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Accounting for Stream Variability in Retrofit Problems using Monte Carlo Simulation

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The aim of this paper is to use Monte Carlo simulation to analyse the effect of stream data variation on the economic performance of retrofit designs. The input stream data is fitted to a distribution which can be sampled from to calculate the outputs of the Heat Exchanger Network model, stochastically. A simple four-stream problem is used to demonstrate the method, comparing two retrofit designs that each reduce the hot utility by 700 kW. Monte Carlo simulation analyses how the similar designs behave differently under the variable conditions and the results show that time-average analysis can not only overestimate the Total Retrofit Profit but can also favour a different design to that favoured by the Monte Carlo results. Of the two compared designs, the Design 2 was selected with an annual Total Retrofit Profit of NZD 215,553, requiring one new exchanger and additional area on an existing one. The Monte Carlo analysis also shed light on controllability and feasibility issues in the Heat Exchanger Network.

1. Introduction

A critical step in any real industrial Heat Exchanger Network (HEN) retrofit is the extraction of the retrofit stream data that accurately reflects the system under consideration. Unlike grassroots designs, where design values are used, actual plant data is required for retrofit projects and can be highly variable. This variability introduces risk and uncertainty into the thermal and economic performance of a retrofit design. Recent developments in the field of HEN retrofit design, such as the Energy Transfer Diagram (Bonhivers et al., 2015), Advanced Composite Curves (Nordman and Berntsson, 2009), and Stream Temperature vs Enthalpy Plots (Lai et al., 2017), have yet to fully factor in stream variability into design even though it can be a significant influence of HEN performance. This analysis of the effects of variability can be conducted using Monte Carlo simulation.

Monte Carlo simulation uses repeated random sampling to obtain results and can handle distributions in data, i.e. stream data variability (fitted to a distribution), as well as optimisation. Monte Carlo simulation is a stochastic tool for design, as opposed to deterministic methods, such as mixed integer linear programming, and is therefore naturally suited to problems where variation in data can be expected. Monte Carlo simulation has been used previously in Process Integration. Monte Carlo simulation has been used for optimisation, such as the optimisation of process flow sheets (Zore et al., 2017) and HEN synthesis design (Novak Pintarič and Kravanja, 2015). Tan et al. (2007) used Monte Carlo simulation to analyse the effect of variability of mass loads on a water network. Benjamin et al. (2017) used Monte Carlo simulation to assess the performance of a bioenergy park when dealing with variable disturbances. These works showed that Monte Carlo simulation could be used to compare different designs based on their response to variabilities or fluctuations.

The aim of this paper is to apply Monte Carlo simulation to the analysis of retrofit design options. This will allow the variability and uncertainty within the stream data to be modelled appropriately, giving additional insight into a retrofit design's performance. In this paper, the recently developed Modified Energy Transfer Diagram (METD) method (Walmsley et al., 2017) is applied to generate various retrofit designs. Using Monte Carlo simulation, the study examines the effect of variability on heat recovery and the economic benefits of a retrofit design. With this approach, greater confidence in the energy savings of retrofit designs can be achieved as the effect of variability can be appropriately assessed and evaluated.

2. Monte Carlo simulation

Variability in important stream properties (e.g. temperature, flow rate) introduces uncertainty into the actual performance of a HEN retrofit compared to design based on average or design values alone. Heat exchangers may perform better or worse than design values depending on this stream variability due to the changes in heat transfer coefficients and/or temperature driving forces. Uncertainty of the performance of the HEN retrofit represents a financial risk in that capital may be applied sub-optimally or economic targets not met. To assess this risk or uncertainty, Monte Carlo simulation can be used. The Monte Carlo simulation takes variable inputs as probability distributions, randomly samples from these distributions for the model calculations, and then returns outputs as a probability distribution of the possible outcomes. This is a stochastic method as each iteration and each simulation will return slightly different results as the calculation uses random values from within the distribution. Therefore, the Monte Carlo simulation can be run over many different iterations to provide better insight into the uncertainty of the inputs and outputs of the model, in this case the HEN. Where the values of input variables are related or correlated in some manner, this is also accounted for in the method. For more details on Monte Carlo modelling see Liu (2008).

3. Method

The proposed method is to be an extension to retrofit analysis that allows retrofit designs to be assessed while considering variability in stream data. The method will be used to compare and analyse retrofit designs using Monte Carlo simulation. The steps of the analysis method are:

1. Identify the retrofit problem.
2. Extract the retrofit stream data
3. Fit input variables to distributions
4. Conduct retrofit analysis and produce retrofit designs
5. Conduct Monte Carlo simulation
6. Evaluate retrofit designs

In the extraction of retrofit stream data, rather than use time-average or design values, stream data will be taken as a series of values recorded over an extended period. Useful stream data may include stream temperatures (inlet and outlet) and heat capacity flow rates. Information about the existing exchangers will also be taken, i.e. existing exchanger area. The variable stream data is then fitted to a distribution of best-fit so that the Monte Carlo simulation can randomly sample the parameter from the probability distribution.

Step 4 of this method involves the retrofit analysis. This will not be presented in this paper as the proposed method is not dependent on a specific retrofit method. To generate the retrofit designs for this paper, Bridge Analysis has been used. This is a method that uses the METD previously developed by Walmsley et al. (2017), adapted from work by Bonhivers et al. (2015) on the Energy Transfer Diagram.

The selected retrofit designs are then modelled, and several outputs are selected. The significant outputs include heat exchanger duties, outlet temperatures, and utility cost. The Monte Carlo simulation is then run for 100,000 iterations where the model inputs are varied based on the input distributions, providing an output distribution of the possible results. The results can then be used to evaluate the performance of each retrofit design and provide guidance with the decision-making. Fitting the inputs to distributions and running the Monte Carlo simulation is handled by @Risk, a Microsoft Excel-based software package developed by Palisade (Palisade, 2018). The proposed method will be explained in more detail using the following illustrative example.

The method differs from techniques based on flexibility or resiliency because rather than examine a HEN's ability to withstand disturbances in the form of variable stream inputs from a controllability perspective, the proposed method looks at how variability affects economic performance as a means to identify potential retrofit designs.

4. Illustrative example

To illustrate the method, a four-stream problem has been used. This HEN has been adapted from Klemeš et al. (2014) and has been retrofitted by Walmsley et al. (2017). The HEN is presented in Figure 1 and has two heat recovery exchangers, two coolers, and one heater. Time-average values have been used for this HEN representation and several set-point temperatures have been identified. These set-point temperatures, or target temperatures, are controlled using the heater or coolers. The only outlet temperature (for a stream within the HEN) that is not controlled is the outlet of E2.

The heat recovery exchangers E1 and E2 have been modelled using the ε-NTU method, where ε is the heat transfer effectiveness and NTU is the number of heat transfer units. All heat exchangers have been assumed to be double pipe counter-flow heat exchangers with fixed UA, where U is the overall heat transfer coefficient and A is the heat transfer area. The UA was fixed at 33.6 W/K for E1 and 12.7 W/K for E2. The overall heat transfer coefficient has been fixed and assumed to be 500 W/m^{2}K for all streams. The heater and coolers have been modelled using $Q = mC_p\Delta T$ as it is assumed that the utility exchangers have been oversized and do not need to be modelled with a fixed UA.

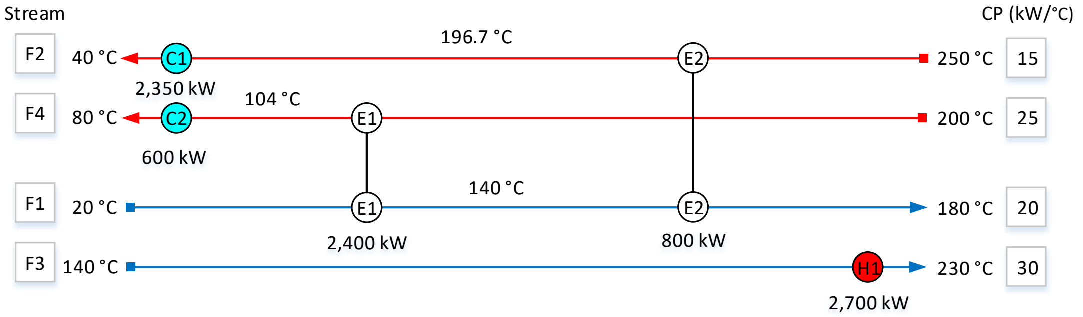

Figure 1: Four-stream HEN to be retrofitted (Walmsley et al., 2017).

4.1 Inputs of the heat exchanger network

The inputs of the model were the supply temperatures and heat capacity flow rates for each of the four streams. The variability of the inputs is based on real plant data that has been scaled so that the values match the time-average values shown in Figure 1. The supply temperature data for stream F1 over approximately 7 months has been presented in Figure 2a. This data is then fitted to a distribution of best-fit. @Risk fits the input data to a distribution using the Akaike Information Criterion (AIC). AIC corresponds to the relative quality of a distribution when compared to other distributions. A wide range of distributions were considered including Normal, Pareto, Weibull, and Beta General Distributions. Based on the AIC values, the best fitting distribution for the F1 supply temperature was the Logistic Distribution. This distribution of the raw data values and the fitted Logistic Distribution is presented in Figure 2b. The ascending cumulative frequencies for the input distribution and Logistic Distribution is also included. The same process of fitting inputs to distributions has been applied to all relevant inputs in the retrofit problem. Additionally, the heat capacity flow rates of F1 and F2 were correlated using @Risk as it was found that there was a correlation between the two inputs.

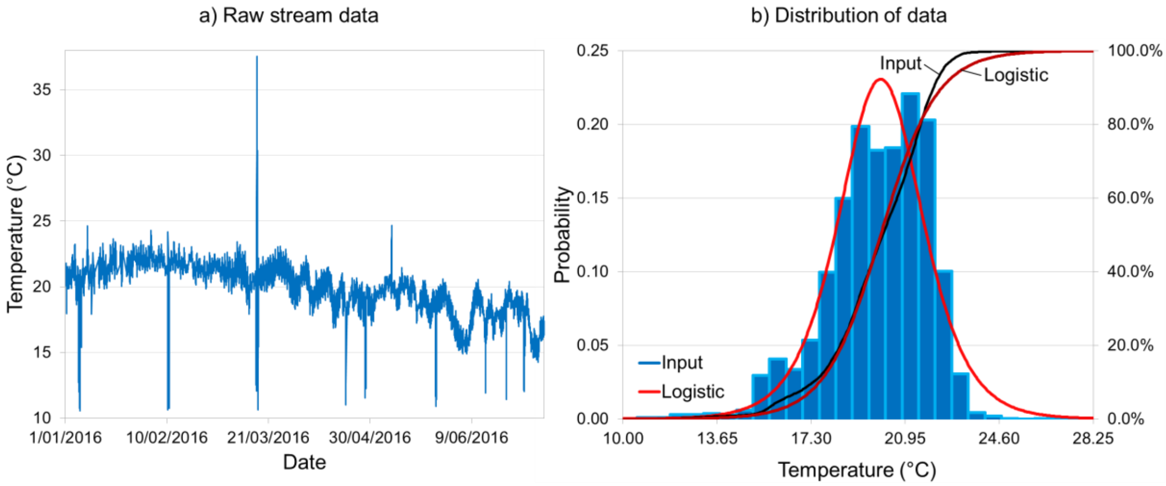

Figure 2: a) Raw stream data over time for the supply temperature of stream F1, and b) distribution of data including fitted distributions.

4.2 Retrofit analysis

For the retrofit analysis, the METD has been used along with the time-average values of the existing HEN, as demonstrated in Walmsley et al. (2017). To illustrate the proposed method, two retrofit designs have selected for comparison from Walmsley et al. (

Figure 3). A global minimum approach temperature of 10 °C was used for the retrofit design. Both retrofit designs are estimated to reduce the utility consumption by 700 kW under time-average design via the addition of a single new heat exchanger, N1 (Figure 3a) or N2 (Figure 3b). Each new exchanger was sized based on time-average values using the ε-NTU method. The UA for each was determined to be 36.0 W/K for N1 and 9.41 W/K for N2, with corresponding areas of 72.1 m^2 and 18.8 m^2, respectively. In addition to this, the second selected retrofit design required additional heat transfer area on E2. The additional area was calculated to be 76.3 m^2. This was required to achieve the 700 kW energy savings. Assessing these retrofit designs using the Monte Carlo simulation will demonstrate how the inherent variability in the stream data will affect the performance of these retrofit designs.

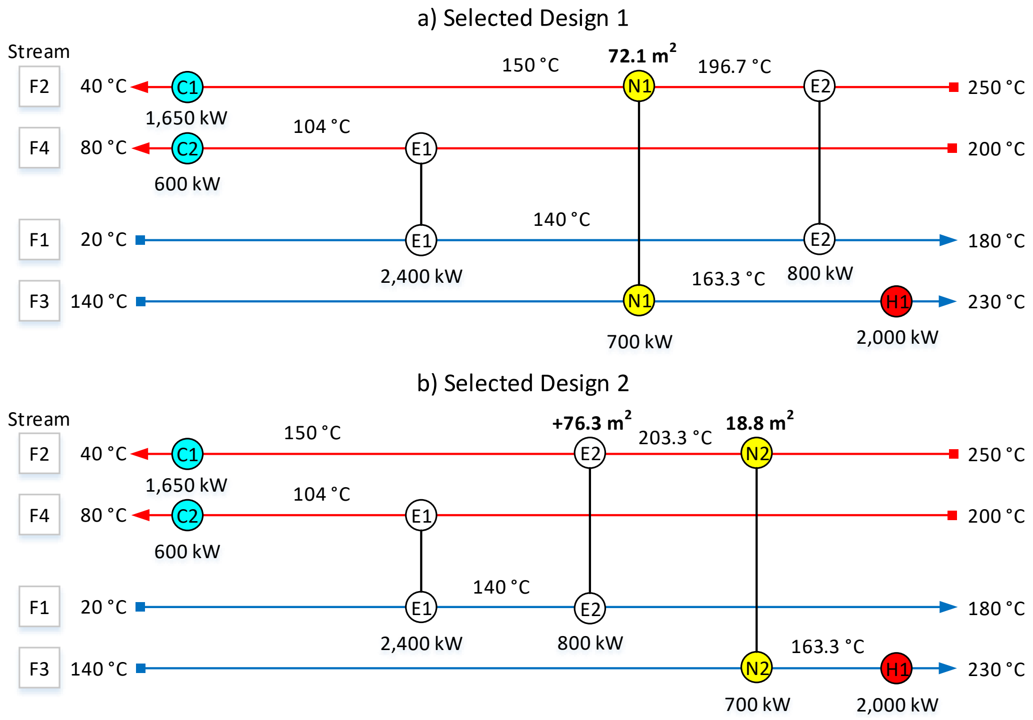

Figure 3: Selected retrofit designs: a) Design 1; b) Design 2.

4.3 Monte Carlo results

The Monte Carlo simulation was run for 100,000 iterations. Several model outputs such as exchanger outlet temperatures, exchanger performance, etc., were identified, and the simulation provided probability distributions for these results. The key results were the duties of all exchangers including utilities. In the two selected retrofit designs, the key differences were the inclusion of the new exchangers, and in the case of Design 2, the additional area on E2. The performance of the new exchangers, and the difference in E2's performance in each design, has been assessed using @Risk and compared in Figure 4. Based on the time-average values, both exchangers should provide 700 kW of heat recovery; however, the Monte Carlo simulation results, shown in Figure 4a, show that N2 performs more consistently than N1. The exchanger duty of N2 is much less variable than that of N1 and the duty of N1 ranges from close to 0 kW to almost 1,400 kW. The implication is that the performance of N2 is much more predictable and reliable while N1 has a chance for increased duty (and potentially improved HEN performance). The reverse is true for the duty of E2. As shown in Figure 4b, the duty of E2 in Design 1 is more consistent than E2 in Design 2. In both cases, this could be because the increased heat transfer area (N1 and E2 in Design 2) is able to handle extremes better than the exchangers with smaller areas (N2 and E2 in Design 1).

The second cooler, C2, has a time-average heat exchanger duty of 600 kW. For both retrofit designs, C2 remains unaffected by the retrofit design, i.e. the output distribution is the same in all cases. However, Monte Carlo simulation highlighted the fact that for approximately 11% of the operating time that the duty of C2 will be negative (i.e. the outlet temperature of F4 from E1 will be below the target temperature) and therefore the operation of the HEN under these conditions will become infeasible (Figure 5a). This may be avoided with proper control strategies and this is highlighted and quantified with Monte Carlo simulation at the design evaluation stage. The output distributions for the duty of H1 is presented in Figure 5b. Using the time-average values, the duties of H1 in Design 1 and 2 would have been 2,000 kW, 700 kW less than 2,700 kW as estimated with the retrofit analysis. In fact, both designs are 20-30 kW short of this target on average.

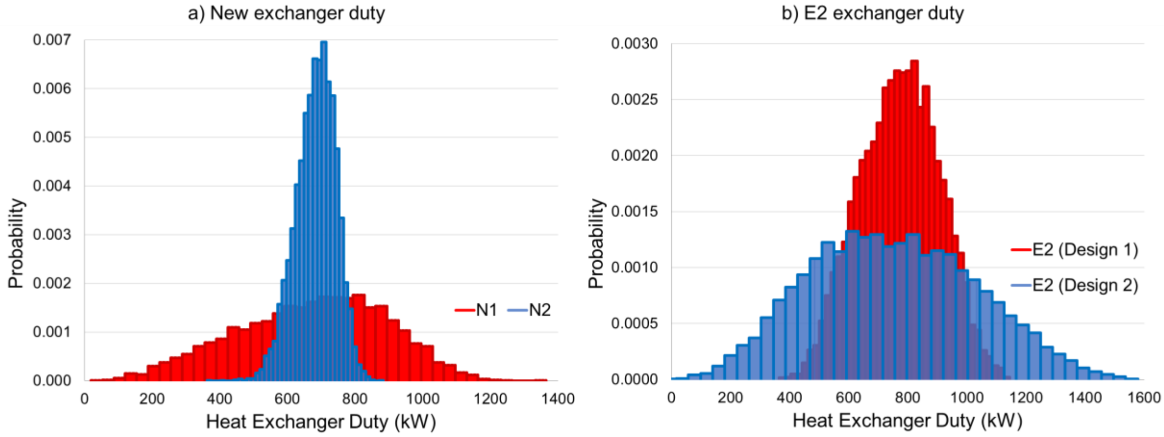

Figure 4: a) Output distribution of the new exchanger (N1 or N2) duty, and b) output distribution of E2's exchanger duty.

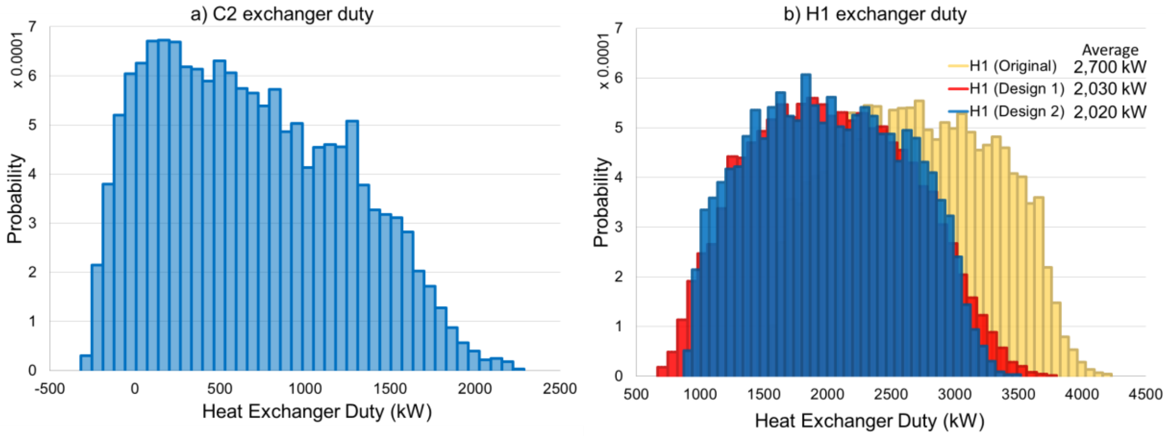

Figure 5: a) Output distribution of C2's exchanger duty, and b) output distributions of H1's exchanger duty in all cases.

Using time-average values, the total retrofit profit (TRP) can be estimated. Utility costs (UC) have been estimated using the hot utility load, a hot utility price of NZD 12/GJ, and 8000 h of operation. Cold utility costs are negligible. Capital costs are based on the heat transfer area (A) and have been annualised (ACC) assuming a discount factor of 10 % and a lifetime of 10 y (Walmsley et al., 2014). The equation for ACC is presented in Eq(1).

$$\text{ACC} = 4000 + 500A^{0.83} \tag{1}$$

Based on time-average, the results show that the TRP of Design 1 is 4 % greater than Design 2. This is unsurprising as the time-average energy savings are near identical and the capital cost of Design 2 is greater than Design 1 due to the additional area on E2. However, a different result is found when accounting for the output probability determined by the Monte Carlo simulation. The output distributions of hot utility (Figure 5b) have been used to determine how often a specific hot utility load is achieved, i.e. how many hours a certain hot utility load can be expected. Calculating the TRP this way gives a different result and shows that based on the Monte Carlo simulation, the TRP of Design 2 is greater than Design 1. Additionally, the TRP based on the Monte Carlo simulation is 16-21% less than the TRP calculated using time-average analysis. This could indicate that without analysing the variability in stream data, profits could be overestimated. Monte Carlo simulation provides an alternative based on probabilistic performance. In the original analysis of these two designs, Design 1 would have been the chosen design based on TRP; however, after analysing the risk due to uncertain stream data, Design 2 becomes the better choice. These results are summarised in Table 1.

Table 1: Summary of Total Retrofit Profit calculations.

Option	Total Retrofit Profit (NZD/y)	
	Time-average Analysis	Monte Carlo Analysis
Design 1	$265,582	$208,965
Design 2	$255,168	$215,553

5. Conclusions

The proposed method incorporates Monte Carlo simulation into the retrofit analysis so that uncertainty introduced by stream data variability can be assessed and used to compare retrofit designs. It has been shown that the Monte Carlo simulation suggests conclusions that differ greatly to the time-average analysis. In the simple example, Design 1 had an annual TRP of NZD 265,582 but only NZD 208,965 after the risk analysis. This showed that there was potential for time-average analysis to over-estimate the economic potential as well as misinform about the more profitable design option. After accounting for stream variability, Design 2 was shown to have the greater TRP, with an annual TRP of NZD 215,553. While the differences between the two designs could be considered insignificant, this analysis is important because of the additional insight it provides into how a retrofit design may respond to stream variability which is not answered by a simple time-average analysis. The Monte Carlo simulation also provides insight into controllability and feasibility issues in the HEN. Future work will compare a range of retrofit designs, analyse the effects on process control design, and examine how Monte Carlo simulation can be used to optimise the heat exchanger sizing in retrofit analysis.

Acknowledgments

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References

Benjamin M.F.D., Tan R.R., Razon L.F., 2017, Assessing the Sensitivity of Bioenergy Parks to Capacity Disruptions using Monte Carlo Simulation, Chemical Engineering Transactions, 56, 475–480.

Bonhivers J.-C., Alva-Argaez A., Srinivasan B., Stuart P.R., 2015, New analysis method to reduce the industrial energy requirements by heat-exchanger network retrofit: Part 2 – Stepwise and graphical approach, Applied Thermal Engineering.

Klemeš J.J., Varbanov P.S., Alwi S.R.W.W., Manan Z.A., 2014, Process Integration and Intensification: Saving Energy, Water and Resources. Walter de Gruyter GmbH & Co KG, Berlin, Germany.

Lai Y.Q., Manan Z.A., Wan Alwi S.R., 2017, Heat Exchanger Network Retrofit Using Individual Stream Temperature vs Enthalpy Plot, Chemical Engineering Transactions, 61, 1651–1656.

Liu J.S., 2008, Monte Carlo Strategies in Scientific Computing. Springer Science & Business Media, Cambridge, U.S.A.

Nordman R., Berntsson T., 2009, Use of advanced composite curves for assessing cost-effective HEN retrofit II. Case studies, Applied Thermal Engineering, 29(2–3), 282–289.

Novak Pintarič Z., Kravanja Z., 2015, A methodology for the synthesis of heat exchanger networks having large numbers of uncertain parameters, Energy, 92, 373–382.

Palisade, 2018, @RISK: Risk Analysis using Monte Carlo Simulation in Excel and Project, Palisade, <www.palisade.com/risk/>, accessed 30.3.2018.

Tan R.R., Foo D.C.Y., Manan Z.A., 2007, Assessing the sensitivity of water networks to noisy mass loads using Monte Carlo simulation, Computers & Chemical Engineering, 31(10), 1355–1363.

Walmsley M.R.W., Lal N.S., Walmsley T.G., Atkins M.J., 2017, A Modified Energy Transfer Diagram for Improved Retrofit Bridge Analysis, Chemical Engineering Transactions, 61, 907–912.

Walmsley T.G., Walmsley M.R.W., Morrison A.S., Atkins M.J., Neale J.R., 2014, A derivative based method for cost optimal area allocation in heat exchanger networks, Applied Thermal Engineering, 70(2), 1084–1096.

Zore Ž., Zirngast K., Pintarič Z.N., Kravanja Z., 2017, Stochastic Multi-Objective Process Optimization by using the Composite Objective Function, Computer Aided Chemical Engineering, 40, 601–606.