Capstone Technology

Industrial Plant Optimization in Reduced Dimensional Spaces

Fields Optimization Lecture
Toronto, ON

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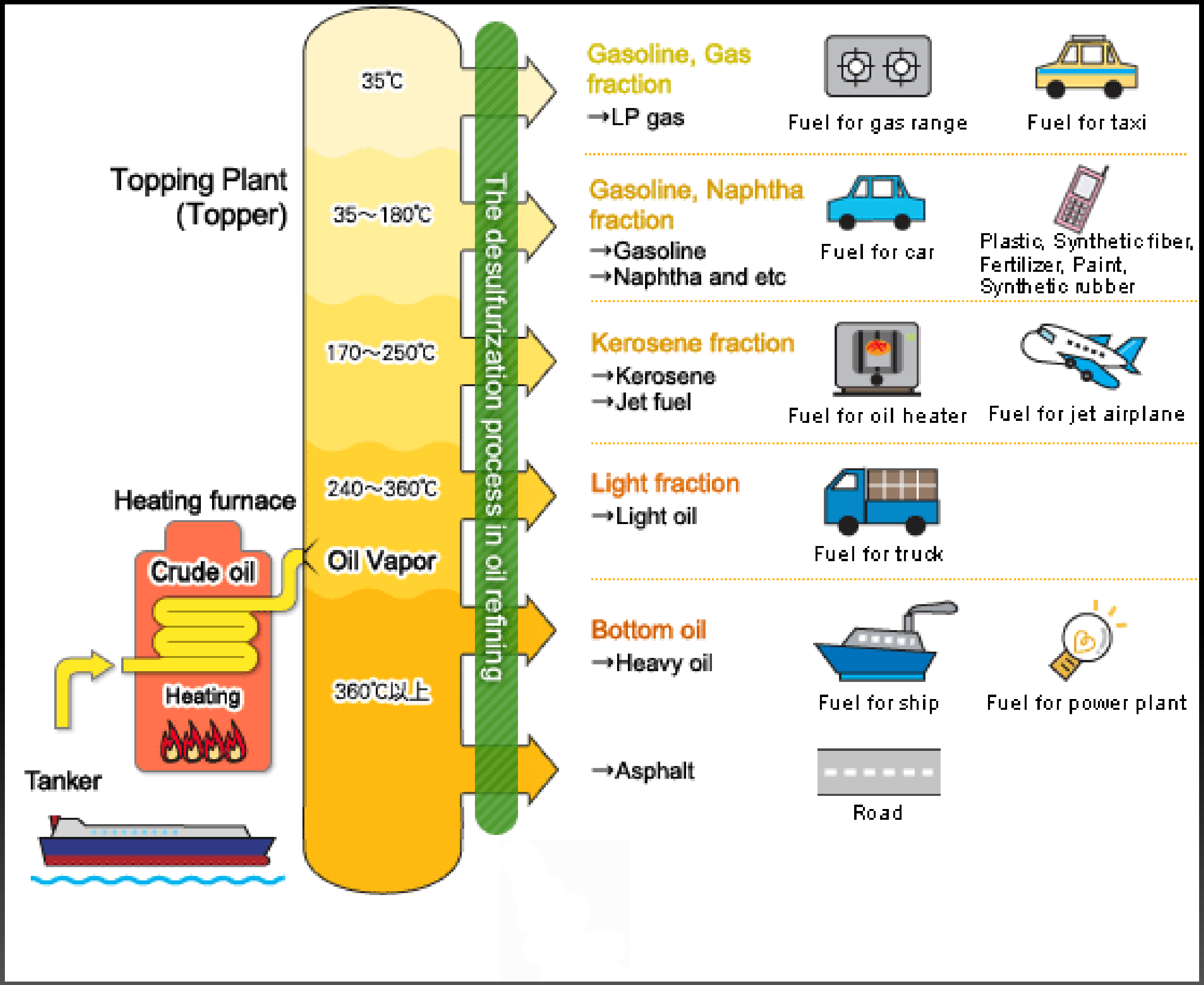
Agenda

- Review of optimization in oil refining
- Real Time Optimization
- Reduced Space Optimization

Petroleum refining

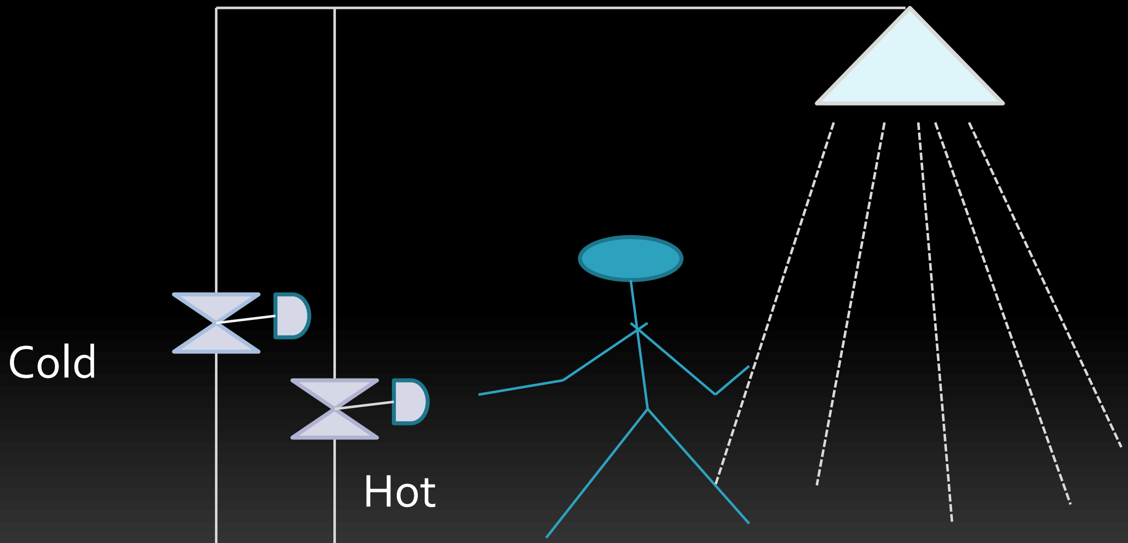


Refining optimization history

- Head office
- Refining early adopters (Exxon 1950's)
  - Crude selection, operating modes
- 1961 early SLP paper (Shell oil)
- LP not just a fast solution technique
    - Tools to interpret the solution and run what-if's.

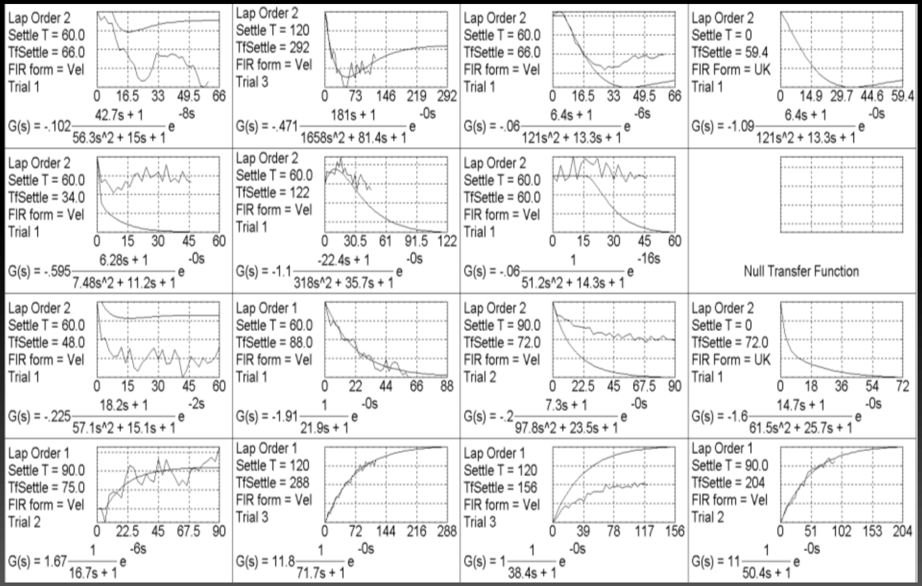
Refining optimization history

- Refineries
  - Improving process control

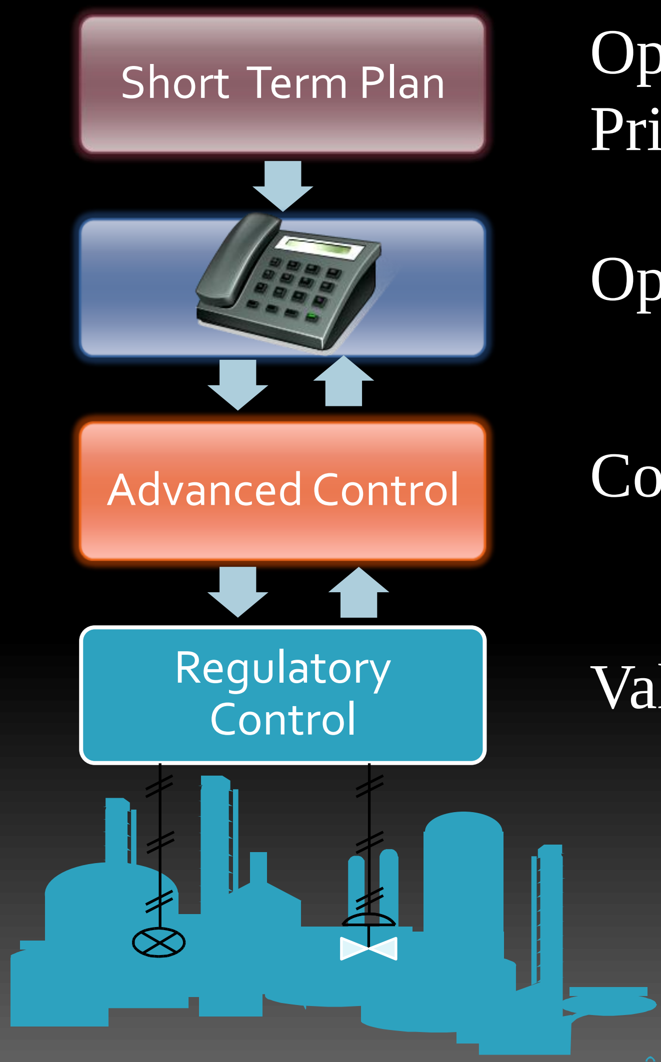


Advanced Control

- 1980's insight that complicated process control problems could be formulated and solved by LP and QP



Refining Optimization Hierarchy



Operating Objectives, Component Prices, Constraints

Operating Targets

Controller Setpoints

Valve Positions

Why Optimize in Real Time?

- Short term planning model based on "sustainable" average operation
  - But things change.....
    - Crude oil may be different
    - Processes may be cleaner/more fouled
    - May be hotter/colder
  - Real process is nonlinear
- Real time optimization intended to capture these opportunities

RTO Approach

- Model plant with engineering equations
  - Heat + mass + hydraulic + equilibrium relationships
- Run simulation in parallel to the plant and calibrate to the plant measurements
- Optimize the model

Building the simulated plant

Sequential modular

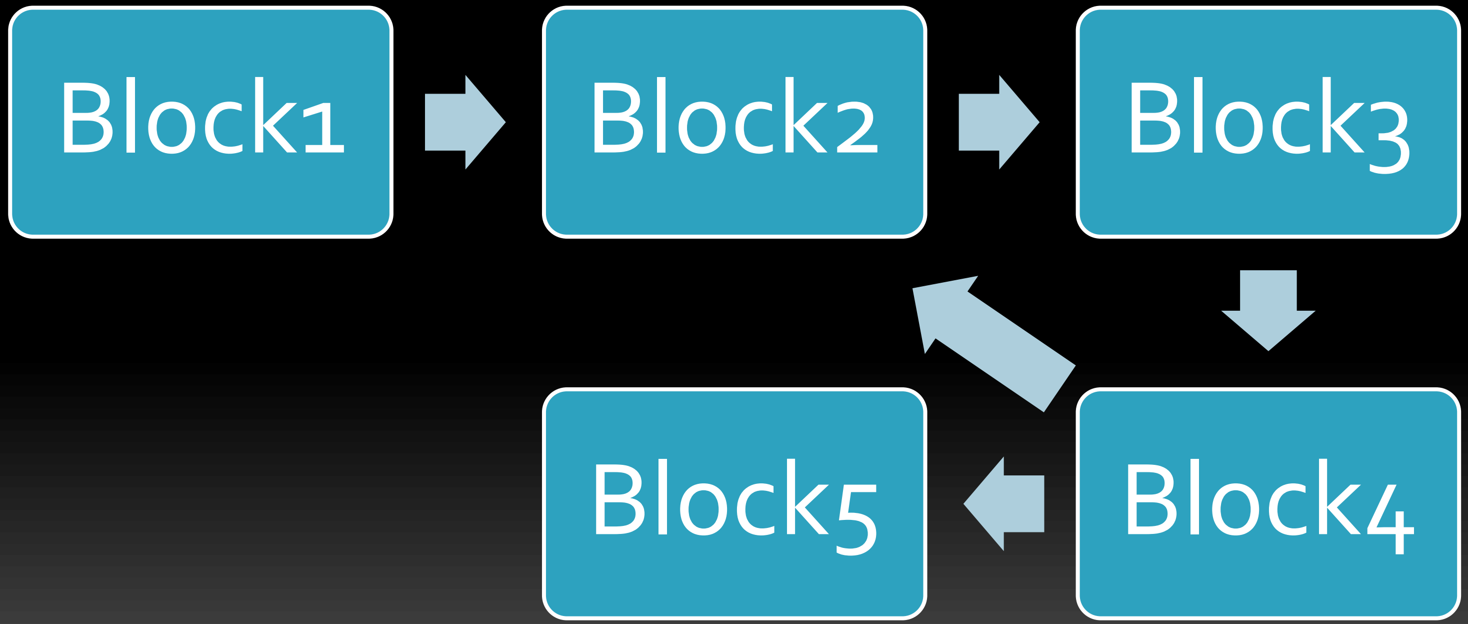
$$x_i^{out} = F_i(x_i^{in})$$

$$x_i^{in} \Rightarrow \boxed{\text{Block 1}} \quad x_i^{out} \Rightarrow \boxed{\text{Block 2}}$$

Blocks are solved in the order of material flow

Sequential modular

Recycles become awkward and need iteration



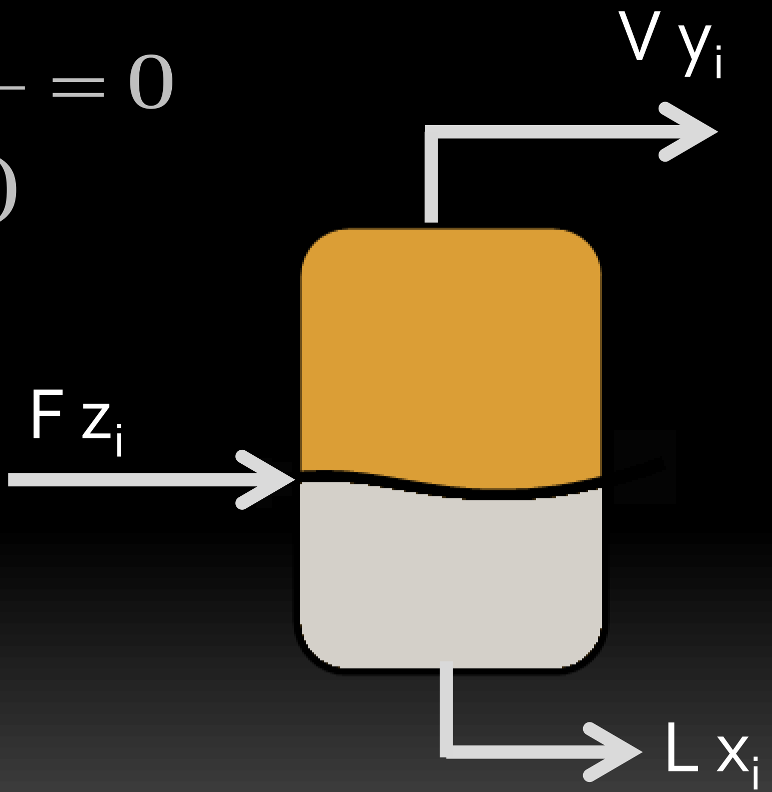
Open Equations

$$f(x) = 0$$

- Complete plant model expressed in one large set of (sparse) equations
- Run it through a nonlinear root solver
- Encouraged by success in solving non linear constraints

Simple still

$$\sum_i \frac{Z_i(K_i - 1)}{1 + \frac{V}{F}(K_i - 1)} = 0$$



Inputs

- Need to fix certain variables to reach solution
- Plant instruments have error

Reconciliation

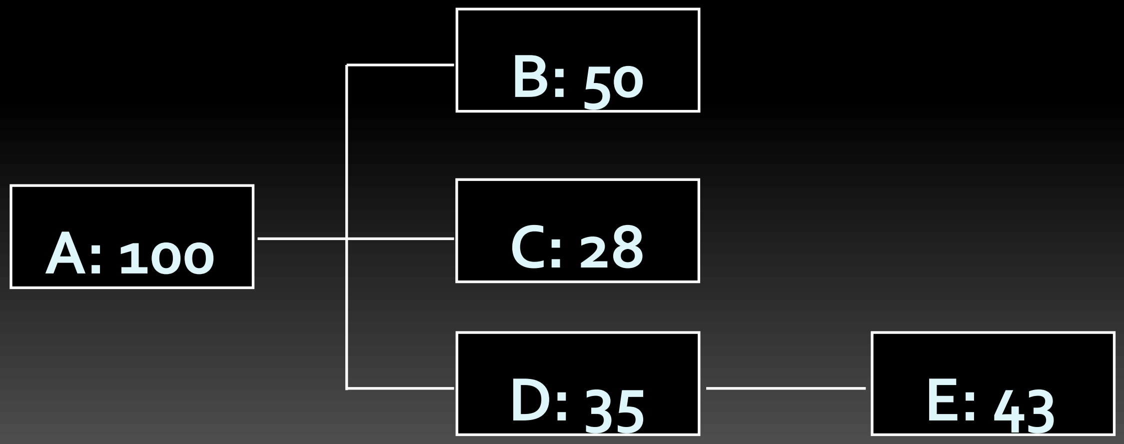
- Find the smallest set of adjustments to the plant measurements that satisfy the equations

$$Min: W_A(A-100)^2 + W_B(B-50)^2 + W_C(C-28)^2 + W_D(D-35)^2 + W_E(E-43)^2$$

subject to:

$$\left.\begin{aligned} &A-B-C-D=0 \\ &D-E=0 \end{aligned}\right\} \quad f(x)=0$$

$$A, B, C, D, E \geq 0$$



Initial Basis

- Offline design software used to fit base case
- Results used to provide initial basis for open equations
- Thereafter, converged online solutions used as starting basis for next online run

Optimization engine

- Minos
  - Projected augmented Lagrangian
- Analytic derivatives
- Convergence not guaranteed!
  - Good starting values
  - Sensible bounds
  - Tuning parameters

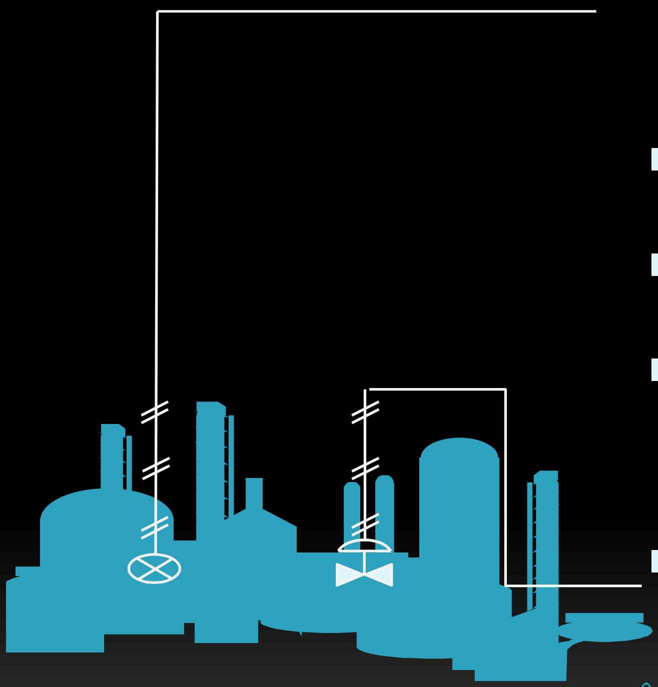
Gross error detection

- Least squares based reconciliation works well when the measurement s are considered to be normally distributed around their true values with approximately known error
- Large errors (eg. instrument failures) violate these assumptions and bias reconciliation
- RTO systems include pre-screening to eliminate values obviously in error (W_i=0)

Optimization

- Fix instrument adjustments and other reconciled performance values
- Change objective function
  - Maximize Profit: $\sum$ Products - Feed – Utilities
  - New setpoints = Old setpoints ± rate limits

RTO Sequence



- Check recent history to confirm that plant is steady
- Eliminate bad measurements
- Fit model to plant data
- Calculate new setpoints to increase profit
- Check process steady, controls available

Technical challenges

- Solving 20+K non linear equations is not fool proof
- 95% convergence failures occurred during reconciliation phase
- Could have put more time trying to make constraints more linear

$$\frac{K_1}{d_1^{4.814}} + \frac{K_2}{d_2^{4.814}} + \ldots \leq P_T^2 - P_0^2$$

Eg: transformations $x_i = 1/d_i^{4.814}$

Catalytic cracker Ultramar QC

- ~ 27,500 equations
- ~ 29,500 variables
- ~ 111,000 derivatives
- Reconciliation – 500+ measurements
- Optimization 60 setpoints
- Execution – 25-40 minutes/cycle

Case study – 40KBPD crude unit

Stream	Before (KBPD)	After (KBPD)	Change (KBPD)
LSR	2.47	2.51	0.041
Naphtha	5.15	4.91	-.246
Distillate	4.66	5.03	0.368
VLGO	1.1	1.1	0
LVGO	1.33	1.22	-.103
HVGO	7.68	7.6	-.075
Asphalt	13	13.02	0.018
NET PROFIT			$2220/Day

RTO Benefits

Unit	Benefit
Crude units	$.01- $.05/BBL
Hydrocracker	$.07-$0.3/BBL
FCCU	2% unit profit
Entire refinery	$0.50/BBL (Solomon)

Doubts and unease

Was the optimization solution correct?

Stream	Before (KBPD)	After (KBPD)	Change (KBPD)
LSR	2.47	2.51	0.041
Naphtha	5.15	4.91	-.246
Distillate	4.66	5.03	0.368
VLGO	1.1	1.1	0
LVGO	1.33	1.22	-.103
HVGO	7.68	7.6	-.075
Asphalt	13	13.02	0.018
NET PROFIT			$2220/Day

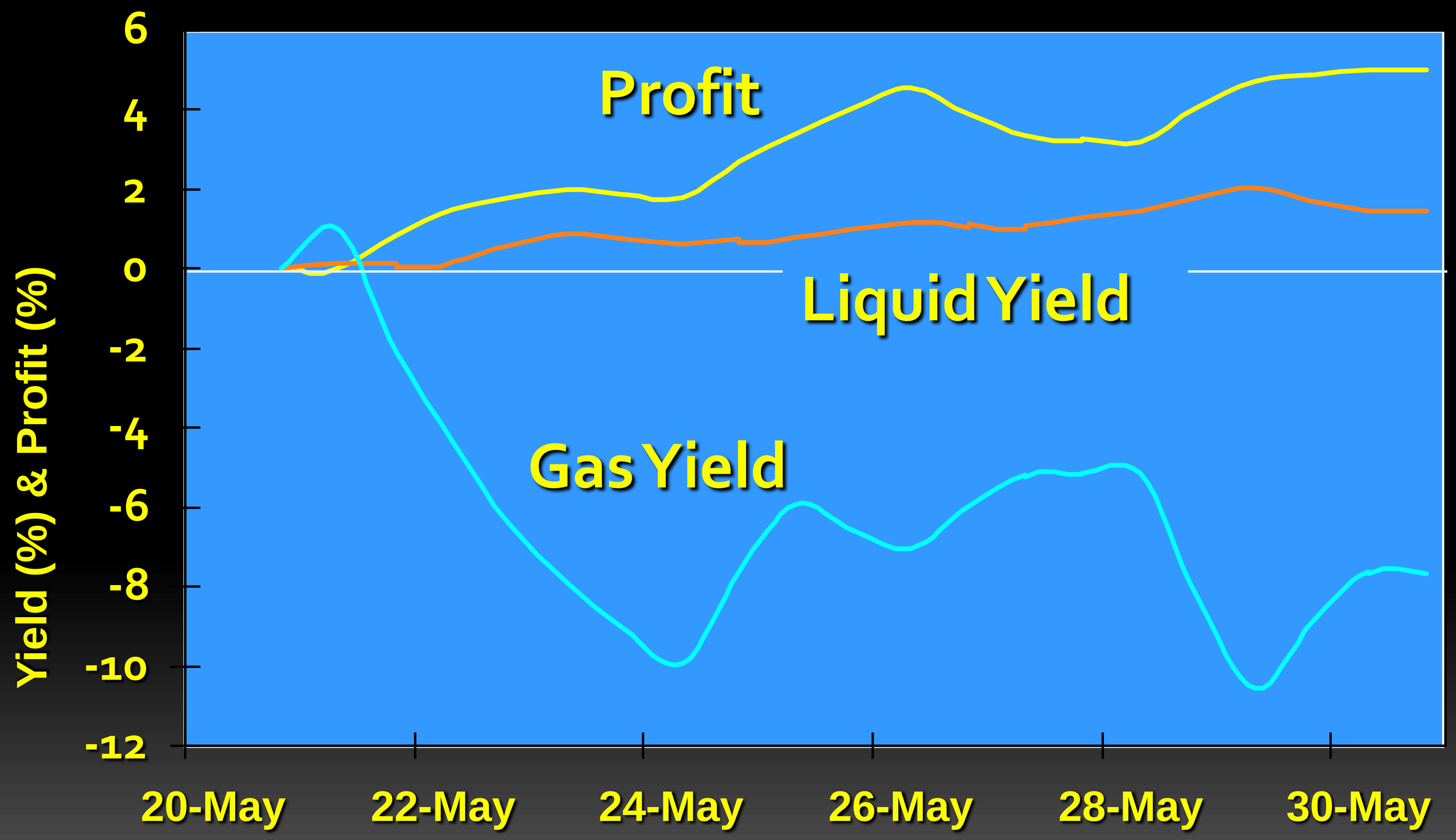
Profit = Product – Energy - Payroll

Intuitive answer:

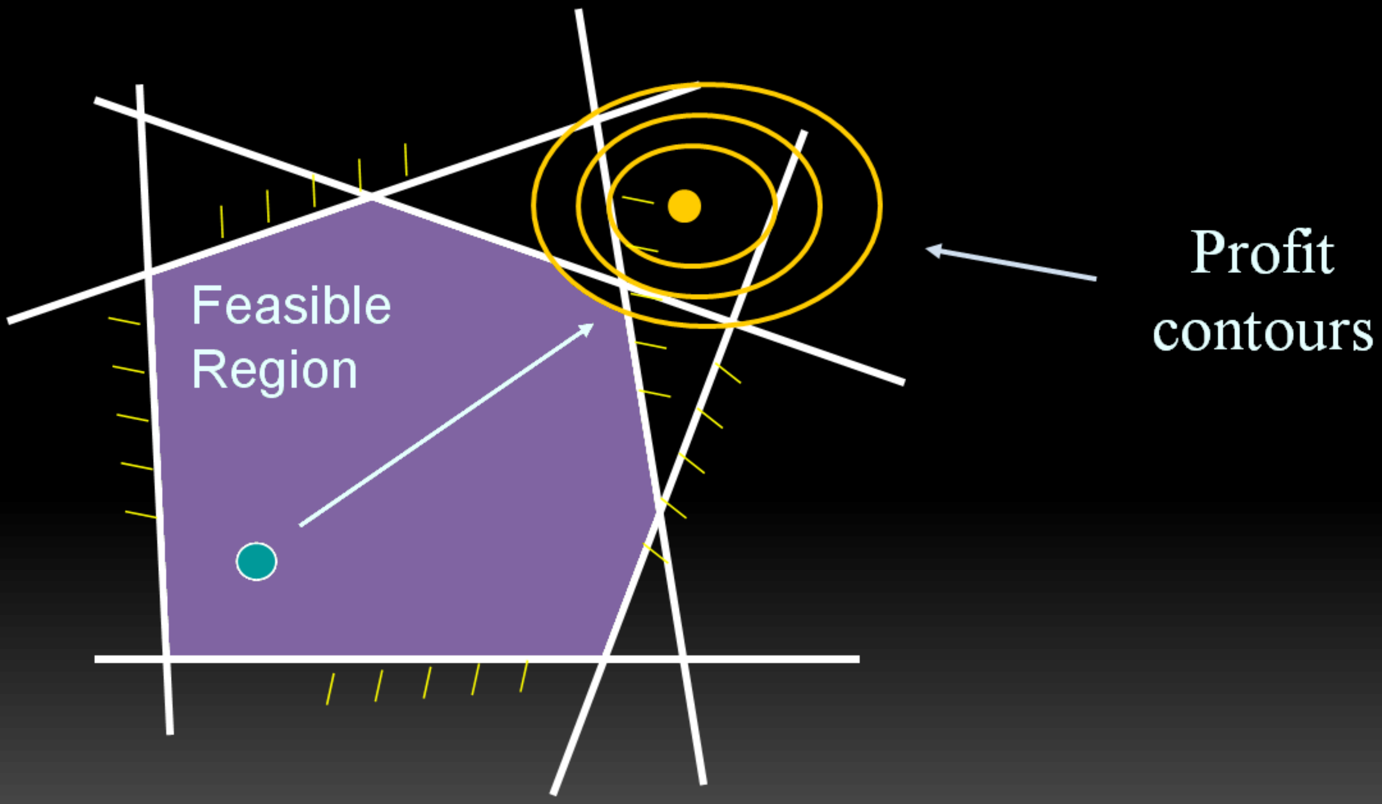
Profit will improve by:

1. Reduce the terms with negative signs
2. Increase the terms with positive

Online performance



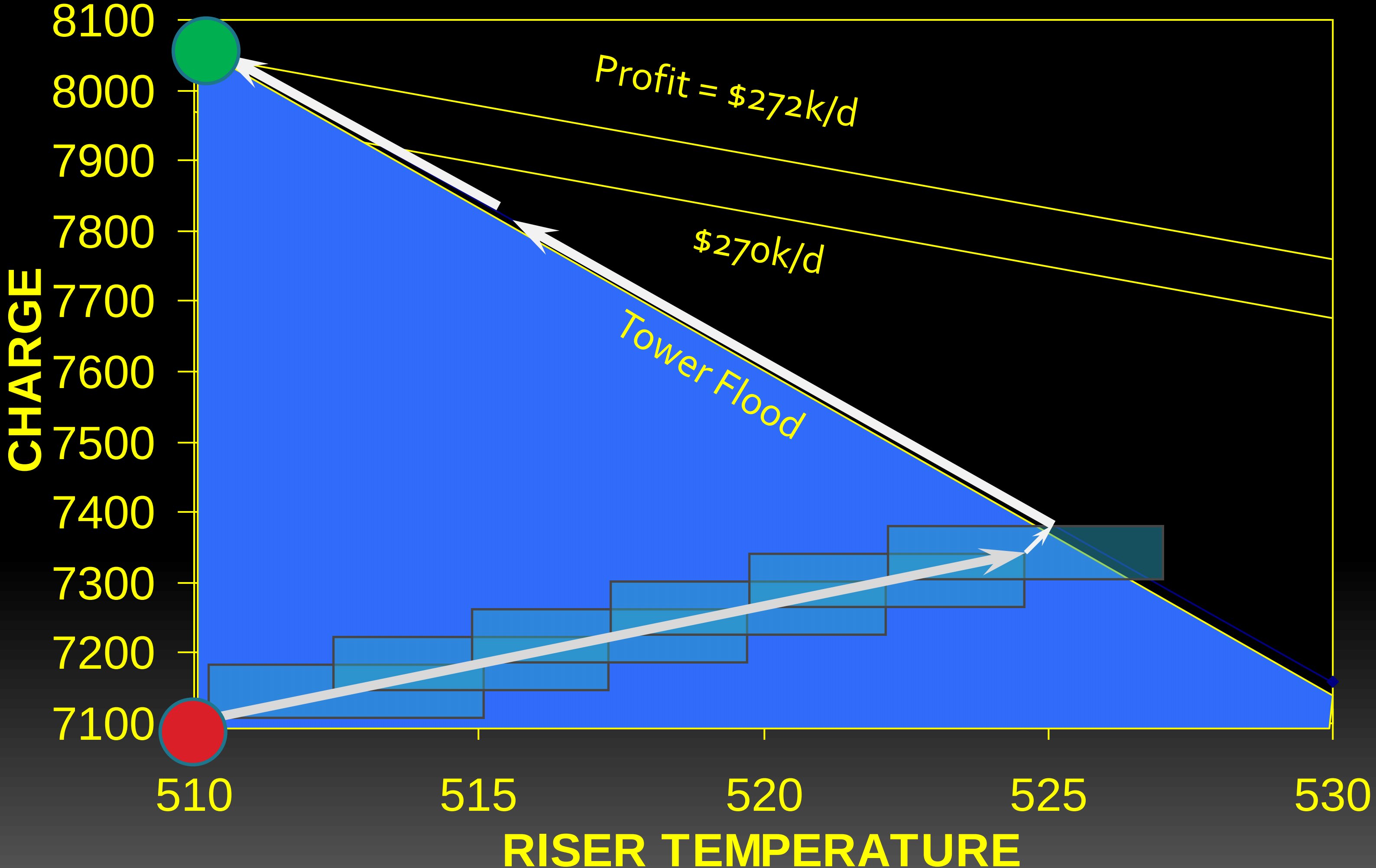
Optimization geometry



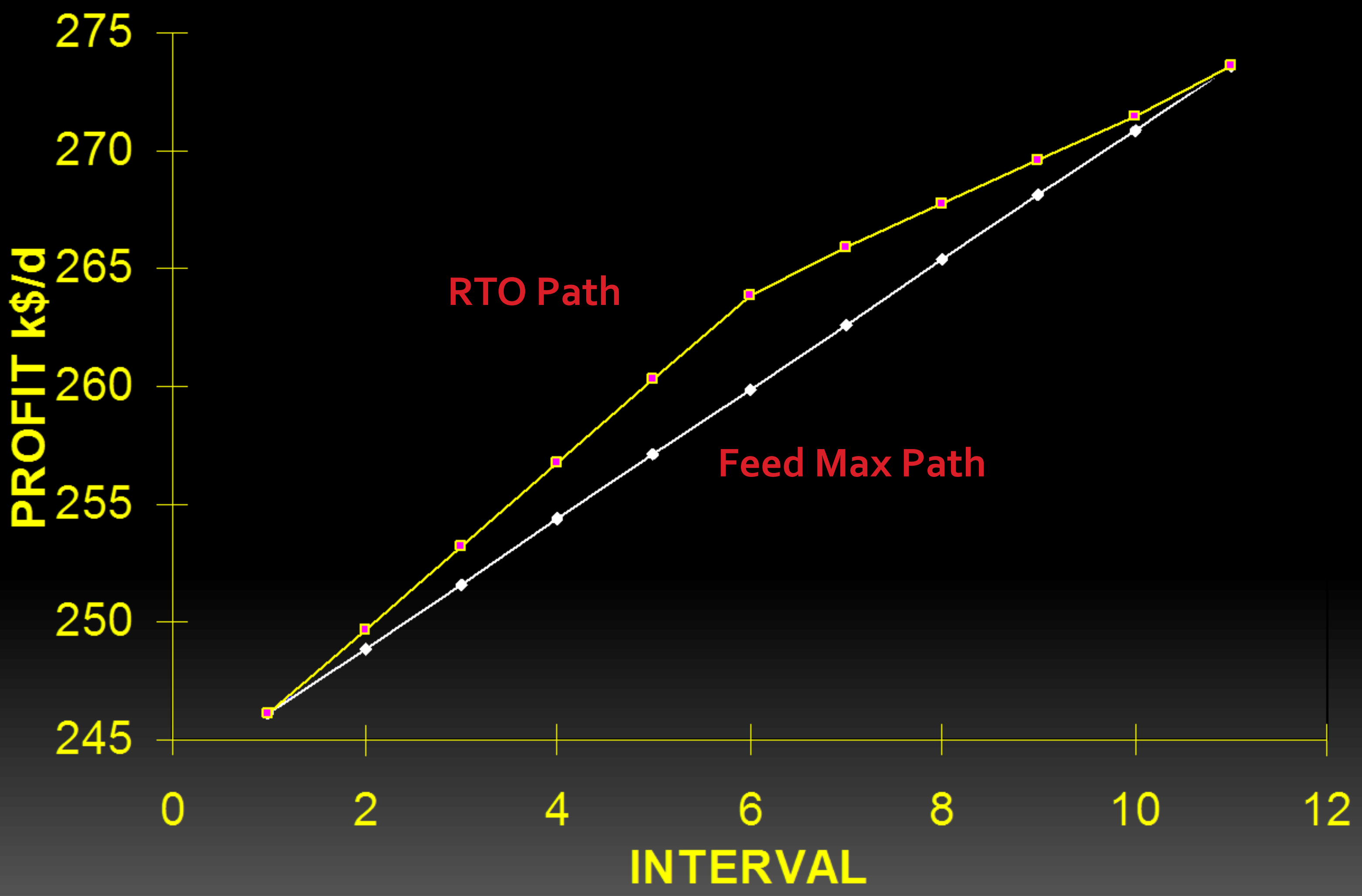
Constraints

- On paper constraints are just a line
- In real life – people spend their time avoiding trouble
- Constraints can be benign or emotionally charged
- In RTO, the operators experienced first hand the simplex method

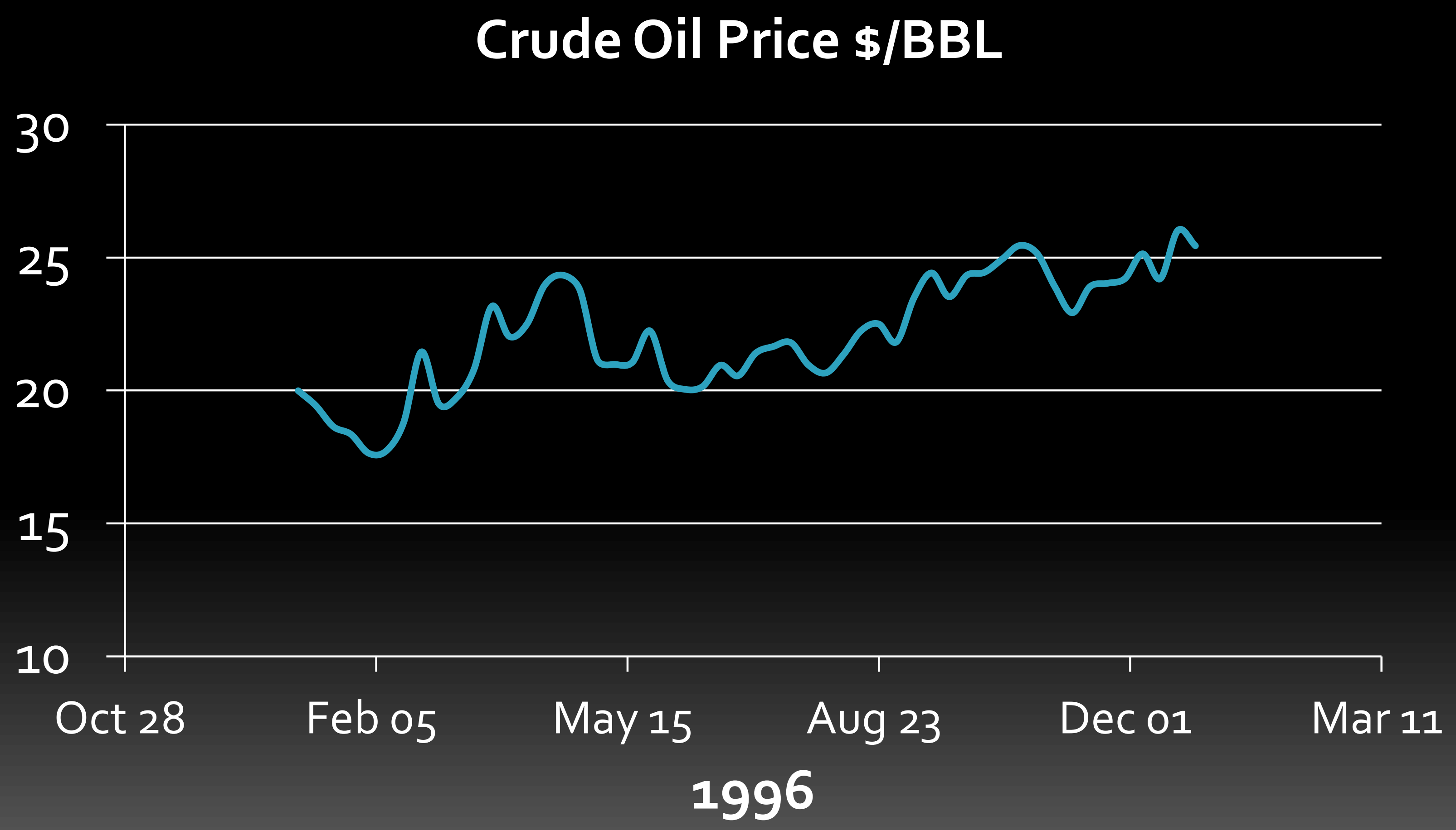
PROFIT PATH ANALYSIS



PROFIT PATH ANALYSIS



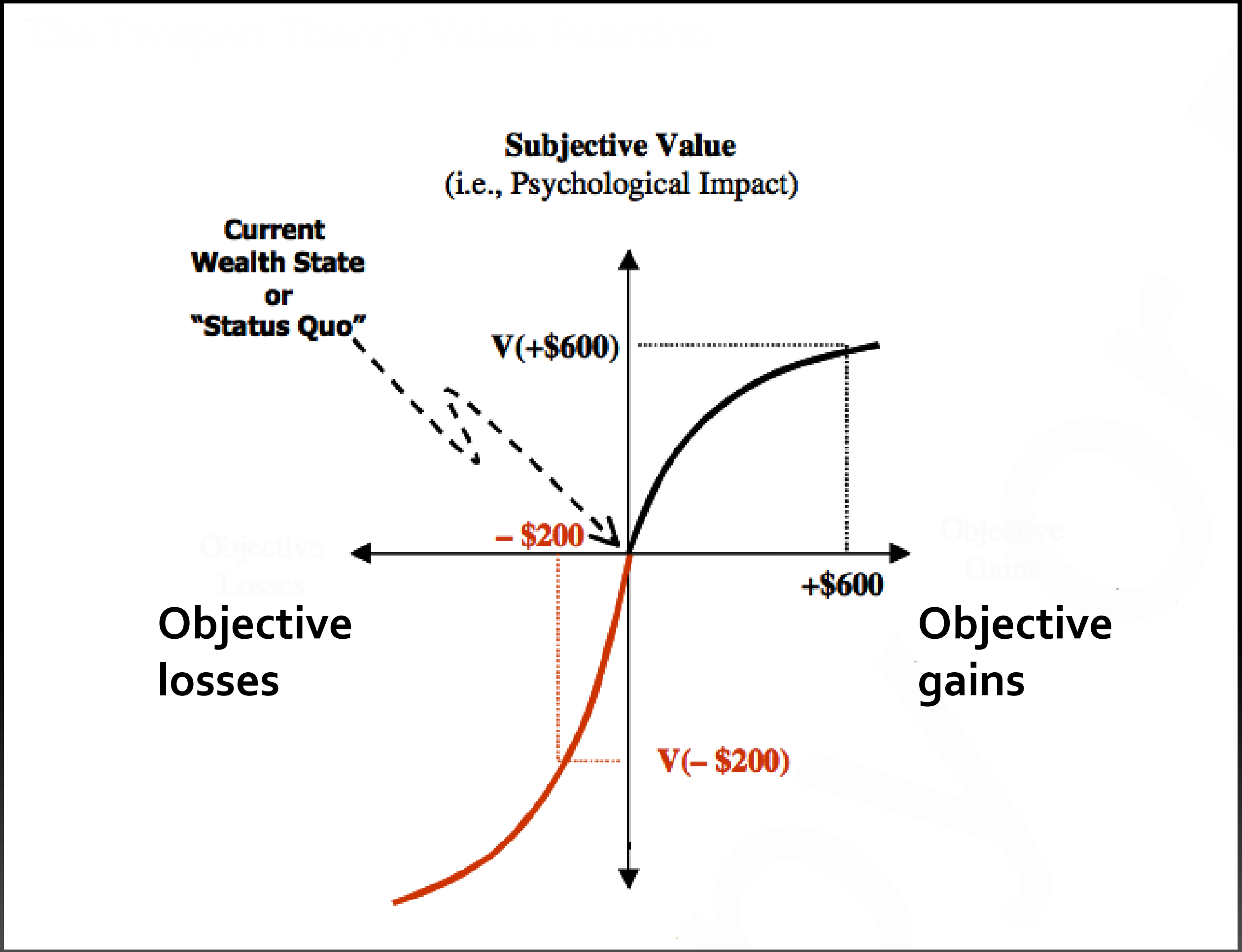
A drop in the bucket



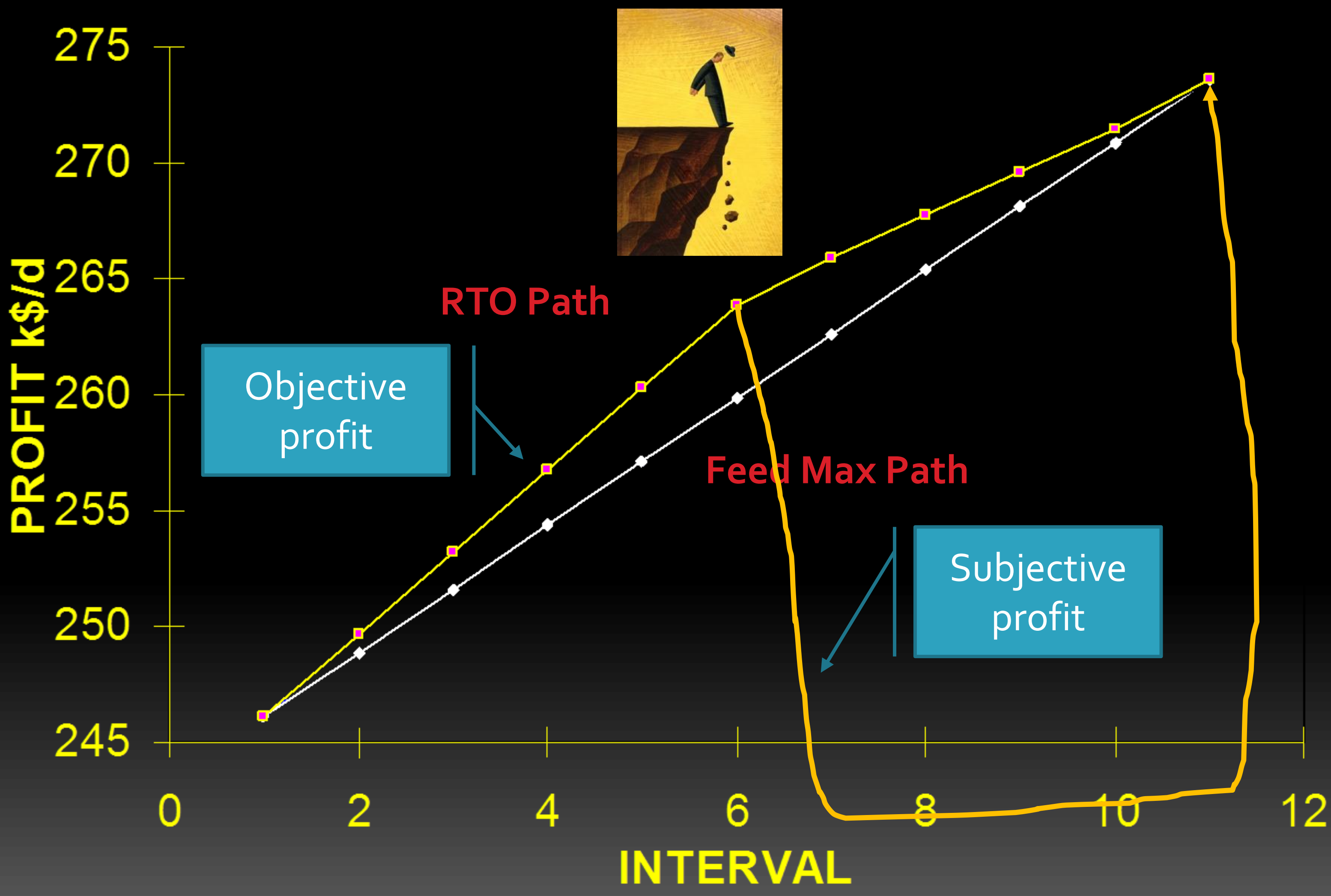
Behavioural Economics

- How emotions and perceptions affect economic decisions
- People math ≠ Algebraic math
  - Risk, reward, gains, losses, time are perceived differently
- Daniel Kahneman – Nobel prize economics 2002

Prospect theory - gains and losses



PROFIT PATH ANALYSIS



Familiarity

- Comfort is based upon pattern recognition
- 10,000 hour rule (Gladwell)
  - Practice makes perfect
- Advanced control - imitated the best operator
- Value proposition of RTO is to seek out non-obvious benefits

Technology for people

- Interact with users
  - Leverage off patterns
    - Cruise control
    - Smart phones

RTO Approach Rethought

- How do we model a plant?
- Familiar

Modeling the plant

- Fundamental design models?
  - Design:
    - What are the best arrangements and sizes of equipment to maximize ROI
- Operating plant
  - Equipment and capability is fixed
  - Processes must be operated around 70% of design to break even
  - RTO benefits consistently estimated to be around 3-5%

Can we model a plant just from its historical operating data?

Projection methods (PCA/PLS)

- Technique to find patterns in sets of data
- Linear algebra (singular value decomposition)

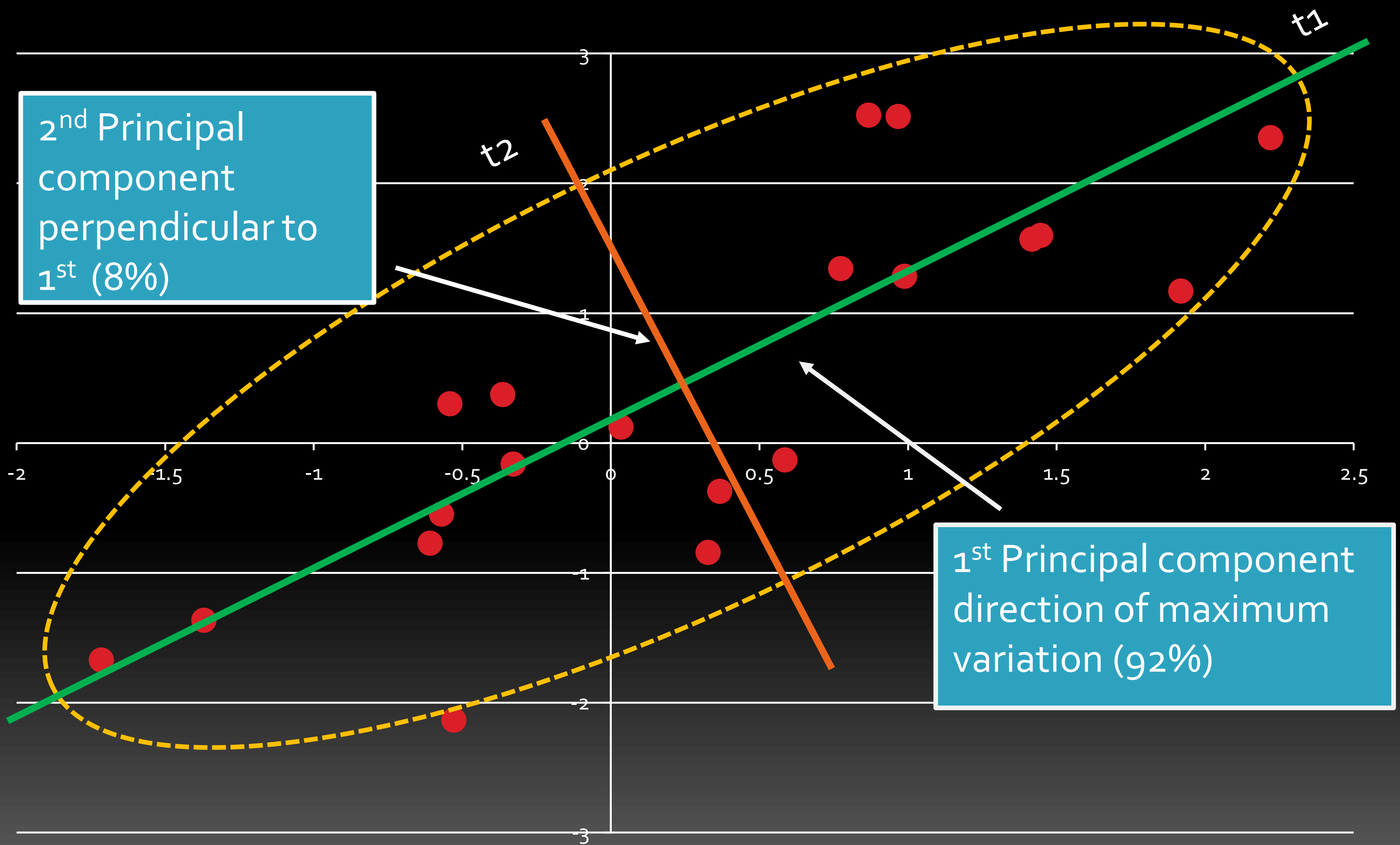
$$X = UWV^T = TP^T$$

$$\underset{m\times n}{\begin{pmatrix} \\ & X & \\ \\ \end{pmatrix}} = \underset{m\times n}{\begin{pmatrix} \\ & U & \\ \\ \end{pmatrix}} \underset{n\times n}{\begin{pmatrix} w_1 & & 0 \\ & \ddots & \\ 0 & & w_n \end{pmatrix}} \underset{n\times n}{\begin{pmatrix} & V^T & \end{pmatrix}}$$

$V^TV = I$

$U^TU = I$

Two dimensional example



Projection Methods

- PCA
  - Find an optimal (least squares) approximation to a matrix X using $T_1..T_k$ $k<<n$
- PLS
  - Find a projection that approximates X well, and correlates with Y

$$X = TP^T$$

$$Y = TC^T$$

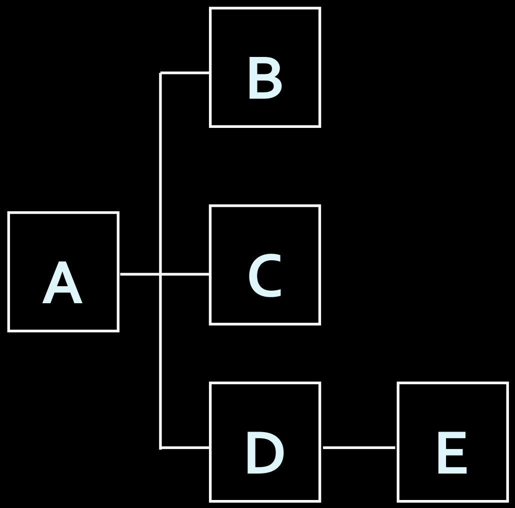
Happenstance plant data

- Number of measurements >> rank (true dimensionality)
- Every engineering relationship removes 1 degree of freedom
- However operator rules of thumb also remove degrees of freedom

Projection Model

- Models the correlation between variables caused by:
  - Fundamental engineering relationships
  - Operator preferences
- This is not the full space
  - It is a subspace within which the operator is familiar

Flow example revisited



$$\begin{pmatrix} A_1 & B_1 & C_1 & D_1 & E_1 \\ A_2 & B_2 & C_2 & D_2 & E_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_m & B_m & C_m & D_m & E_m \end{pmatrix}$$

Although we have 5 columns, the rank of the matrix =3

A = B + C + D

D = E

Latent space optimization

$$maximize \quad F(x,y)+\mathrm{c}^T\mathrm{x}+d^t y$$

subject to

$X = TP^T$ PCA model (linear)

$Y = TC^T$ PLS model (linear)

$\sum_i \left(\frac{T_i}{s_{Ti}}\right)^2 \leq B$ Boundaries of sphere

$$l \leq \begin{pmatrix} X \\ Y \\ T \end{pmatrix} \leq u$$

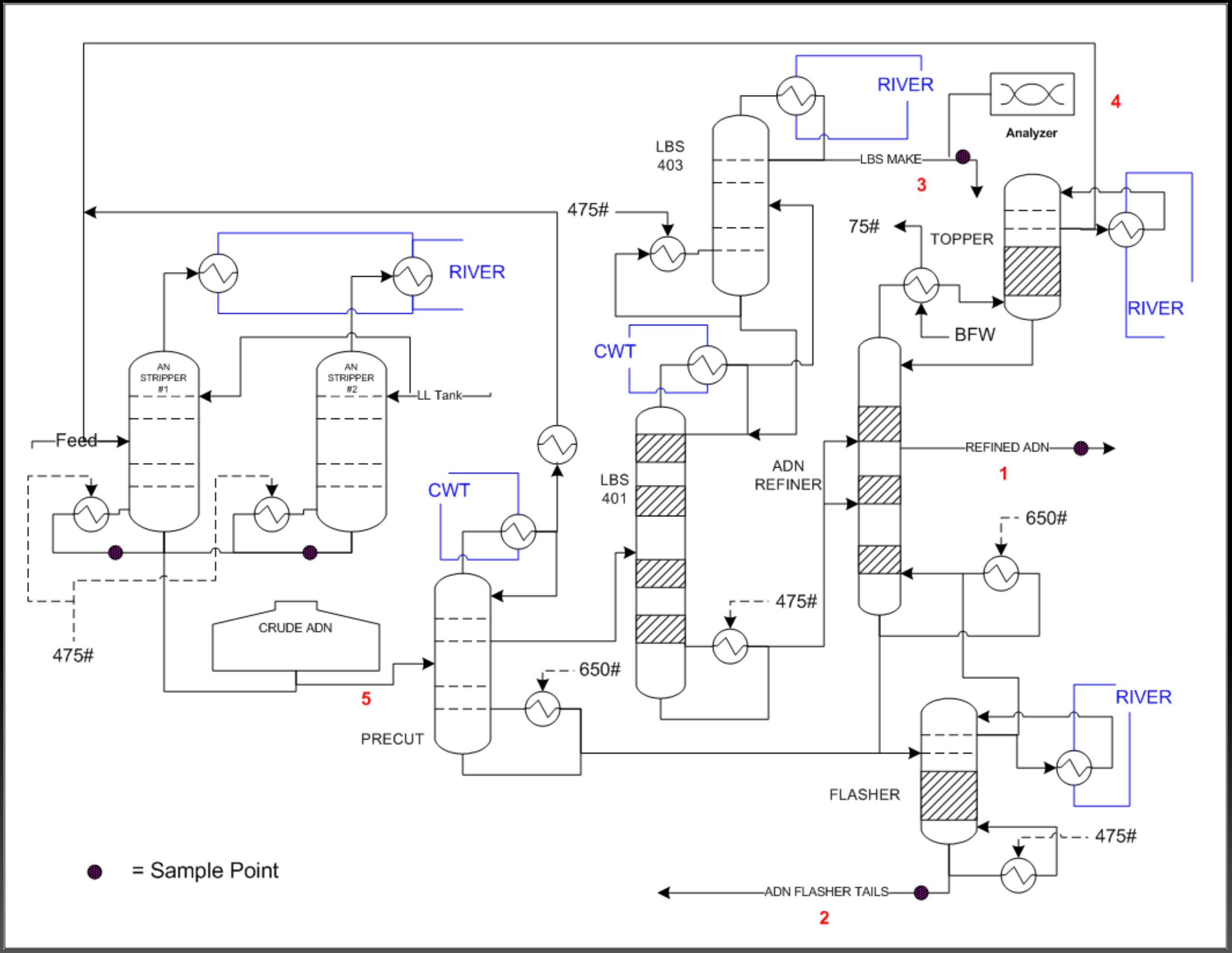
Key ideas

- Model the plant data directly
- Operators don’t like surprises
  - Projection methods implicitly model the the operator
- Does it work?
- Is this optimal?

Case Study

- Chemical company
  - If we expand our feed system, how much can we produce and still make on specification product

Flowsheet

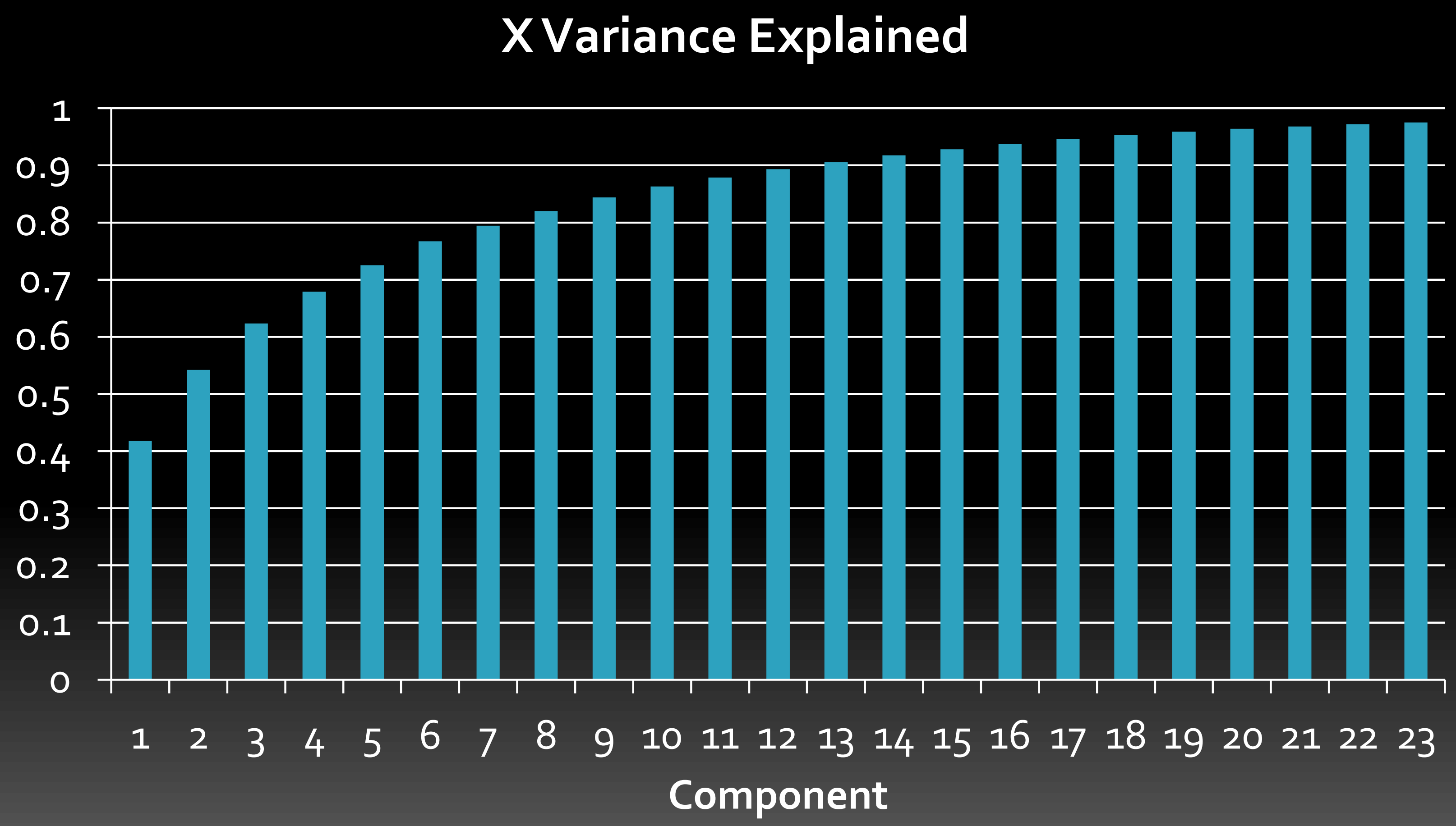


RIVER
Analyzer
4
LBS
403
LBS MAKE
3
475#
75#
TOPPER
RIVER
BFW
RIVER
RIVER
AN
STRIPPER
#1
AN
STRIPPER
#2
LL Tank
CWT
Feed
REFINED ADN
1
ADN
REFINER
LBS
401
CWT
650#
475#
475#
CRUDE ADN
650#
5
PRECUT
RIVER
FLASHER
475#
ADN FLASHER TAILS
2
= Sample Point

Dimensions and data

- 70 operator setpoints and valve positions
- 22 lab analyses
- 1 year of operating data (hourly averages)

PCA analysis results



Conclusions

- Although there were 70 setpoints…
  - The underlying dimensionality of this data was much lower
- With a purely linear model
  - 13 components could explain 90% of the variation
  - 23 components could explain > 97% of the variation
    - Nonlinearity is not significant over the operating range studied

Results

- Latent space optimization
  - Plant capable of 10% rate increase while keeping product qualities within specification
  - Identified bottlenecks (valves wide open)
  - Optimum plausible and familiar
    - Restricted to “typical” plant envelope
- Effort
  - 2 man weeks
- Result
  - Production within 0.2% of predicted

Globally optimal?

- Probably not
- Better and feasible
  - Certainly

Final thoughts

- Optimization math ≠ human math
- Our ability to make sense of high dimensional and complicated situations is limited

Politics is the art of the possible

Bismarck