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A methodology for improving large scale thermal energy systems

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Abstract

This paper presents a new methodology for improving large scale thermal energy systems. A major problem when analysing large scale thermal energy systems is the complexity of the system. If a simplified mathematical model of the system is made, it can be combined with mathematical models of how modifications influences the system. By using these models it is possible to considerably reduce the size of the mathematical programming model. This means that larger and more complex systems can be optimised. This is the idea behind the new methodology developed in this work. By combining *simulation* and *experimental design* it is possible to obtain a simple but sufficiently accurate model of a thermal energy system. The obtained model can then be used to evaluate improvements to the system using *mathematical programming*.

Keywords: Large scale energy systems; Simulation; Mathematical programming

1. Introduction

The problem of improving large scale thermal energy systems is to determine which structural and parametric modifications give rise to the most economic design. This task can be seen as a synthesis of flow sheet schemes. As shown in for instance the work by Grossmann and Kravanja [3], mathematical programming is very well suited for solving process synthesis problems. However, for sufficiently large and complex systems the mathematical programming approach runs into problems. The mathematical programming formulations of process synthesis problems are often nonlinear and contain binary or integer variables (MINLP problems). MINLP problems can be

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solved to a global optimum with algorithms that exist today. However, for complex problems these algorithms soon become prohibitively inefficient. It has also been shown that some MINLP problems are NP-complete (nondeterministic polynomial) problems, which means that no efficient algorithm has been found for solving these problems. When trying to solve large problems of these kinds it is therefore often necessary to simplify the problems or to decompose them into smaller sub-problems. As a result of the simplifications the solutions to the mathematical programming problems might not be accurate enough to be used in the design of a real plant. A lot of work has been made to try and overcome these problems. One example is in the field of power plant design. Power plant design is relevant to this work since it is closely related to the synthesis of thermal energy systems. In earlier work, Bruno et al. [1] developed a rigorous MINLP model for the synthesis of power plants. By using the formulations they suggested it is possible to solve larger synthesis problems of real plants. The fundamental problem, however, remains. For sufficiently large and complex systems the mathematical programming solvers are unable to solve the problems. In their work Manninen and Zhu [7] took a different approach and developed a methodology for power plant synthesis, where the problem size is reduced using thermodynamic analysis. The problem size is primarily reduced in two ways; firstly by reducing the size of the superstructure and thus the integer variables and secondly by giving tighter bounds of the variables, and thus reduce the size of the search space. Similar ideas were presented in the work by Hostrup et al. [5], where the focus was on chemical processes. Common for the methodologies mentioned above is that they all require a detailed mathematical model of all the units included in the superstructure. If a simplified mathematical model of the system is made, it can be combined with mathematical models of how modifications influences the system. By using these models it is possible to considerably reduce the size of the mathematical programming model. This means that larger and more complex systems can be modelled. This is the idea behind the new methodology developed in this work. By combining *simulation* and *experimental design* it is possible to obtain a simple, but sufficiently accurate model of a thermal energy system. The obtained model can then be used to evaluate improvements to the system using *mathematical programming*.

2. Description of the methodology

The main steps of the new methodology are *Data extraction*, *Simulation model building*, *Process analysis* and *Experimental design*.

2.1. Data extraction

The first step in the methodology is the *data extraction* step. The purpose of the data extraction step is to find sufficient data about the plant and the processes and verifying these. This data consists of the structure or topology of the system, the process parameters and the lower and upper bounds of the parameters. On the basis of this data, a representative simulation model of the system can be built. It also involves analysing the system or process. The idea behind this analysis is to identify the components of the system and how they work. As the data extraction forms the basis for the simulation model, two decisions about the simulation model should also be made at this stage. The first decision to make is to decide what the actual purpose of the simulation is. The second decision is related to the first, and that is to decide what kind of calculations the simulation model should be able to perform.

The data extraction is the most time extensive part of building a representative simulation model. There are two major problems with data extraction. The first problem is that all the necessary data might simply not be available. The second major problem is that in many cases the data that *is* available is ambiguous. It is important to notice that it is only possible to identify ambiguous data in the case where there is enough data to make an over-determined model. The ambiguousness of the data can for instance arise when measurements are taken at different operation points, or when the measurements are incorrect. In many cases only the trends are valuable for the operation of the plant, so there is no need to get an absolute value from the measurements. This will be a problem when building a simulation model as it is in most cases crucial to get values that are in balance, or at least close to being in balance. The above mentioned problems with the data extraction are difficult, if not impossible to avoid. This makes it also necessary to verify the data extracted.

2.2. Simulation model building

The next step in the methodology is to build the *simulation model*.

The purpose of this step is twofold. Firstly, the purpose is to make a simulation model that can be used to test and evaluate changes to the system. Secondly, the purpose is to make a simulation model from which it is possible to generate data. The data is then used for building a regression model of the behaviour of the system. The simulation model ensures that models of the different units are in energy and mass balance. This gives the somewhat counter-intuitive result, that in many cases the properties obtained from a simulation model are more reliable than the properties that are measured at the plant. As mentioned above, there are many contributions to the unreliability of measured data; for instance, the measurements might be taken at different operation points, the instruments are not calibrated properly or are straight out faulty. Another source is that in many cases the measurements are not meant to give absolute values, but rather to monitor changes in the process. The way the simulation model is built depends on what kind of simulation model that is chosen, and also on what kind of software is being used. Care must be taken, so that the simulation becomes robust. When using high-level simulation software that has a good user interface, it is hardly ever a problem. However, simplicity comes at a cost and will in many cases restrict the flexibility of the software. More flexible software is in general more demanding and requires more attention from the user. After the simulation model is built, it is important to verify that the simulation model is a sufficiently good model of the real process at hand. This can for instance be done by choosing a few trustworthy measurements and compare them with the simulated ones. If the simulation model does not give a sufficiently good representation of the real process, it needs to be revised.

2.3. Process analysis

The next important step is to *analyse* the simulation model for possible improvements to the process or the system. These improvements can be parametric, e.g. changing pressure or temperature, or structural, e.g. adding a heat exchanger or changing a reactor. A good systematic method for analysing a general system has not been found, but many specialised methods have been developed for analysing a thermal system. Pinch analysis is one example of such methods. It is based on the fact that the minimal utility requirements for a heat exchanger network can be calculated from the stream information and some information about the minimum driving forces, $\Delta T_{\min}$. This was first noted by Hohmann [4]. The concept was also independently discovered by Linnhoff et al. [6]. Exergy is as pinch analysis widely used in process synthesis. Sorin et al. [9] developed, for example a new approach for chemical process synthesis based on exergy optimisation of a superstructure. Thermoeconomics is another example of methods for analysing thermal systems. Thermoeconomics blends the field of thermodynamics and economics, and is a combination of the analysis of thermal efficiency and capital investments. This method was published by El-Sayed and Evans [2].

2.4. Experimental design

The most novel approach in the new methodology developed in this work, is to take advantage of the methods developed in the field of *experimental design*. As the name suggests, experimental design is in general used in experimental work. In a lot of cases an experiment is timely and costly, thus a lot of work has been put in to the development of methods that reduce the amount of times different combinations of an experiment has to be performed. The new idea is that it should also be possible to exploit these methods in the development of optimisation models. The purpose of the *experimental design*-step is thus to reduce the amount of simulation runs, but still be able to get sufficient data for a regression model. The strategy used in this work, is the *factorial* experiment. In a factorial experiment, the factors are varied together and not one at the time. In the case of thermal energy systems a factor, or in other words a variable, can be for instance pressure or temperature. A factorial experiment will allow the experimenter to model the individual effects of each factor as well as the way the factors interact. The traditional way of building regression models from simulations is to find the parameters that one would like to change, and then incrementally change them one at a time. For complex simulation models this approach will soon become prohibitively time consuming. For instance if six variables are chosen and each variable can have 10 different values, 10^6 simulation runs would have to be made. If each simulation run takes 5 s it would take about 58 days to complete all the simulation runs. A more reasonable way would be to do a 2^6 factorial design, which would take about 5 min to complete. This is, however, at the cost of accuracy, so care must be taken to ensure that the regression model is accurate enough.

3. Illustrative example

To illustrate the method a simple power plant process is considered. The flowsheet of the power plant is shown in Fig. 1. The mass flow of superheated steam is kept constant at 10 kg/s. The system consists of the following modules (the numbers refer to the numbers in Fig. 1):

- a steam generator (boiler with superheater) (2);
- a steam turbine with two extractions, one after the 2nd stage and one after the 3rd stage (3, 4, 5, and 6);

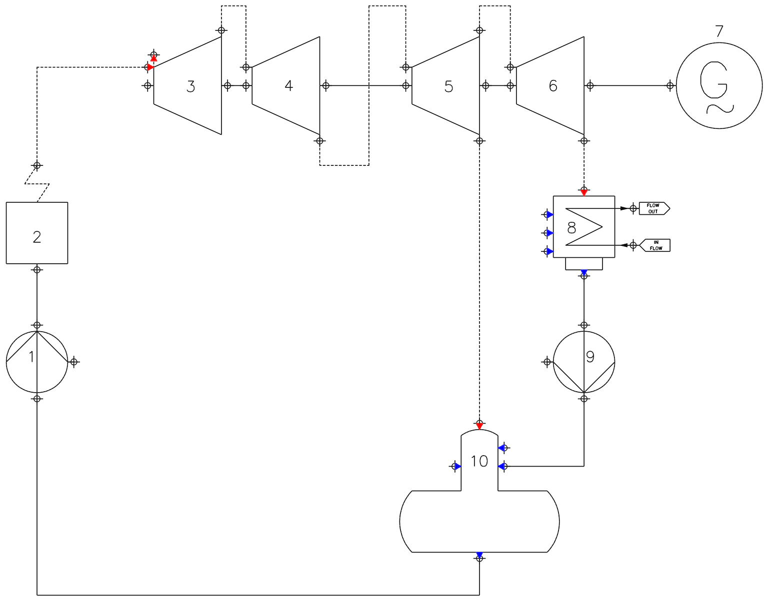

Fig. 1. Flowsheet of the power plant in the example.

- a generator (7);
- a condenser (8);
- two feedwater pumps (1 and 9);
- a feedwater tank (10).

Let us assume that a new tax based on the efficiency of power plants is suggested. The idea behind the tax is to create incentives for improving the efficiency, and thus reduce the environmental impact of the process. For the process discussed here, the new tax will be calculated as follows:

$$\text{tax} = \frac{75}{200 \cdot \eta_{\text{el}} - 70} \quad [1000\ \text{euro/a}] \tag{1}$$

The goal of the study is to suggest modifications to the power plant that will increase the efficiency, η_{el}, of the plant, and then choose the most cost-efficient combination of the modifications.

3.1. Analysis of the power plant

As a part of an analysis of the plant it is noted that steam is only extracted at one level. The extracted steam is used for heating the feedwater to the saturation temperature in the feedwater tank. By analysing the process further two structural changes to the process that will improve the overall efficiency are found:

- the reheat of steam;
- the use of an additional feedwater heater;

The reheat requires the addition of a reheater section in the boiler, but will increase the efficiency as higher pressure can be used without deteriorating the quality of the steam at the turbine exhaust. The additional feedwater heater would make the feedwater enter the boiler at a higher temperature. This will result in a higher cycle efficiency as the average temperature of the heat addition will be increased. It is important to realise, that now a decision is made to only take the parameters that are connected with the two changes into account. If for instance it is thought that changes in the pressure will improve the efficiency, the changes in pressure must also be included in the study.

3.2. Simulation

The simulation model of the plant must be modified to be able to calculate the modifications to the process that are needed. For this case it is possible to include the full superstructure in the simulation model. The flowsheet of the simulation model is shown in Fig. 2. The new feedwater heater is numbered 16, whilst the new reheater is numbered 12 in the figure.

3.3. Experimental design

After completing the simulation model, the next step is to identify the parameters that will have to be changed to simulate the new modifications to the process. In experimental design these

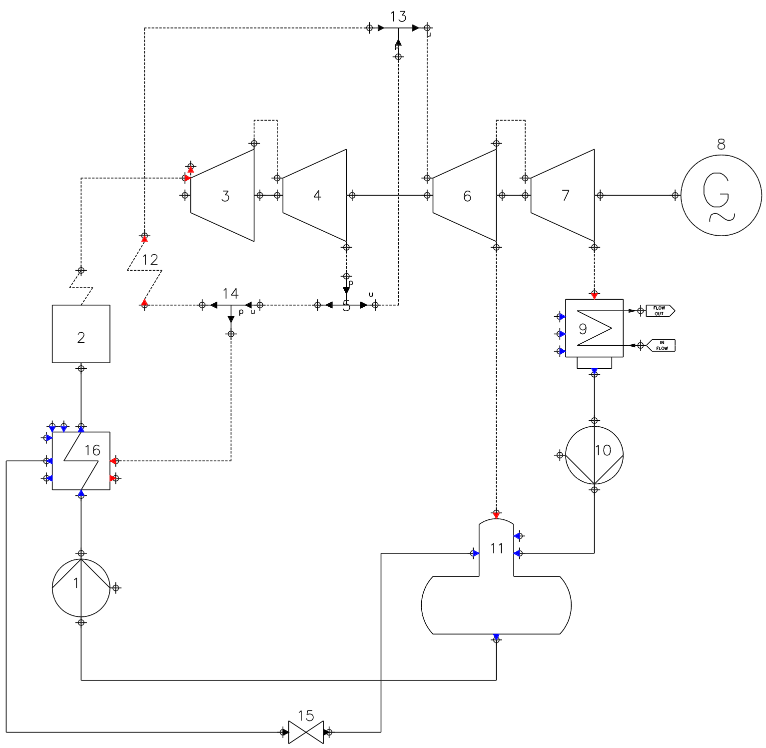

Fig. 2. Simulation model for the superstructure of the power plant in the example.

parameters are often referred to as *factors*. It is also necessary to determine the levels and range of the variables. For the reheater the parameter could be the mass flow to the reheater. For the feedwater heater and the reheater the parameter could for instance be the mass flow of steam to the new units. The lower bound of both variables is 0, corresponding to the case where the new unit is not built. The upper bound for the mass flow to the new feedwater heater is approximately 1.1 kg/s. This upper bound is due to the minimum temperature difference between the two streams in the heat exchanger. The upper bound for the mass flow to the reheater is set to $10.0 - 1.1 = 8.9$ kg/s.

The next step is to identify which variables or parameters should be monitored. This is referred to as the *response variables* in experimental design. Since we are interested in improving the efficiency of the plant, it is natural to choose the variable(s) that enables us to calculate the efficiency. The equation for calculating the efficiency is given in Eq. (2).

$$\eta_{el} = \frac{W_{el} - (W_{pump1} + W_{pump10})}{\dot{Q}} \tag{2}$$

where W_{el} is the alternator power, W_{pump1} and W_{pump10} are the work added to the feedwater pumps and $\dot{Q}$ is the heat added to the process (in the boiler and reheater).

We are then left with a 2^k factorial design experiment with one centre point with the following factors and response variables:

- factors
  - mass flow to feedwater heater, m_1;
  - mass flow to reheater, m_2;
- response variables
  - alternator power, W_{el};
  - work to feedwater pumps, W_{pump1} and W_{pump10};
  - heat added to the process, $\dot{Q}$.

The number of simulation runs needed is $2^2 + 1$, where the last simulation run is the centre point. The results of the simulation runs are given in Table 1.

The next step is to take the relevant data from Table 1 and transform them into two blocks of variables (**X** and **Y**). The result is shown in Eq. (3).

Table 1
Example data from the simulation runs of the power plant simulation model

Total heat flow (MW)	Alternator power (MW)	Pump power (kW)	Pump power (kW)	Efficiency	m_1 (kg/s)	m_2 (kg/s)
28.3	10.2	108.9	2.2	0.357	0.0000	0.0000
26.0	9.6	108.9	2.0	0.365	1.0942	0.0000
31.6	11.9	108.9	2.2	0.373	0.0000	8.9058
29.3	11.3	108.9	2.0	0.381	1.0942	8.9058
28.8	10.7	108.9	2.1	0.369	0.5471	4.4529

$$\mathbf{X} = \begin{bmatrix} 0.0000 & 0.0000 \\ 1.0942 & 0.0000 \\ 0.0000 & 8.9058 \\ 1.0942 & 8.9058 \\ 0.5471 & 4.4529 \end{bmatrix}, \quad \mathbf{Y} = \begin{bmatrix} 0.35720 \\ 0.36523 \\ 0.37257 \\ 0.38147 \\ 0.36852 \end{bmatrix} \tag{3}$$

where the column vectors of **X** are the mass flow $\dot{m}_1$ and $\dot{m}_2$ for the different simulation runs. The column vector **Y** is the corresponding efficiency of the process. The linear least squares regression model is shown in Eq. (4).

$$\eta_{el} = \begin{bmatrix} \dot{m}_1 & \dot{m}_2 \end{bmatrix} \begin{bmatrix} 0.007736 \\ 0.001775 \end{bmatrix} + 0.356863 \tag{4}$$

We now have a linear model of how the system reacts to the suggested modifications. The model relates the mass flow of steam to the new units to the electrical efficiency of the system. A nonlinear model could be made, for instance by fitting a power curve to the data. Since this would only make mathematical programming model more complex, only the linear model is used in this work.

The next task is to build a mathematical programming model, where the objective function is the total annual costs of the system. The costs of the modifications are the investment costs of the heat exchangers. Let us assume that the annual cost of a heat exchanger can be formulated as:

$$C_{hex} = \text{annu} \cdot (30 + 0.6 \cdot A_{hex}^{0.8}) \quad [1000\ \text{euro/a}] \tag{5}$$

where annu is the annuity factor, A_{hex} is the heat exchanger surface area in square metres. Here the annuity factor is set to 0.26, based on an interest rate of 10% and a period of 5 years. The heat exchanger surface area can be calculated as follows:

$$A_{hex} = \frac{Q}{U_{hex} \cdot \text{LMTD}} \tag{6}$$

where Q is the heat flux, U_{hex} is the overall heat transfer coefficient and LMTD is the logarithmic mean temperature difference. To avoid numerical problems when solving a mathematical programming model it is common to use an approximation for the LMTD. In this work the approximation by Paterson [8] is used. The overall heat transfer coefficient is set to 4 and 0.1 kW/m^2 K for the feedwater heater and reheater respectively. For the boiler, let us assume that the steam is produced by a hot gas. Let us further assume that the gas leaves the boiler at 650 °C, and that this gas can be used to reheat the steam. The mass-flow of the gas, m_{gas}, is 14.5 kg/s. Binary variables can be used to make sure that the cost of a heat exchanger is added only if the mass flow (either m_1 or m_2) to the exchanger is greater than zero. For instance if M_1 is the upper bound for m_1, the in-equality in Eq. (7) says that m_1 can only take values greater than zero if the binary variable y_1 is 1.

$$m_1 - M_1 \cdot y_1 \leqslant 0 \tag{7}$$

The full mathematical programming model is given in Eq. (8). The subscripts f and r refer to the feedwater heater and the reheater respectively. Since the steam entering the feedwater heater is superheated, the calculation of the heat exchanger surface area is divided into two parts; one part for cooling the steam to the saturated temperature and one part for the condensing of the steam.

$$
\begin{aligned}
\text{minimise}\quad & \text{tax} + C_{\text{hex},f} + C_{\text{hex},r}\\
\text{subject to}\quad & h_{fg} \cdot m_1 = m_p \cdot cp_{\text{water}} \cdot (T_{fc,\text{sat}} - T_{fc,\text{in}})\\
& m_p \cdot cp_{\text{water}} \cdot (T_{fc,\text{out}} - T_{fc,\text{cond}}) = m_1 \cdot cp_{\text{steam}} \cdot (T_{fh,\text{in}} - T_{fh,\text{sat}})\\
& \theta_{1,\text{hex},f,1} = T_{fh,\text{in}} - T_{fc,\text{out}}\\
& \theta_{2,\text{hex},f,1} = T_{fh,\text{sat}} - T_{fc,\text{cond}}\\
& \theta_{1,\text{hex},f,2} = T_{fh,\text{sat}} - T_{fc,\text{cond}}\\
& \theta_{2,\text{hex,f},2} = T_{fh,\text{sat}} - T_{fc,\text{in}}\\
& \theta_{1,\text{hex},r} = T_{rh,\text{in}} - T_{rc,\text{out}}\\
& \theta_{2,\text{hex},r} = T_{rh,\text{out}} - T_{rc,\text{in}}\\
& T_{rh,\text{out}} = T_{rh,\text{in}} - \frac{m_2 \cdot cp_{\text{steam}} \cdot (T_{rc,\text{out}} - T_{rc,\text{in}})}{m_{\text{gas}} \cdot cp_{\text{gas}}}\\
& \text{LMTD}_{\text{hex},f,1} = (2/3) \cdot \sqrt{\theta_{1,\text{hex},f,1} \cdot \theta_{2,\text{hex},f,1}} + \frac{\theta_{1,\text{hex},f,1} + \theta_{2,\text{hex},f,1}}{6}\\
& \text{LMTD}_{\text{hex},f,2} = (2/3) \cdot \sqrt{\theta_{1,\text{hex},f,2} \cdot \theta_{2,\text{hex},f,2}} + \frac{\theta_{1,\text{hex},f,2} + \theta_{2,\text{hex},f,2}}{6}\\
& \text{LMTD}_{\text{hex},r} = (2/3) \cdot \sqrt{\theta_{1,\text{hex},r} \cdot \theta_{2,\text{hex},r}} + \frac{\theta_{1,\text{hex},r} + \theta_{2,\text{hex},r}}{6}\\
& A_{\text{hex},f,1} \cdot U_{\text{hex},f} \cdot \text{LMTD}_{\text{hex},f,1} = m_1 \cdot cp_{\text{steam}} \cdot (T_{fh,\text{in}} - T_{fh,\text{sat}})\\
& A_{\text{hex},f,2} \cdot U_{\text{hex},f} \cdot \text{LMTD}_{\text{hex},f,2} = m_1 \cdot h_{fg}\\
& A_{\text{hex},f} = A_{\text{hex},f,1} + A_{\text{hex},f,2}\\
& A_{\text{hex},r} \cdot U_{\text{hex},r} \cdot \text{LMTD}_{\text{hex},r} = m_2 \cdot cp_{\text{steam}} \cdot (T_{rc,\text{out}} - T_{rc,\text{in}})\\
& C_{\text{hex},f} = \text{annu} \cdot (30 \cdot y_1 + 0.6 \cdot A^{0.8}_{\text{hex},f})\\
& C_{\text{hex},r} = \text{annu} \cdot (30 \cdot y_2 + 0.6 \cdot A^{0.8}_{\text{hex},r})\\
& \eta_{\text{el}} = 0.3568 + 0.007736 \cdot m_1 + 0.001775 \cdot m_2\\
& \text{tax} \cdot (200 \cdot \eta_{\text{el}} - 70) = 75\\
& m_1 - M_1 \cdot y_1 \leqslant 0\\
& m_2 - M_2 \cdot y_2 \leqslant 0\\
& 0.0 \leqslant m_1 \leqslant 1.1\\
& 0.0 \leqslant m_2 \leqslant 8.9\\
& y_1, y_2 \in \{0, 1\}
\end{aligned}
\tag{8}
$$

where $h_{fg} = 2015.3$ kJ/kg, $m_p = 10$ kg/s, $cp_{\text{water}} = 4.3$ kJ/kg K, $cp_{\text{steam}} = 2.1$ kJ/kg K and $cp_{\text{gas}} = 1.1$ kJ/kg K. The solution to the problem is an annual cost of 32,300 euro/a. The reheater is added, but not the feedwater heater. The mass-flow of m_2 is 8.9 kg/s resulting in a heat exchanger area of 135 m^2. The solution to the problem given in Eq. (8) is already calculated by the simulation model, however, for other nonlinear models this might not be the case.

4. Conclusions and discussion

A new methodology for improving large scale thermal energy systems has been presented.

A major problem when analysing large scale thermal energy systems is the complexity of the system. It is necessary to make some kind of simplification in order to be able to solve the problems with the existing algorithms. One common solution is to model parts of the system in low detail. The new methodology tries to handle this complexity through a combination of simulation and experimental design in addition to mathematical programming. The complexity of the optimisation problem is much smaller than it would be if each unit is modelled in detail. The result is an optimisation problem where the effect of the modification candidates on the whole system is included as a regression model.

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References

[1] J.C. Bruno, F. Fernandez, F. Castells, I.E. Grossmann, A rigorous MINLP model for the optimal synthesis and operation of utility plants, Institution of Chemical Engineers Trans IChemE 76 (1998) 246–258.

[2] Y.M. El-Sayed, R.B. Evans, Thermoeconomics and the design of heat systems, Journal of Engineering for Power, ASME Transactions 92 (1970) 17–26.

[3] I.E. Grossmann, Z. Kravanja, Mixed-integer nonlinear programming techniques for process systems engineering, Computers and Chemical Engineering 19 (1995) S189–S204.

[4] E.C. Hohmann, Optimum networks for heat exchange. Ph.D. thesis, University of Southern California, 1971.

[5] M. Hostrup, R. Gani, Z. Kravanja, A. Sorsak, I.E. Grossmann, Integration of thermodynamic insights and MINLP optimization for the synthesis, design and analysis of process flowsheets, Computers and Chemical Engineering 25 (2001) 73–83.

[6] B. Linnhoff, D.R. Mason, L. Wardle, Understanding heat exchanger networks, Computers and Chemical Engineering 3 (1979) 295–302.

[7] J. Manninen, X.X. Zhu, Thermodynamic analysis and mathematical optimisation of power plants, Computers and Chemical Engineering 22 (1998) S537–S544.

[8] W.R. Paterson, A replacement for the logarithmic mean, Chemical Engineering Science 39 (1984) 1635–1636.

[9] M. Sorin, A. Hammache, A. Diallo, Exergy based approach for process synthesis, Energy 25 (2000) 105–129.