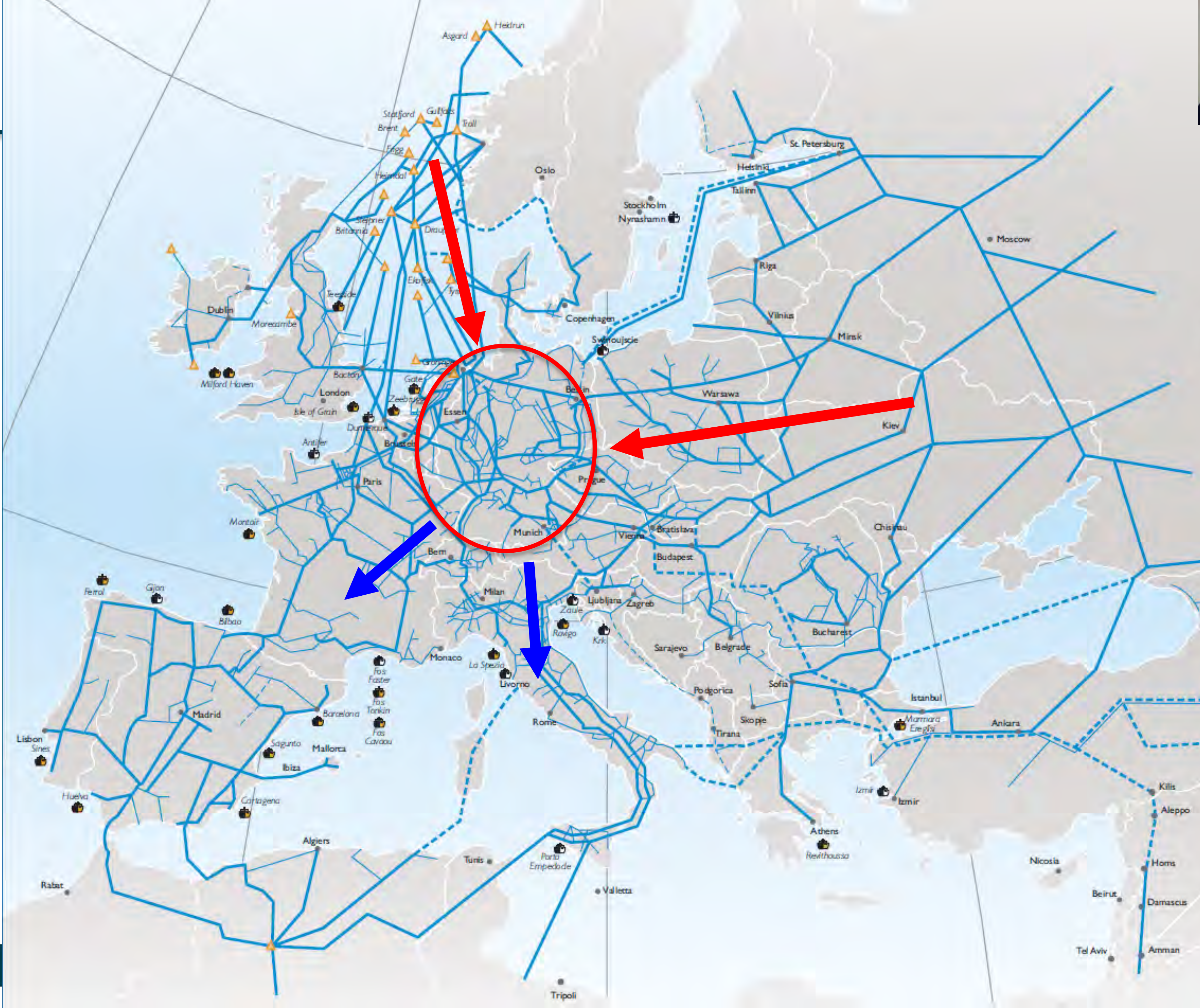
Given: A country-wide century-old infrastructure, worth 3 billion $ that is responsible for delivering 25% of Germany's energy consumption and a plan calling for a 690 million $ construction upgrade to support the Energiewende and go green.

Goal: Build an intelligent decision support system that makes this network ready for the 21st century to avoid burying billions of € in steel.

The German Gas Network

is the Heart of European Gas Transport

and a critical infrastructure to supply Central, Southern and Western Europe with natural gas from Russia and Norway.



The Unboundled European Gas Market since 2009

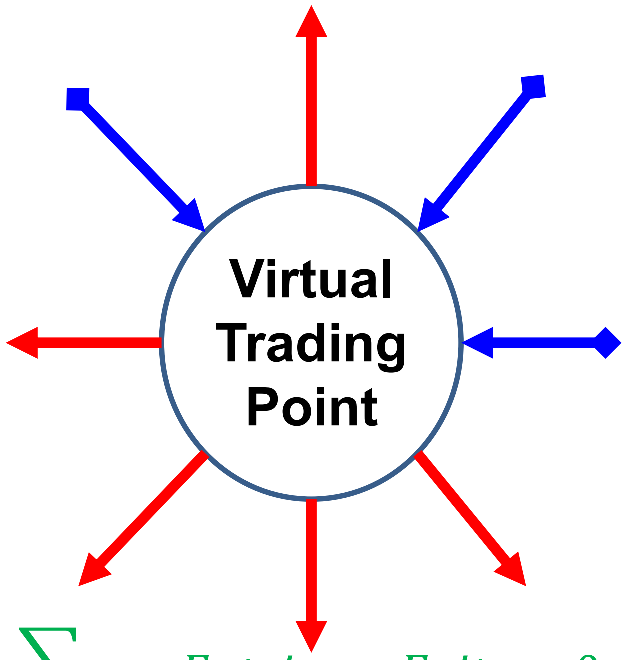
Gas Trading Companies ∩ Transport System Operators = ∅

REGULATION (EC) No 715/2009 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL

Traders buy and sell gas | transmission system operators transport it.

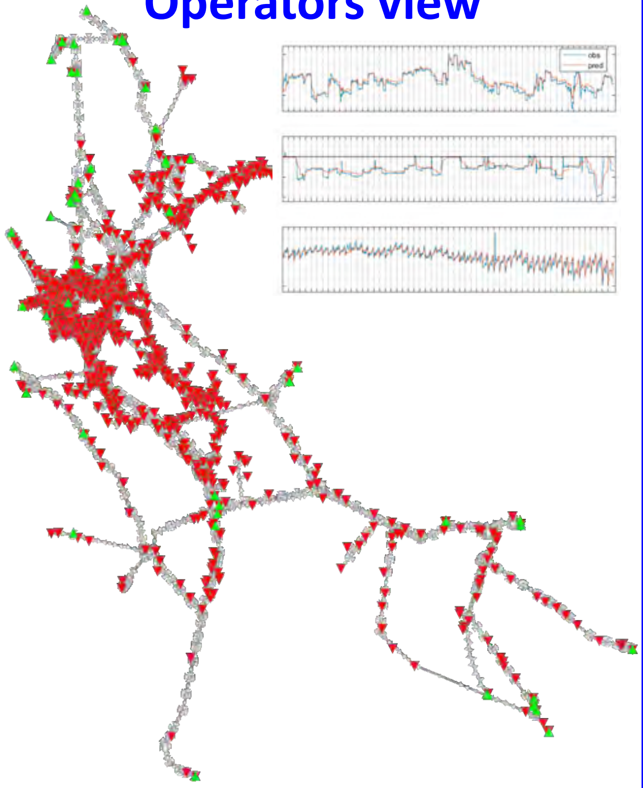
- Capacity products are typically either **firm** = sure deliver **or flexible** = best effort.
- The traders give transport orders to the TSO within the limits of the acquired capacity.
- The TSO then has to fulfill the order accordingly.
- German market p.a.:
  trading $ > 54 billion
  transport $ > 2 billion

Trader view

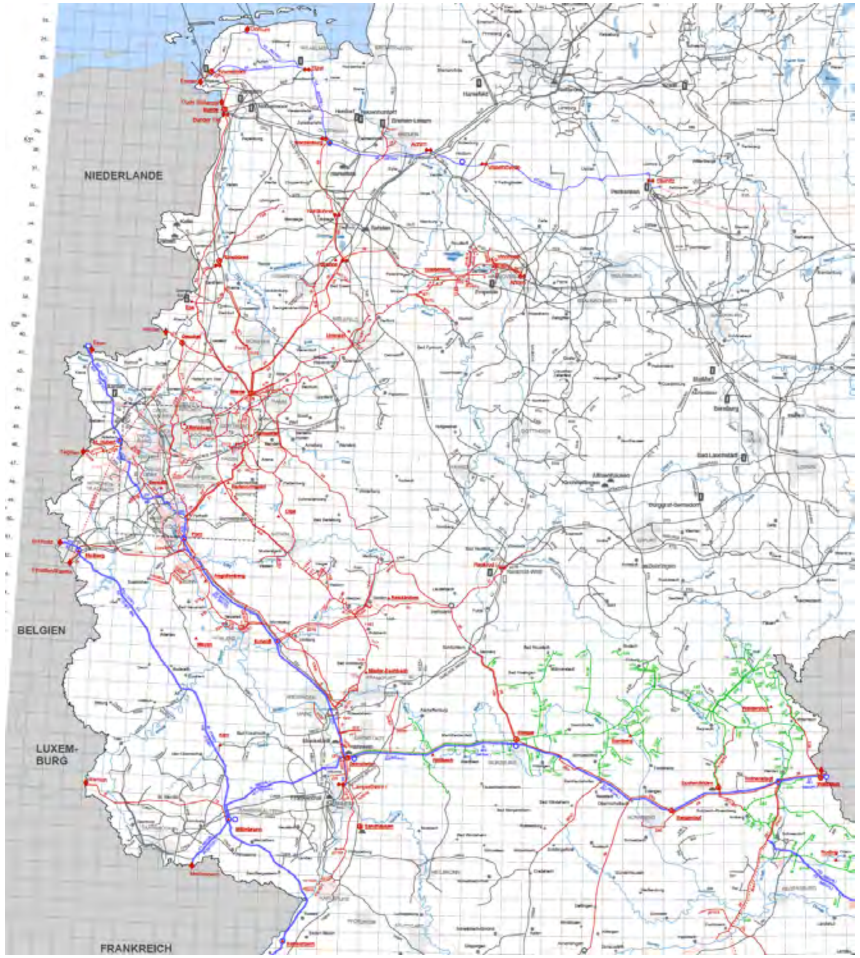


$$\sum_{\substack{1\ day \\ (6am\ to\ 6am) \\ over\ all\ nodes}} Entries - Exits = 0$$

Transmission System Operators view

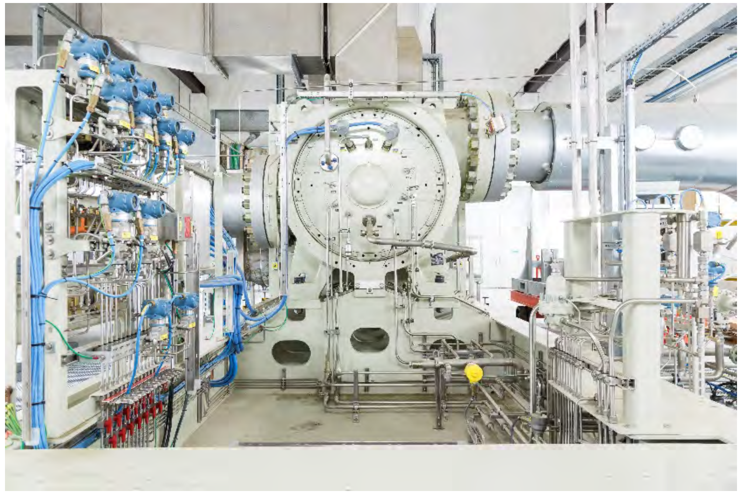


The Challenge – Gas Transport Network Operations

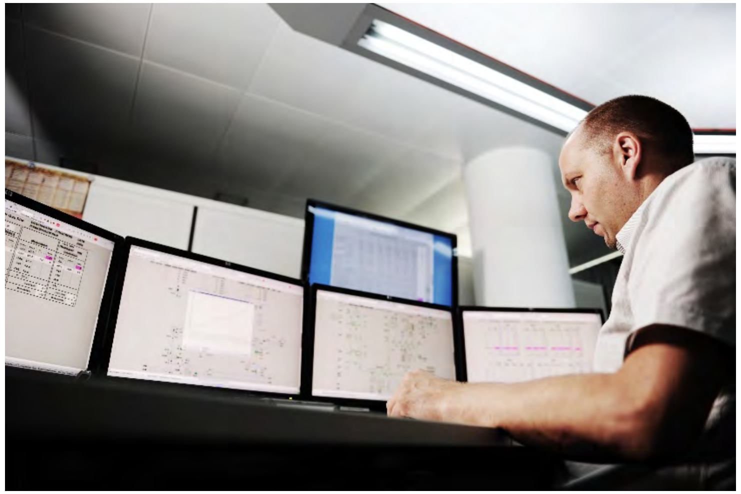


Colored: OGE operated pipelines

- Central dispatching of OGE controls the operation of more than 100 compressor units, almost 300 control valves and more than 3,000 valves in a 12,000 km gas network.
- In order to guarantee a secure supply in the future, further IT systems are needed to support the dispatcher.



Turbo Compressor

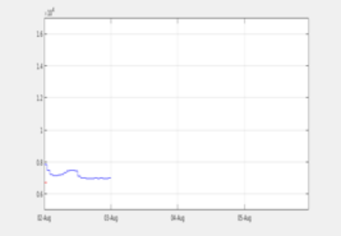


Dispatcher at work

Business Impact of Optimized Execution of Dispatching

Digital Transformation	The use of **AI** for an optimized dispatching addresses **one of our core objectives** within the framework of OGE’s digital transformation.
Corporate Strategy	OED will enable OGE to deal with the more complex requirements of a **future gas grid with more or pure hydrogen.**
Economic Benefits	OED can **avoid network expansion costs** of **one billion $ for Germany**, based on planning scenarios for the supply of gas power plants.

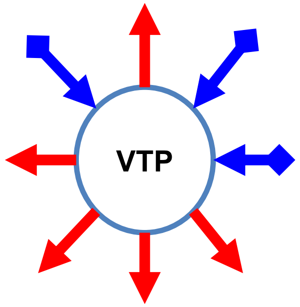
3 Goals to **Optimize Execution of Dispatching**



- **Forecast** – High-precision gas-flow prediction

  Increases the accuracy by 34% compared to industry standard.

Used in **operations** since 2018

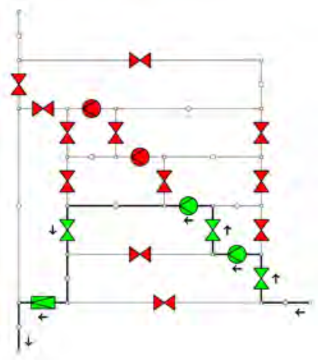


- **FDAC** – **F**irm **D**ynamically **A**llocable **C**apacity product

  Enables the German Energiewende while saving $ 690,000,000.

  Based on high quality flow forecasts, detects network conditions, where critical power plants can no longer be safely supplied by the Virtual Trading Point (VTP).

Used in **operations** since 2018



- **KOMPASS** – High Quality Recommendations for Control Operation

  Will ensure security of supply even in more complex environments Improves efficiency of operations.

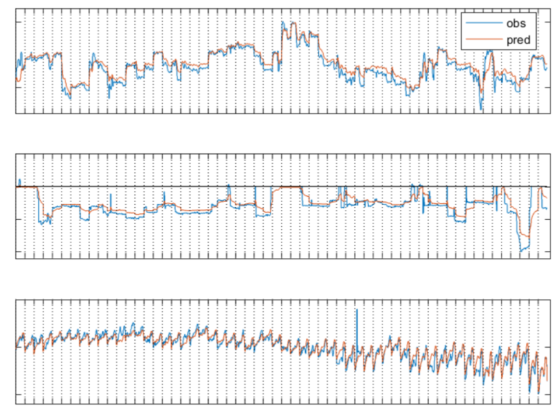
  Enables future possibilities: H_2, NH_3, power2gas

First version in **test phase** since 2019

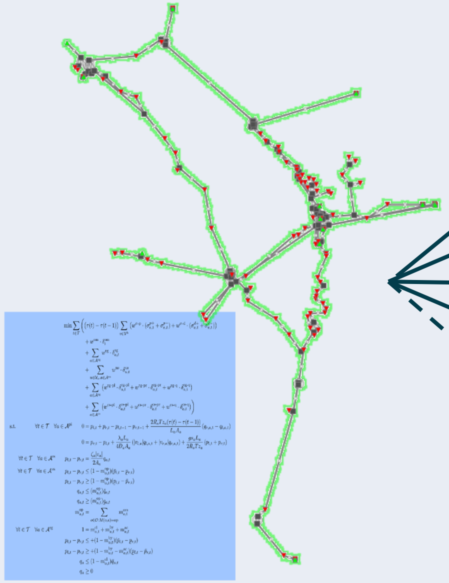
OED/KOMPASS Overview

Descriptive
Predictive
Prescriptive

1. Forecasting



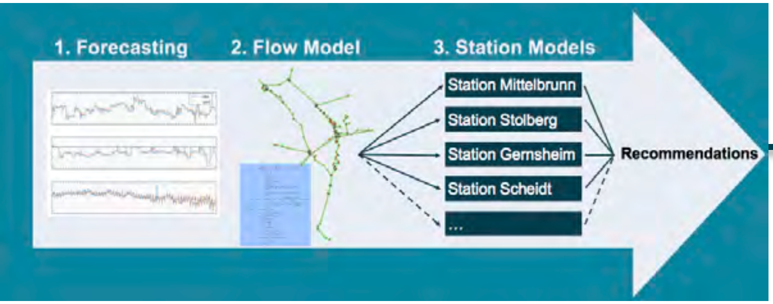
2. Flow Model



3. Station Models

- Station Mittelbrunn
- Station Stolberg
- Station Gernsheim
- Station Scheidt
- …

Recommendations

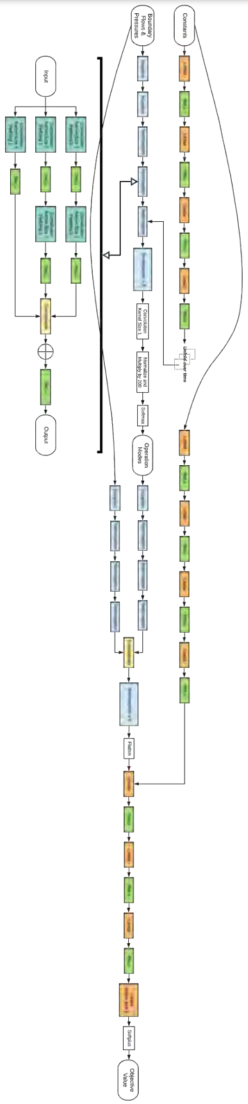


The KOMPASS near real-time Decision Support System

Descriptive
Predictive
Prescriptive

Running 24/7, providing updated recommendations every 15 min.

1. Control Database aggregates new data from 3 external systems every 15 min.
2. Based on the data a valid initial state is constructed.
3. Several heuristics try to devise possible solutions to the overall flow situation.
4. Mixed-Integer Programing (MILP) based flow model, warm starting using the heuristic solutions, computes an optimized overall strategy.
5. Result of the flow model defines the demand curves for the individual stations.
6. For each station in parallel:
   - Heuristics quickly devise initial solutions.
   - The MILP station model computes optimized actions for the stations.
7. Actions are combined and postprocessed into recommendations.



Example: GAN DNN ML Station Heuristic

Two stage architecture inspired by Generative Adversarial Networks

Learning good control decisions with a time-convolutional residual deep neural network

Good, but not optimal decisions in < 0.1 s

Mixed-Integer Program for Optimal Network Control

Descriptive
Predictive
Prescriptive

Objective function

$$\min \sum_{t\in\mathcal{T}} \Bigg((\tau(t)-\tau(t-1)) \sum_{v\in\mathcal{V}^{\mathrm{b}}} \left(w^{\sigma\text{-p}}\cdot(\sigma^{p+}_{v,t}+\sigma^{p-}_{v,t}) + w^{\sigma\text{-d}}\cdot(\sigma^{d+}_{v,t}+\sigma^{d-}_{v,t})\right)$$
$$+ w^{\mathrm{om}}\cdot\delta^{\mathrm{om}}_t$$
$$+ \sum_{a\in\mathcal{A}^{\mathrm{rg}}} w^{\mathrm{rg}}\cdot\delta^{\mathrm{rg}}_{a,t}$$
$$+ \sum_{u\in\mathcal{U}_a, a\in\mathcal{A}^{\mathrm{cs}}} w^{\mathrm{us}}\cdot\delta^{\mathrm{us}}_{u,t}$$
$$+ \sum_{a\in\mathcal{A}^{\mathrm{rg}}} \left(w^{\text{rg-pl}}\cdot\delta^{\text{rg-pl}}_{a,t} + w^{\text{rg-pr}}\cdot\delta^{\text{rg-pr}}_{a,t} + w^{\text{rg-q}}\cdot\delta^{\text{rg-q}}_{a,t}\right)$$
$$+ \sum_{a\in\mathcal{A}^{\mathrm{cs}}} \left(w^{\text{cs-pl}}\cdot\delta^{\text{cs-pl}}_{a,t} + w^{\text{cs-pr}}\cdot\delta^{\text{cs-pr}}_{a,t} + w^{\text{cs-q}}\cdot\delta^{\text{cs-q}}_{a,t}\right)\Bigg)$$

Momentum equation

s.t. $\forall t\in\mathcal{T} \quad \forall a\in\mathcal{A}^{\mathrm{pi}}$

$$0 = p_{l,t} + p_{r,t} - p_{l,t-1} - p_{r,t-1} + \frac{2R_sTz_a(\tau(t)-\tau(t-1))}{L_aA_a}(q_{r,a,t}-q_{l,a,t})$$

Pressure loss

$$0 = p_{r,t} - p_{l,t} + \frac{\lambda_aL_a}{4D_aA_a}(|v_{l,a}|q_{l,a,t} + |v_{r,a}|q_{r,a,t}) + \frac{gs_aL_a}{2R_sTz_a}(p_{l,t}+p_{r,t})$$

Resistor constraint

$\forall t\in\mathcal{T} \quad \forall a\in\mathcal{A}^{\mathrm{rs}}$

$$p_{l,t} - p_{r,t} = \frac{\zeta_a|v_a|}{2A_a}q_{a,t}$$

Valves

$\forall t\in\mathcal{T} \quad \forall a\in\mathcal{A}^{\mathrm{va}}$

$$p_{l,t} - p_{r,t} \le (1-m^{\mathrm{op}}_{a,t})(\bar{p}_{l,t} - \underline{p}_{r,t})$$
$$p_{l,t} - p_{r,t} \ge (1-m^{\mathrm{op}}_{a,t})(\underline{p}_{l,t} - \bar{p}_{r,t})$$
$$q_{a,t} \le (m^{\mathrm{op}}_{a,t})\bar{q}_{a,t}$$
$$q_{a,t} \ge (m^{\mathrm{op}}_{a,t})\underline{q}_{a,t}$$
$$m^{\mathrm{op}}_{a,t} = \sum_{o\in\mathcal{O}:M(o,a)=\mathrm{op}} m^{\mathrm{om}}_{o,t}$$

Regulators

$\forall t\in\mathcal{T} \quad \forall a\in\mathcal{A}^{\mathrm{rg}}$

$$1 = m^{\mathrm{cl}}_{a,t} + m^{\mathrm{by}}_{a,t} + m^{\mathrm{ac}}_{a,t}$$
$$p_{l,t} - p_{r,t} \le +(1-m^{\mathrm{by}}_{a,t})(\bar{p}_{l,t} - \underline{p}_{r,t})$$
$$p_{l,t} - p_{r,t} \ge +(1-m^{\mathrm{by}}_{a,t} - m^{\mathrm{ac}}_{a,t})(\underline{p}_{l,t} - \bar{p}_{r,t})$$
$$q_a \le (1-m^{\mathrm{cl}}_{a,t})\bar{q}_{a,t}$$
$$q_a \ge 0$$

Compressor station

$\forall t\in\mathcal{T} \quad \forall a\in\mathcal{A}^{\mathrm{cs}}$

$$1 = \sum_{c\in\mathcal{C}_a} m^{\mathrm{cf}}_{c,a,t} + m^{\mathrm{by}}_{a,t} + m^{\mathrm{cl}}_{a,t}$$
$$p_{l,t} = p^{\mathrm{by}}_{a,t} + p^{\text{l-cl}}_{a,t} + \sum_{c\in\mathcal{C}_a} p^{\text{l-cf}}_{c,a,t}$$
$$p_{r,t} = p^{\mathrm{by}}_{a,t} + p^{\text{r-cl}}_{a,t} + \sum_{c\in\mathcal{C}_a} p^{\text{r-cf}}_{c,a,t}$$
$$q_{a,t} = q^{\mathrm{by}}_{a,t} + \sum_{c\in\mathcal{C}_a} q^{\mathrm{cf}}_{c,a,t}$$
$$\underline{p}^{\text{l-cf}}_{c,a,t}m^{\mathrm{cf}}_{c,a,t} \le p^{\text{l-cf}}_{c,a,t} \le \bar{p}^{\text{l-cf}}_{c,a,t}m^{\mathrm{cf}}_{c,a,t} \quad \forall c\in\mathcal{C}_a$$
$$\underline{p}^{\text{r-cf}}_{c,a,t}m^{\mathrm{cf}}_{c,a,t} \le p^{\text{r-cf}}_{c,a,t} \le \bar{p}^{\text{r-cf}}_{c,a,t}m^{\mathrm{cf}}_{c,a,t} \quad \forall c\in\mathcal{C}_a$$
$$\underline{q}^{\mathrm{cf}}_{c,a,t}m^{\mathrm{cf}}_{c,a,t} \le q^{\mathrm{cf}}_{c,a,t} \le \bar{q}^{\mathrm{cf}}_{c,a,t}m^{\mathrm{cf}}_{c,a,t} \quad \forall c\in\mathcal{C}_a$$
$$\underline{p}^{\mathrm{by}}_{a,t}m^{\mathrm{by}}_{a,t} \le p^{\mathrm{by}}_{a,t} \le \bar{p}^{\mathrm{by}}_{a,t}m^{\mathrm{by}}_{a,t}$$
$$\underline{q}^{\mathrm{by}}_{a,t}m^{\mathrm{by}}_{a,t} \le q^{\mathrm{by}}_{a,t} \le \bar{q}^{\mathrm{by}}_{a,t}m^{\mathrm{by}}_{a,t}$$
$$\underline{p}^{\text{l-cl}}_{a,t}m^{\mathrm{cl}}_{a,t} \le p^{\text{l-cl}}_{a,t} \le \bar{p}^{\text{l-cl}}_{a,t}m^{\mathrm{cl}}_{a,t}$$
$$\underline{p}^{\text{r-cl}}_{a,t}m^{\mathrm{cl}}_{a,t} \le p^{\text{r-cl}}_{a,t} \le \bar{p}^{\text{r-cl}}_{a,t}m^{\mathrm{cl}}_{a,t}$$
$$w\cdot p^{\text{l-cf}}_{c,a,t} + x\cdot p^{\text{r-cf}}_{c,a,t} + y\cdot q^{\mathrm{cf}}_{c,a,t} + zm^{\mathrm{cf}}_{c,a,t} \le 0 \quad \forall(w,x,y,z)\in\mathcal{H}_c \quad \forall c\in\mathcal{C}_a$$

Station selection

$$m^{\mathrm{by}}_{a,t} = \sum_{o\in\mathcal{O}:M(o,a)=\mathrm{by}} m^{\mathrm{om}}_{o,t}$$
$$m^{\mathrm{cl}}_{a,t} = \sum_{o\in\mathcal{O}:M(o,a)=\mathrm{cl}} m^{\mathrm{om}}_{o,t}$$
$$m^{\mathrm{cf}}_{c,a,t} = \sum_{o\in\mathcal{O}:M(o,a)=c} m^{\mathrm{om}}_{o,t} \quad \forall c\in\mathcal{C}_a$$

$\forall t\in\mathcal{T}$

$$1 = \sum_{o\in\mathcal{O}} m^{\mathrm{om}}_{o,t}$$
$$1 = \sum_{f\in\mathcal{F}} m^{\mathrm{fd}}_{f,t}$$

Flow conservation and demand

$\forall t\in\mathcal{T} \quad \forall v\in\mathcal{V}^{\mathrm{b}}$

$$0 = \sum_{(l,v)=a\in\mathcal{A}^{\mathrm{pi}}} q_{v,a,t} - \sum_{(v,r)=a\in\mathcal{A}^{\mathrm{pi}}} q_{v,a,t} + \sum_{(l,v)=a\in\mathcal{A}\setminus\mathcal{A}^{\mathrm{pi}}} q_{a,t} - \sum_{(v,r)=a\in\mathcal{A}\setminus\mathcal{A}^{\mathrm{pi}}} q_{a,t} + d_{v,t}$$
$$d_{v,t} \ge (1 - \sum_{f=(f^+,f^-)\in\mathcal{F}:v\notin f^-} m^{\mathrm{fd}}_{f,t})\underline{d}_{v,t}$$
$$d_{v,t} \le (1 - \sum_{f=(f^+,f^-)\in\mathcal{F}:v\notin f^+} m^{\mathrm{fd}}_{f,t})\bar{d}_{v,t}$$
$$\hat{p}_{v,t} = p_{v,t} - \sigma^{p+}_{v,t} + \sigma^{p-}_{v,t}$$

$\forall t\in\mathcal{T} \quad \forall v\in\mathcal{V}^0$

$$0 = \sum_{(l,v)=a\in\mathcal{A}^{\mathrm{pi}}} q_{v,a,t} - \sum_{(v,r)=a\in\mathcal{A}^{\mathrm{pi}}} q_{v,a,t} + \sum_{(l,v)=a\in\mathcal{A}\setminus\mathcal{A}^{\mathrm{pi}}} q_{a,t} - \sum_{(v,r)=a\in\mathcal{A}\setminus\mathcal{A}^{\mathrm{pi}}} q_{a,t}$$

$\forall t\in\mathcal{T} \quad \forall o\in\mathcal{O}$

$$m^{\mathrm{om}}_{o,t} \le \sum_{(o,f)\in\mathcal{OF}} m^{\mathrm{fd}}_{f,t}$$

Exit pressure

$\forall t\in\mathcal{T} \quad \forall v\in\mathcal{V}^{\text{b-ex}}$

$$p_{v,t} \le \bar{p}^{\mathrm{exit}}_v + (1 - \sum_{f=(f^+,f^-)\in\mathcal{F}:v\in f^-} m^{\mathrm{fd}}_{f,t})(\bar{p}_{v,t} - \bar{p}^{\mathrm{exit}}_v)$$

Flow direction

$\forall t\in\mathcal{T} \quad \forall(f,\mathcal{V}^{w_1},\mathcal{V}^{w_2})\in\mathcal{W}$

$$0 \le (1 - m^{\mathrm{fd}}_{f,t})C_1 - \sum_{v\in\mathcal{V}^{w_1}} \mathrm{sgn}(f,v)d_{v,t} + \sum_{v\in\mathcal{V}^{w_2}} \mathrm{sgn}(f,v)d_{v,t}$$

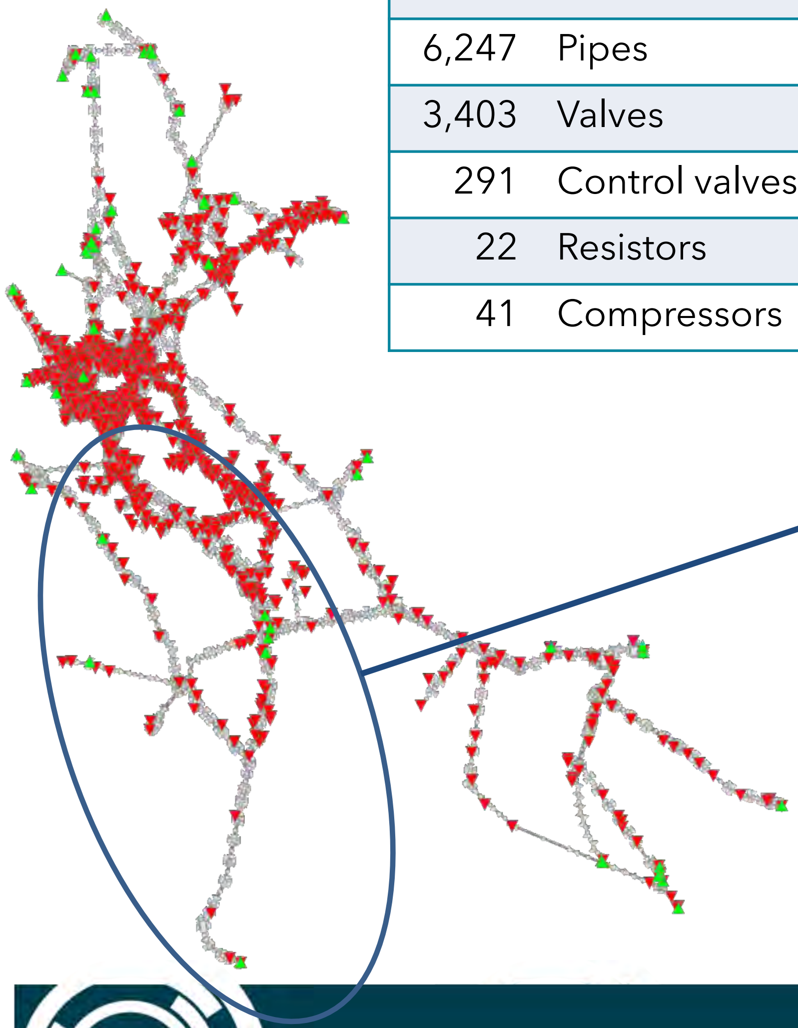
$\forall t\in\mathcal{T} \quad \forall g\in\mathcal{FG}$

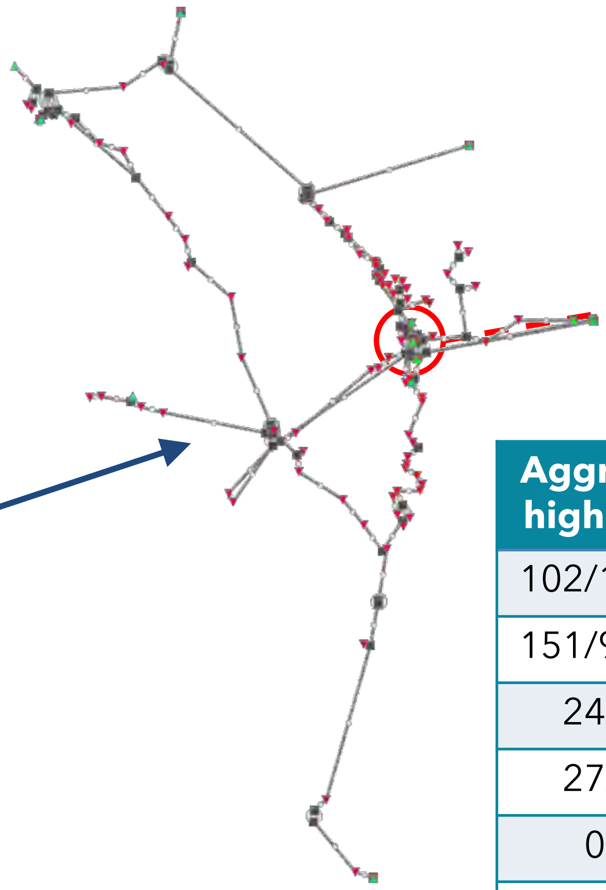
$$\hat{d}_{g,t} = \sum_{v\in g}(d_{v,t} - \sigma^{d+}_{v,t} + \sigma^{d-}_{v,t})$$

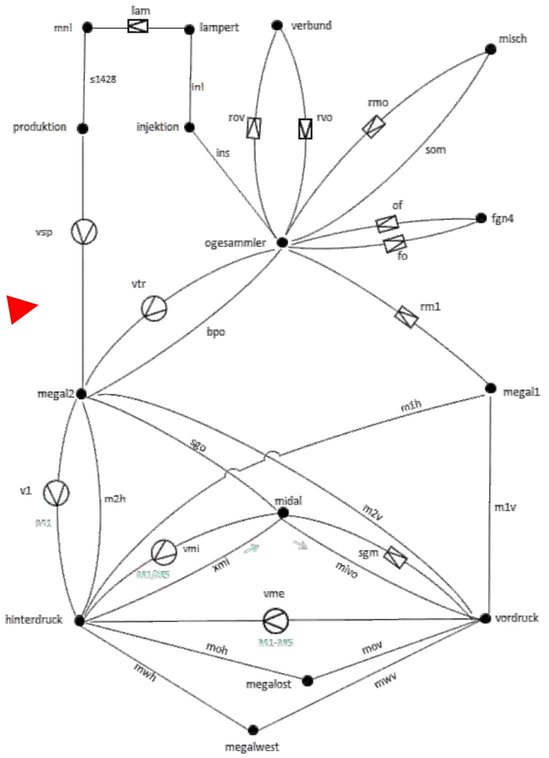
Determine Transient Gas Flows with Network Optimization

Descriptive
Predictive
Prescriptive

Full Network	
1,194	Entries+Exits
6,247	Pipes
3,403	Valves
291	Control valves
22	Resistors
41	Compressors



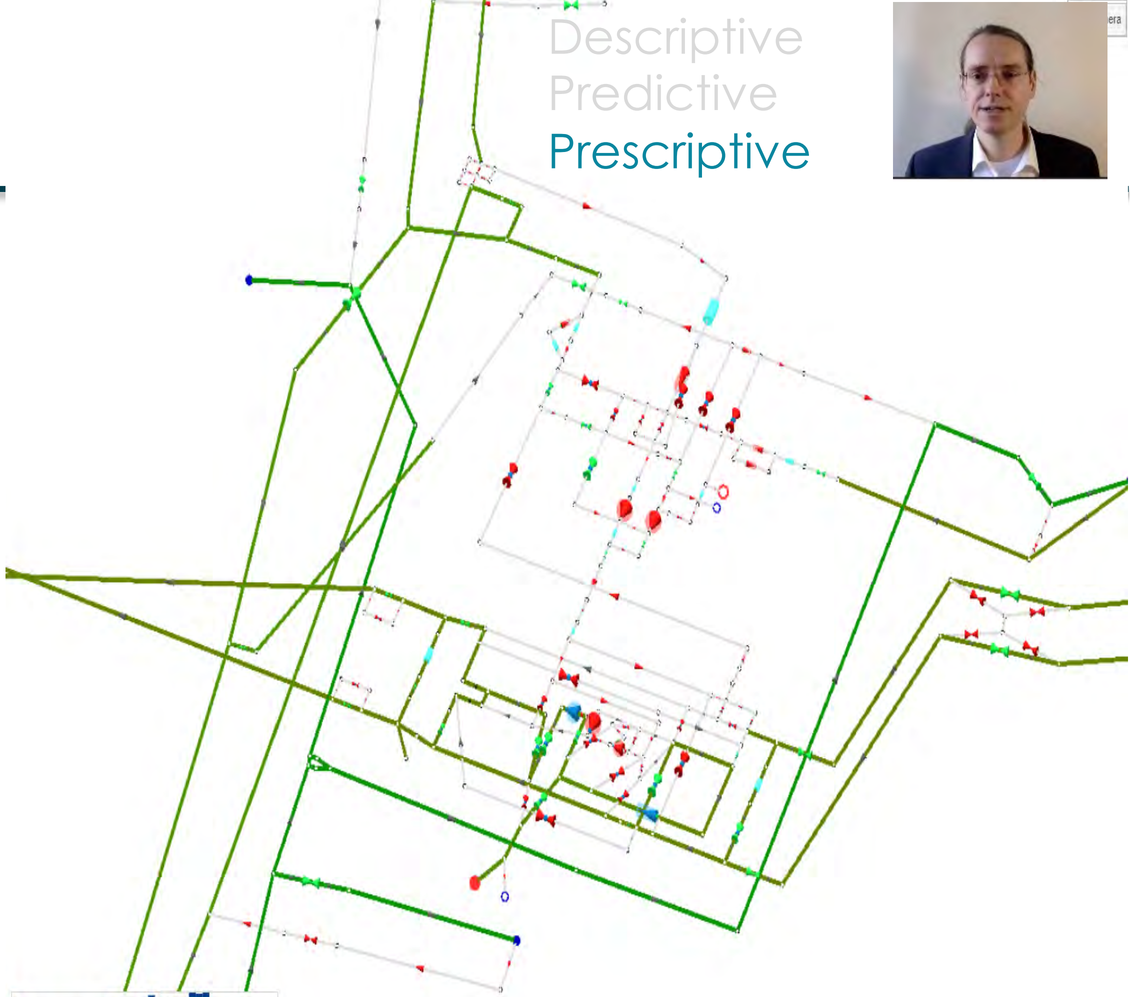


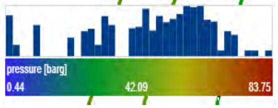


Aggregated subnet with high level station model	
102/124	Entries+Exits
151/964	Pipes
24/81	Valves
27/50	Control valves
0/11	Resistors
16/16	Compressors

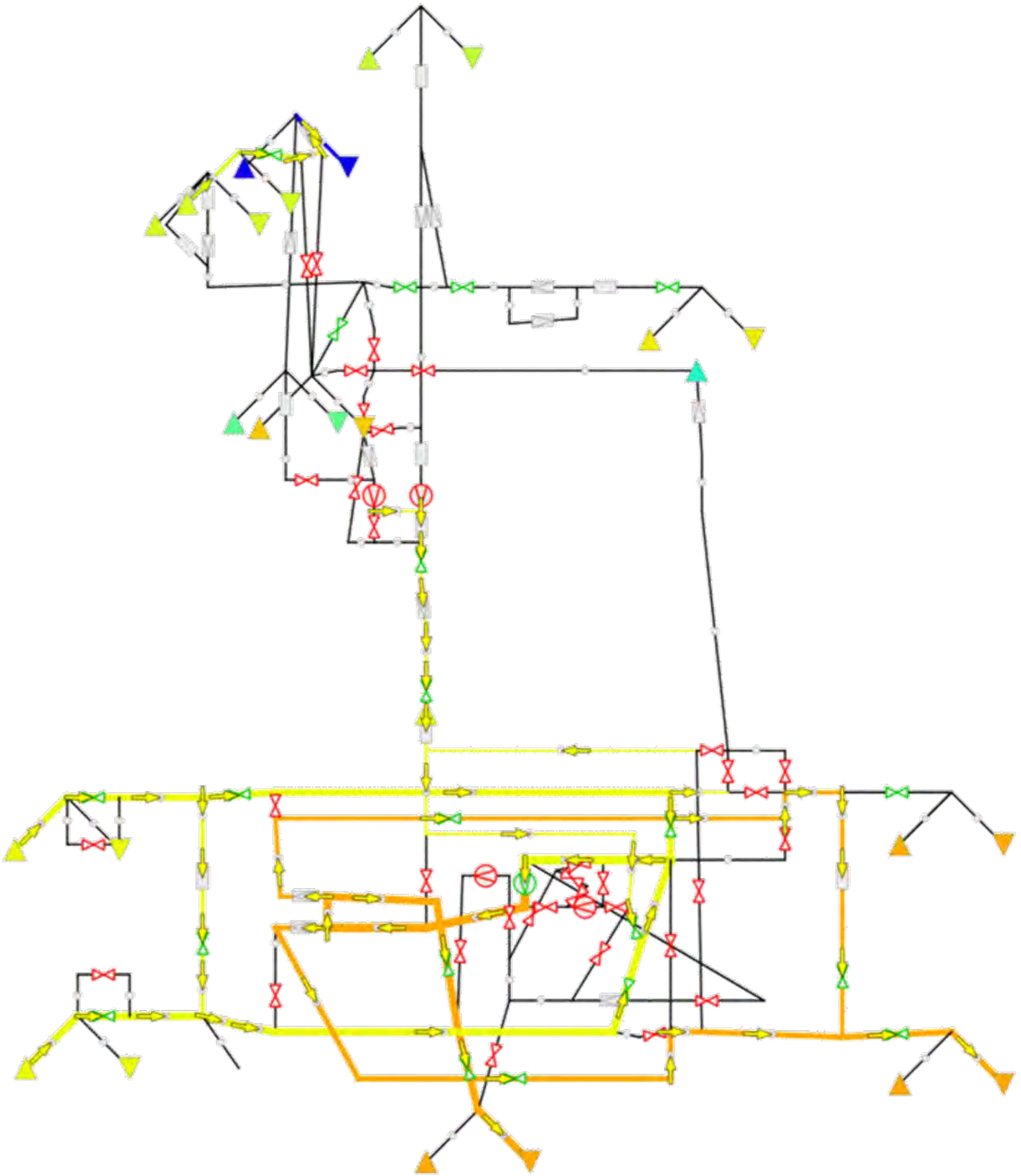
The Combinatorics of Gernsheim

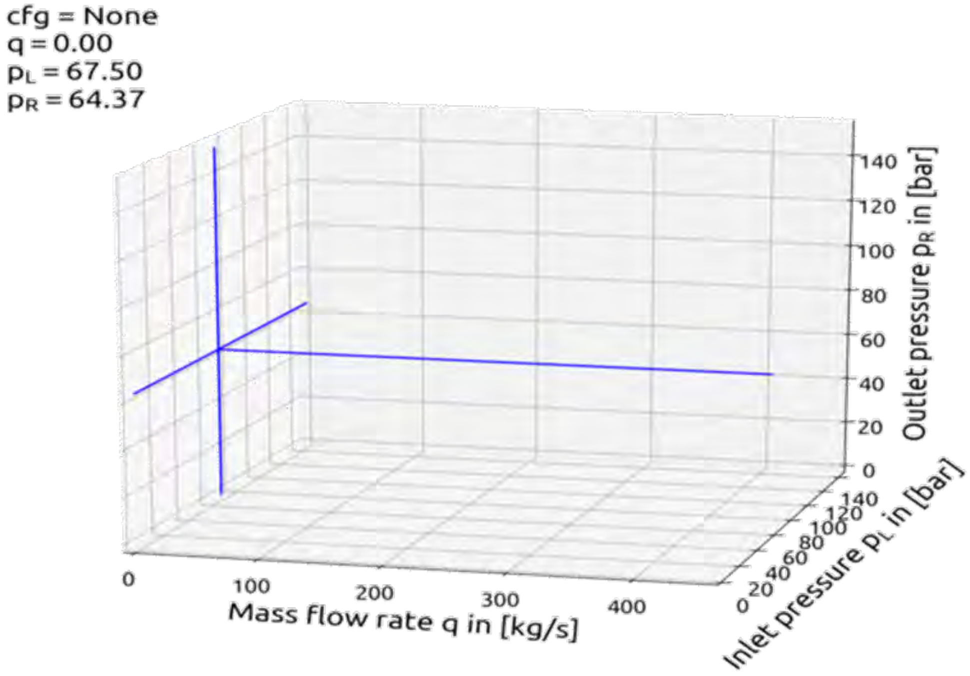
Descriptive
Predictive
Prescriptive

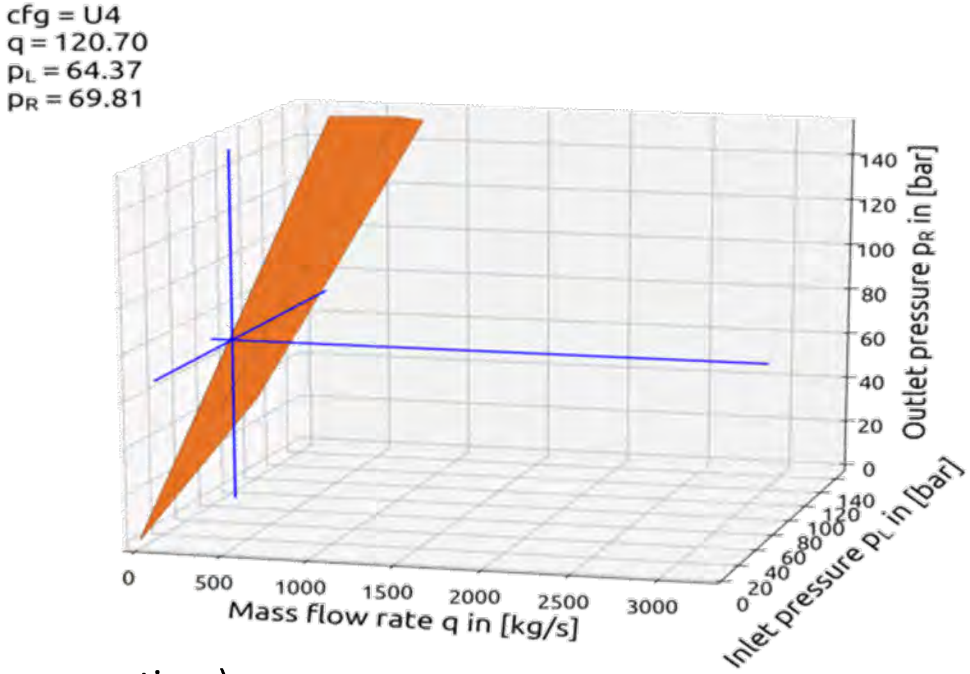




- 30,000,000,000,000,000 mathematically possible combinations of valve and compressor states.
- 200,000 feasible operation modes identified based on practitioners knowledge.
- 1,285 relevant operation modes extracted using analytical evaluation of historical data.







Pressure levels (color)

Amount of flow (line thickness)

Flow direction (arrows)

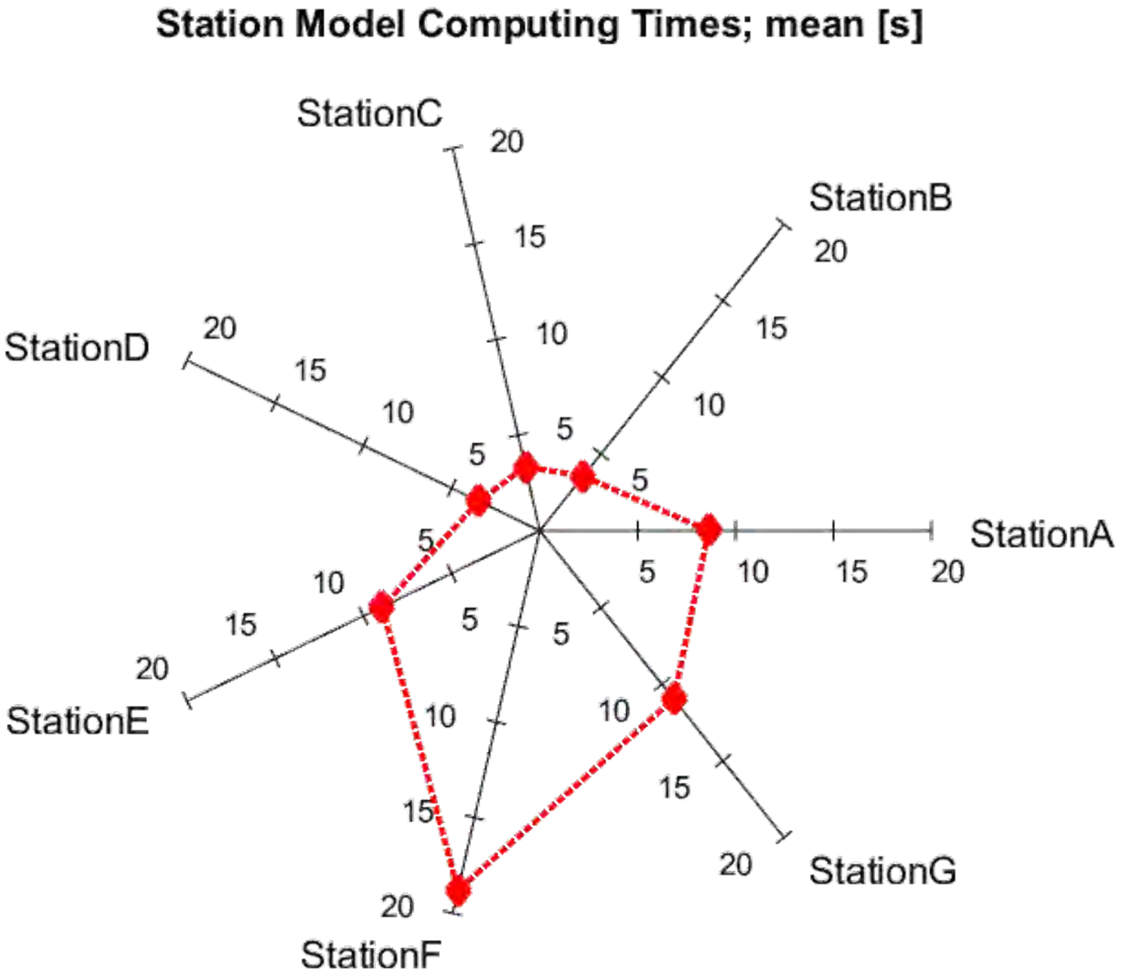
Element usage (red/green syms)

Current point of operation for the two active compressors in the station (Blue lines cross)

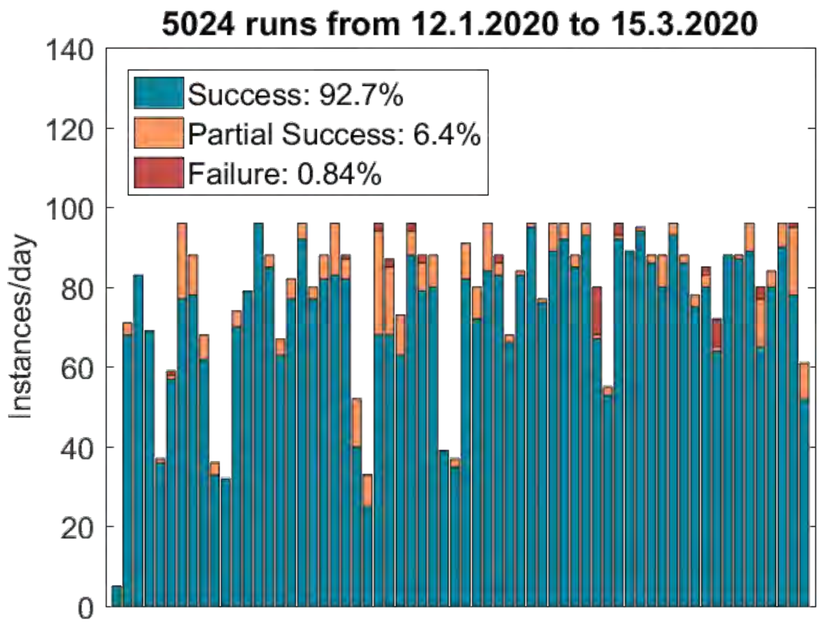
Feasible operating range for chosen set of machines:
Orange: a single machine
Blue: multiple parallel machines

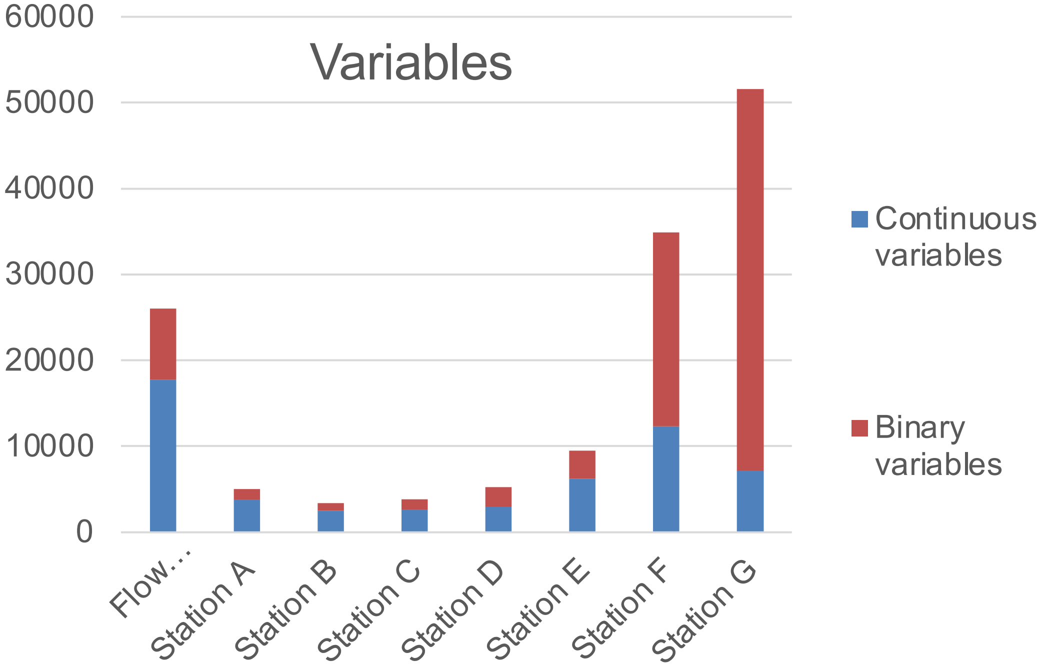
Demonstrator: Station control for a flow direction change (series of states over time)

Computational results

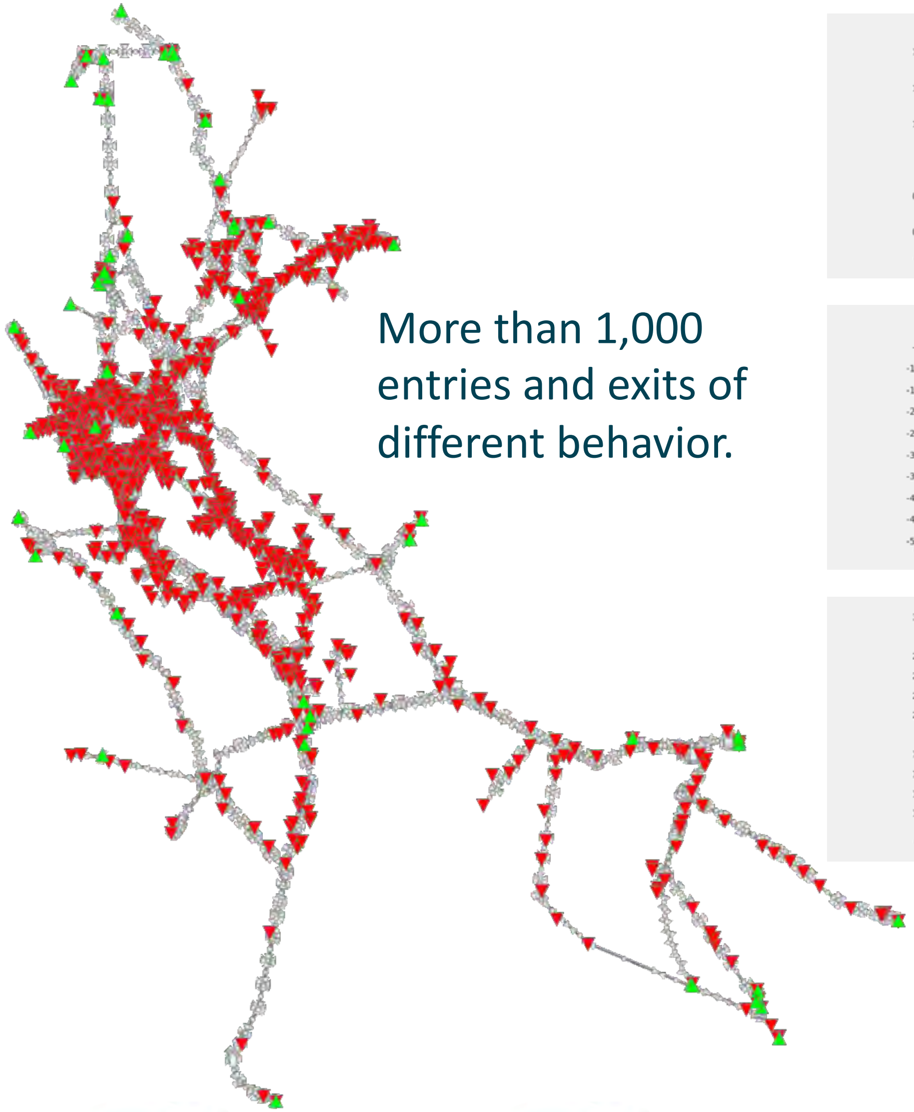


Netmodel Computing Time; mean: 21 min.
Computed from 2,559 successful runs with 14 time steps

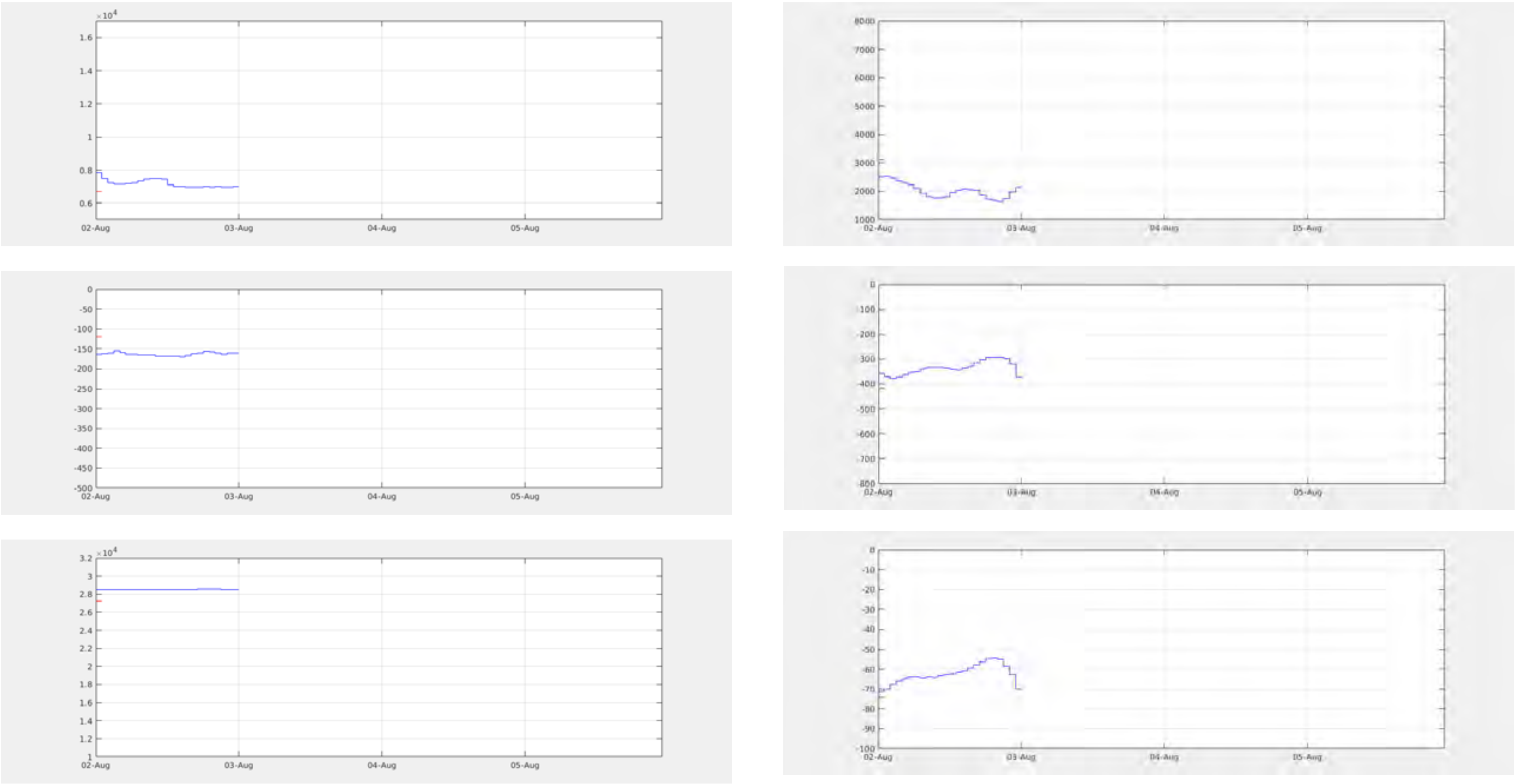




Online Forecasting of Demand and Supply



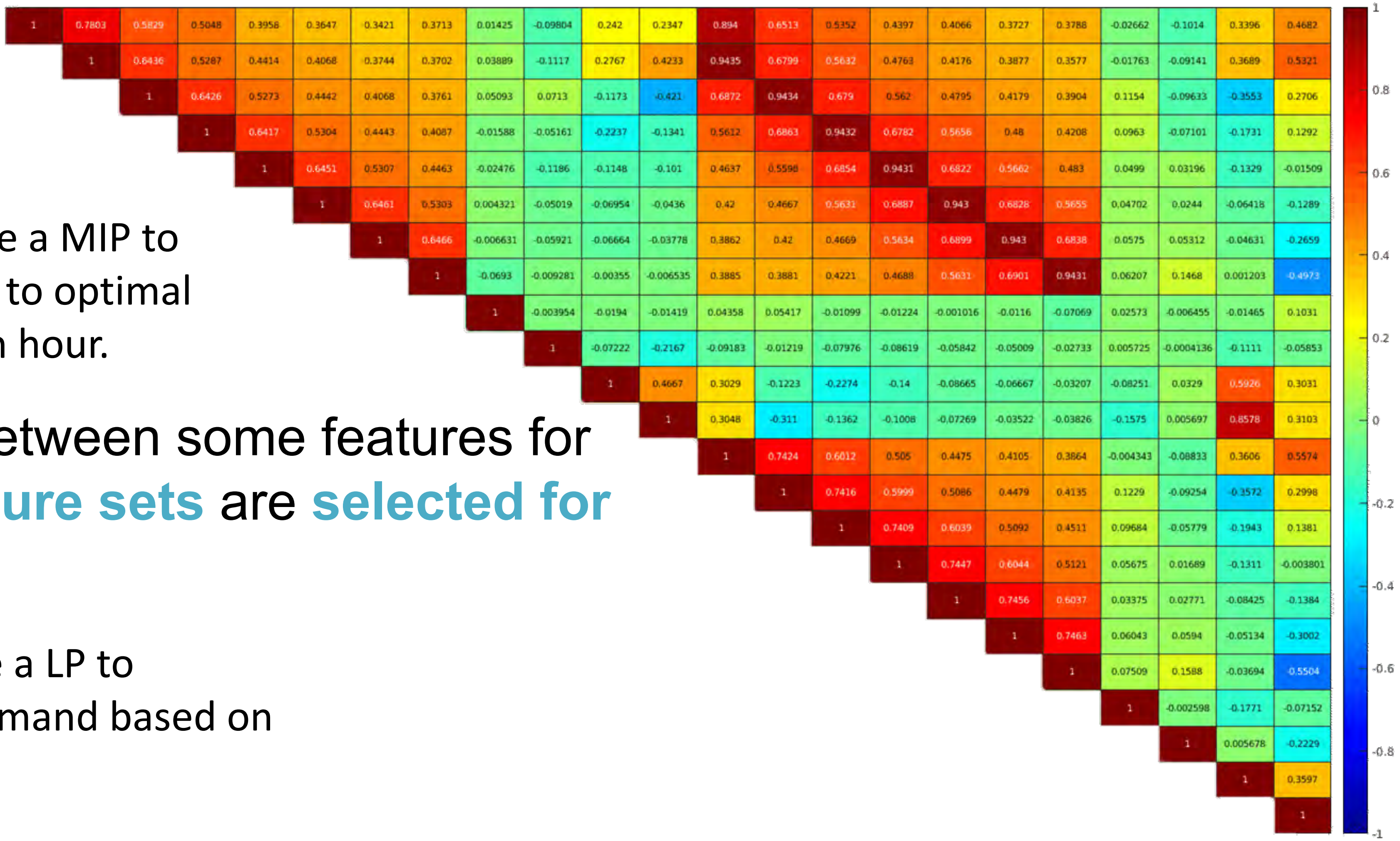
More than 1,000 entries and exits of different behavior.



Preprocessing
Solve the most relevant points with sophisticated forecast model, use computationally less expensive model for less important points.

Combining ML and Optimization for Forecasting

Heat Map of correlations between features



- Step 1 (offline computation): Solve a MIP to compute sparse solutions leading to optimal feature sets for each node at each hour.

Due to high correlations between some features for some nodes, **optimal feature sets** are **selected for each node** individually.

- Step 2 (online 24/7 at OGE): Solve a LP to forecast hourly supply and the demand based on these feature sets.

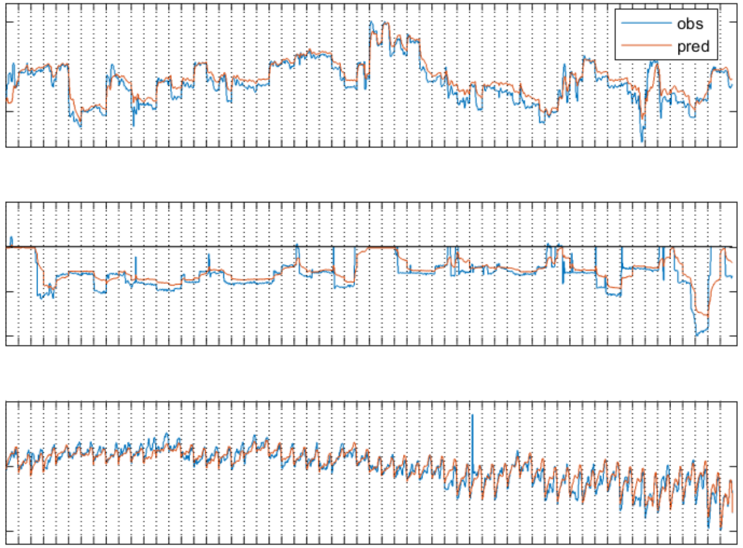
Innovative use of Analytics

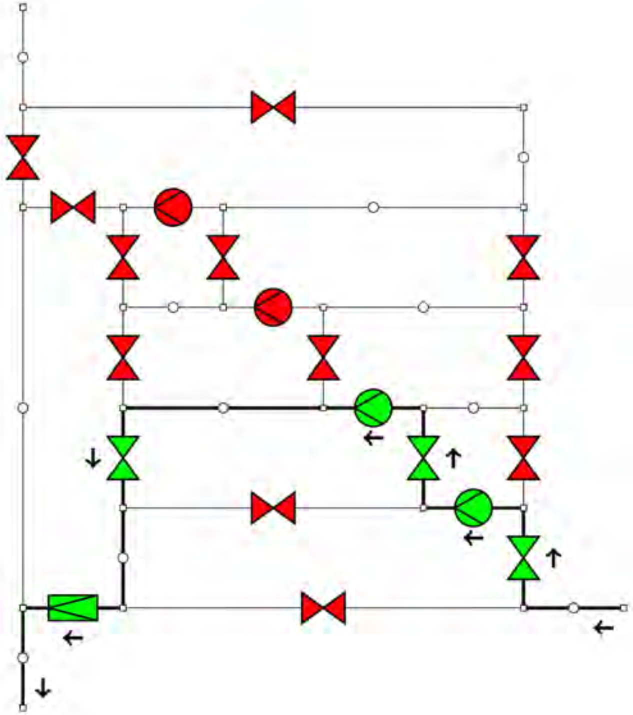
- **Describe** a model of an existing network infrastructure built during the past 100 years.
- **Predict** the future gas supply and demand at over 1,100 network points for the next 24 h.
- **Prescribe** the necessary action to ensure safe operation and security of supply.

$$\frac{\partial \rho}{\partial t} + \frac{\partial (\rho v)}{\partial x} = 0$$

$$\frac{\partial (\rho v)}{\partial t} + \frac{\partial (p + \rho v^2)}{\partial x} + \frac{\lambda}{2D} |v| v \rho + g s \rho = 0$$

$$\frac{\partial}{\partial t} \left(\rho (\frac{1}{2} v^2 + e) \right) + \frac{\partial}{\partial x} \left(\rho v (\frac{1}{2} v^2 + e) + p v \right) + \frac{k_w}{D} (T - T_w) = 0$$





The OED Team

ZIB and research colaborators	Open Grid Europe	Soptim, LBW, other company
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Thank you very much for your attention!

“The final test of a theory is its capacity to solve the problems which originated it.”

George Dantzig (1963) in
Linear Programming and Extensions

Thank you very much!