Recent Developments in Process Integration Design Techniques

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1. Graphical and Optimization Approaches to Process Integration
Heat Integration using Pinch Analysis

Well established methodology
- many successful applications around the world
Pinch Analysis - Summary

- An approach to the design of heat recovery systems based on thermodynamic rules
- Applies well to the design of new systems
- Fundamentally not suited to retrofit
  - Tries to turn the existing design into a grassroot design
  - Often leads to complex and uneconomic retrofits
- Fundamentally not suited to operational optimization
Pinch Analysis - Summary

BUT

• It is a useful tool used in the right way on the right problems
• Can be used to set target performance for new processes
• Can be used to set the ultimate performance of an existing process, but this will not necessarily be economic
• It is one of a number of tools that can be used to improve the performance of processes
Graphical/Thermodynamic Methods

- Target and design for simple problems straightforward
- Difficulties with large problems
- Does not allow constraints to be included
- Difficult to include capital costs
- Difficult to deal with cost trade-offs

BUT

Graphical techniques extremely popular with designers
Superstructure Optimization

- Reducible structure (superstructure) is first developed
- Contains redundant features

  e.g. heat exchanger network

- Must contain all features that are candidates for the optimal design
Superstructure Optimization - contd

Initial Design (Superstructure)

- Difficult mathematical optimisation problem - due to nonlinear nature of the problem
- Difficult to get practical solutions reliably for large complex problems
- Designer is removed from decision making

Final Design
Superstructure approach has limited exploitation in commercial software:

- heat exchanger network design
- water minimisation
- refinery hydrogen networks
Most Superstructure Optimization Exploits Deterministic Optimization

Deterministic Optimisation

Discrete
- \( \text{IP} \)
- \( \text{MILP} \)
- \( \text{MINLP} \)

Continuous
- \( \text{LP} \)
- \( \text{QP} \)
- \( \text{NLP} \)
• Superstructure approach now well developed
  ▶ main problem is the optimization engine

• More powerful optimization engines will increase the application of the approach and the quality of the solutions

BUT.....

Most users still demand the insights that automated techniques do not provide
Graphical Approaches

Optimisation Methods
(Deterministic Optimisation)

Trial & Error

MILP

MINLP

NLP

Complexity

Graphical Approaches

Number of Design Configurations
How can we extend the scope of process integration techniques?
Different Approaches to Design

Stochastic Optimization

• Avoids local optima problems
• Generates optimal solutions, independent of initial guess
• No gradients required
• Final distribution of solutions
• But, slower than deterministic methods
Simulated Annealing

Derives inspiration from physics

Algorithm

1. Initial solution
2. Initial temp
3. Generate new solution
4. Evaluate new solution
5. If new solution improves, accept; otherwise, adjust temp
6. Update store
7. If temp drops below a threshold, terminate; otherwise, repeat

End
Genetic Algorithms

Derives inspiration from biology

Evolution

Survival of the fittest

Algorithm

Start

Generate Random Initial Population

Meets Criteria ? (ε or $N_{gen}$)

Yes

Stop

No

Reproduction

Crossover ($P_c$) & Mutation ($P_m$)

New Generation

$N_{gen}++$
Deterministic vs. Stochastic Search Methods

**Deterministic methods**

- Requires good initialisation
- Computational problems
- Exact local optimum
- No guarantee for good quality solution
- Fast

**Stochastic Methods**

- Does not require good initialisation
- Gradient free
- Avoids local valley
- Good for structural changes
- Multiple solutions in the region of the optimum
- System dependent parameters
- Slow
Optimisation Methods

Graphical Approaches

Complexity

Trial & Error

NLP

MINLP

Stochastic Methods

Number of Design Configurations

MILP

Graphical Approaches
2. Heat Integrated Process Design
Conventional design of the overall system

Stage 1
Process design

Stage 2
Heat recovery system design
But, there are significant interactions

Stage 1
Separation design

Stage 2
Heat recovery system design
Simultaneous design and optimization necessary

Stage 1
Separation design

Stage 2
Heat recovery system design

Strong Interactions
Heat Exchanger Network Modeling

- Methods of energy targeting (Pinch Analysis) can be used for some features of grassroot design

- Cannot be used for:
  - Operational optimization
  - Retrofit
Heat Exchanger Network Modeling

- Need to model the detailed configuration of the heat exchanger network for operational optimization and retrofit
  - load on individual heat exchangers?
  - refrigeration implications?
  - which heat exchangers would benefit from heat transfer enhancement
  - cost-effective retrofit for heat exchanger network
How is a distillation system simulated?
## Distillation Models

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy</th>
<th>Robustness</th>
<th>Less computing time</th>
<th>Suitable for optimisation (HEN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rigorous</td>
<td>++</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Simplified</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Statistical</td>
<td>+</td>
<td>++</td>
<td>++</td>
<td>++</td>
</tr>
</tbody>
</table>
Simplified Model for Distillation

Decomposition approach for column modeling

Decompose

Then use short-cut or semi-rigorous modeling for the components
Statistical/Empirical - ANN distillation model

- Distillation model is regressed using samples from rigorous model simulations

- Accuracy + Robustness → ANN model → Input to optimisation
• Artificial Neural Networks

- Non-linear statistical data modelling tool inspired by the structure of biological neural networks

- Changes its structure based on learning from information
ANN Distillation Model

Simple regression (i.e. two variables)

Artificial Neural Network: relates many complex variables
3. CASE STUDY – Sinopec Maoming CDU
Case Study for Heat recovery optimisation and retrofit

- Refinery crude oil distillation process in one of the SINOPEC refinery sites.
  - One of 3 CDUs was studied to identify energy saving potential.
  - All contain a two-stage desalter, a prefractionator, an atmospheric column, and a vacuum column.
  - All process heavy and sour crudes.
Distillation Model

Simplified (Decomposed) Models used for the Columns
Pre-heat Train Model
Energy Optimization

Objective function

Total annualized cost

= annualized capital cost + operating cost

Constraints

• Hydraulic limits of distillation column
• maximum pump-around flow rate increase
• Product Specifications
• Product flows
• Product boiling curve properties
• Steam flow rates
Stage 1: Operation Optimization

Optimizing the operation of the distillation columns together with the heat exchanger network!
After Operation Optimization:
CIT is increased by 7°C

<table>
<thead>
<tr>
<th>Item</th>
<th>Before</th>
<th>After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude Oil Inlet (ºC)</td>
<td>26</td>
<td>26</td>
</tr>
<tr>
<td>Crude Oil to Desalter (ºC)</td>
<td>112</td>
<td>115</td>
</tr>
<tr>
<td>Crude Oil to Prefractionator (ºC)</td>
<td>175</td>
<td>175</td>
</tr>
<tr>
<td>CIT (ºC)</td>
<td>255.4</td>
<td>262.4</td>
</tr>
<tr>
<td>COT (ºC)</td>
<td>360</td>
<td>360</td>
</tr>
<tr>
<td>Crude Oil Flow (m³/h)</td>
<td>90</td>
<td>90</td>
</tr>
</tbody>
</table>

Economic benefit: $900,000/y without capital investment!
Now we have reached the optimal operating condition, can we improve the energy efficiency further?

Stage 2: Revamping investigation
### Revamping Options

**Option 1: Exchange position of H7-3 and H5-3AB**

<table>
<thead>
<tr>
<th>Effect</th>
<th>Crude to Desalter Temp (°C)</th>
<th>CIT (°C)</th>
<th>Savings $/y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exchange the sequence of H5-3AB and H7-3</td>
<td>+1.0</td>
<td>+0.9</td>
<td>115,000</td>
</tr>
<tr>
<td>Crude goes to H7-3 first, then to H5-3AB</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


**Revamping Options**

**Option 2:** Add a new HX between the column OHVD and Desalter Feed Water

<table>
<thead>
<tr>
<th>Effect</th>
<th>Desalter Temp (°C)</th>
<th>CIT (°C)</th>
<th>Saving $/y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Add a new HX between the column OHVD and Desalter Feed Water</td>
<td>+5.0</td>
<td>+4.1</td>
<td>515,000</td>
</tr>
<tr>
<td>Repiping for Desalter Feed Water</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Crude oil refining energy reduction

- Client: Sinopec
- Scope
  - Optimise preheat train and operation of distillation columns simultaneously
  - Operational optimisation only

<table>
<thead>
<tr>
<th>Site</th>
<th>Energy saving</th>
<th>Capital investment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maoming Unit 1</td>
<td>14.7% (2.57 m$/yr)</td>
<td>No capital investment</td>
</tr>
<tr>
<td>Maoming Unit 2</td>
<td>9.3% (1.68 m$/yr)</td>
<td></td>
</tr>
<tr>
<td>Maoming Unit 3</td>
<td>8.2% (0.88 m$/yr)</td>
<td></td>
</tr>
</tbody>
</table>

NOTE: Savings based on verified implemented results, not calculation
Acknowledgments

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Thank you!