

## Pinch Analysis Approach to Energy Planning Using Weighted Composite Quality Index

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Pinch Analysis has evolved over the past four decades from a methodology originally developed for optimising energy efficiency of industrial plants. Applications of Pinch Analysis applications are based on common principles of using stream quantity (e.g., enthalpy) and quality (e.g., temperature) to determine optimal system targets. This targeting step identifies the Pinch Point, which facilitates problem decomposition for subsequent network design. One important class of Pinch Analysis problems is energy planning with footprint constraints. This area of work began with the development of Carbon Emissions Pinch Analysis (CEPA), where energy sources and demands are characterized by carbon footprint as the quality index. This methodology has been extended by using alternative quality indexes, such as water footprint, land footprint, energy transformity, inoperability risk, energy return on investment (EROI) and human fatalities. Despite such developments, these Pinch Analysis variants have the limitation of being able to use one quality index at a time. To date, attempts at developing multiple-index Pinch Analysis methods have only been partially successful. In this work, a multiple-index Pinch Analysis method is developed by using a composite quality index; the latter is assumed to be a weighted linear function of different quality indexes normally used in energy planning, as discussed previously. The weights used to compute the composite index are determined via the Analytic Hierarchy Process (AHP). A case study adapted from a literature example is solved to illustrate this approach.

### 1. Introduction

Pinch Analysis was originally developed as a systematic methodology for determining optimal targets for heat recovery in process plants (Linnhoff et al., 1982). This approach uses information about process stream quantity (enthalpy) and quality (temperature) to determine thermodynamically rigorous targets at the system level; furthermore, problem decomposition principles were developed to allow the systematic design of heat exchanger networks (HENs) to achieve the previously determined targets. The development and popularity of Pinch Analysis grew from the 1980s onwards, leading to the widespread use of Process Integration principles in industry as well as the growth in the body of scientific literature (Linnhoff, 1993). Today, this field is sufficiently well established such that contributions are integrated in modern textbooks (e.g., Smith, 2016), reference books (Klemeš et al., 2011) and handbooks (Klemeš, 2013). A recent review paper gives an account of broad trends in Process Integration (Klemeš et al., 2013). In addition, after four decades of progress, Pinch Analysis and Mathematical Programming have evolved from competing to complementary schools of thought (Klemeš and Kravanja, 2013).

Process Integration techniques have also diversified based on analogies with heat transfer. The earliest such extension was proposed by El-Halwagi and Manousiathakis (1989), which led to the emergence of Mass Integration based on the structural similarities between heat and mass transfer phenomena. Next, integration of water reuse/recycle systems developed as a special case of Mass Integration (Wang and Smith, 1994). This led to the generalization to Resource Conservation Networks (RCNs) by El-Halwagi et al. (2003); key

concepts in this area are to be found in the textbook by Foo (2012). The concept of RCNs covers a broad class of industrial systems, such as networks for efficient use of hydrogen in refineries (Alves and Towler, 2002), ethanol in biorefineries (Shenoy and Shenoy, 2014), solvent recovery systems (Geldermann et al., 2006) and for material recovery using application-specific “properties” or measures of functionality (Kazantzi and El-Halwagi, 2005). Other Pinch Analysis extensions use time as the “driving force” instead of temperature; these approaches have been demonstrated in the literature to diverse problems, such as supply chain/production management (Singhvi and Shenoy, 2002), human resource allocation (Foo et al., 2010), small enterprise production planning (Lim et al., 2013). The broad range of applications that have been developed thus far suggests the potential for further diversification (Tan et al., 2015).

One important class of Pinch Analysis applications is energy planning with quality constraints. This problem was originally proposed as Carbon Emissions Pinch Analysis (CEPA) by Tan and Foo (2007), using CO<sub>2</sub> intensity or carbon footprint as an index of energy quality. Subsequent works have proposed to extend the methodology using different quality indexes, such as water footprint (Tan et al. 2009), energy transformity (Bandyopadhyay et al., 2010), inoperability risk (Tan and Foo, 2013) and energy return on investment (EROI) (Walmsley et al., 2014). A recent review paper (Foo and Tan, 2016) documents the key developments in this sub-area of Process Integration. The introduction of different quality metrics for energy systems planning is based partly on the need to link this area to broad sustainability themes, for which safe limits have been proposed on a global scale (Rockström et al., 2009). In Process Integration literature, these sustainability themes have been operationalized as footprint metrics used within the context of process selection (Sikdar, 2003) or life cycle assessment (De Benedetto and Klemeš, 2009). The review by Čuček et al. (2012) provides a comprehensive overview of important footprint metrics that reflect various sustainability dimensions. Thus, there have been recent attempts to consider more complex problems in the Pinch Analysis framework. For example, Jia et al. (2016) used simultaneous graphical approach to multiple quality indices for the case of China, while Krishna Priya and Bandyopadhyay (2016) proposed a prioritized cost approach applied to the Indian power sector.

In this work, an alternative approach to Pinch Analysis with multiple quality indices is proposed based on the concept of aggregation, which has been extensively applied in the context of sustainability analysis (e.g., Sikdar, 2009). The proposed aggregation method makes use of the Analytic Hierarchy Process (AHP) (Saaty, 1980) to determine weights of different energy quality indices. While AHP is a popular decision analysis approach that has been combined with other methodologies such as Mathematical Programming (Ho, 2008), this work presents a novel hybridization of AHP with Pinch Analysis for sustainable energy systems planning considering multiple quality metrics. The rest of this paper is organized as follows. A formal problem statement is given in Section 2. Then, the detailed steps of the methodology are given in Section 3. An illustrative case study is solved in Section 4 to illustrate the hybrid AHP/Pinch Analysis approach. Finally, conclusions and prospects for future work are given in Section 5.

## 2. Problem Statement

The formal problem statement is adapted from the original energy planning problem proposed by Tan and Foo (2007) and may be stated as follows:

- Given a set of energy sources, designated as SOURCES =  $\{i | i = 1, 2, \dots, M\}$ , to be allocated to energy demands. Each source (e.g. coal, oil, etc.) has an available energy of  $S_i$  and is characterized by quality indices  $SQ_{ik}$  with respect to a set of quality aspects QUALITY =  $\{k | k = 1, 2, \dots, O\}$ .
- It is assumed that all quality indices  $k$  have two important properties (Tan and Foo, 2013). Firstly, low numerical values are more desirable. Secondly, the indices must conform to linear mixing rules. Appropriate mathematical transformations may be used for indices that do not possess these properties. Furthermore, the quality indices may be measurable quantitative factors (e.g., carbon footprint) or numerical expressions of subjective factors (e.g., social acceptability).
- A composite quality index,  $SCQ_i$  can be determined for each source  $i$ . This factor is assumed to be a weighted average of multiple quality indices,  $SCQ_i = \sum_k W_k SQ_{ik}$ . The weights are assumed to be determined via AHP, and are normalized such that  $1 = \sum_k W_k$ . These weights reflect the priority assigned by the decision-maker to different quality aspects.
- Given a set of energy demands, designated as DEMANDS =  $\{j | j = 1, 2, \dots, N\}$ . Each demand requires an energy supply of  $D_j$  and has a maximum composite quality limit of  $DCQ_j$ . As with the sources, this factor is assumed to be a weighted average of multiple impact scores,  $DCQ_j = \sum_k W_k DQ_{jk}$ . However, no unique limit is set for each quality index, which differentiates this problem from the generalized form described by Tan and Foo (2013). Instead, overall quality is measured in terms of the limiting factor  $DCQ_j$ , which allows a compensatory effect to be considered for different criteria.

- It is further assumed that there exists an external, high quality energy resource  $F$ , whose composite quality index is  $FCQ$ , which is again determined as  $FCQ = \sum_k w_k FQ_k$ .
- The energy sources and demands in the system can potentially be matched as shown in the superstructure given in Figure 1. The problem is to optimally allocate energy streams, so as to maximize utilization of internal energy sources (i.e., minimize requirement for the external resource) while ensuring that the composite quality index limits of the demands are satisfied.

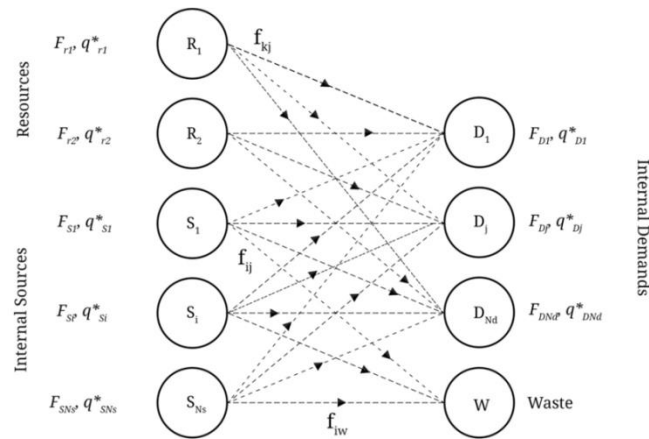


Figure 1: General superstructure for source-sink problems

### 3. Methodology

Different graphical and algebraic methods have been developed for solving source-sink problems (see review paper by Foo (2009) for resource conservation problems; or Foo and Tan (2016) for various environmental footprint problems). The underlying similarity of all these seemingly diverse methodologies is highlighted in a recent paper (Bandyopadhyay, 2015), while the wide range of applicability to different industrial problems can be seen in the textbook by Foo (2012).

The broad objective of the method is to obtain an allocation network of all sources which satisfy the demands based on several quantitative and qualitative indicators. The first step in doing so is to form a linear combination of all quality indices. To do this, AHP is used for weighting. Eigen vector corresponds to the largest eigen vector of the pair-wise comparison of all quality indices yields the weight for each quality index. Using these weights, an overall sustainability index can then be calculated. However, each quality index must be normalised before calculation of the overall sustainability index. Quantitative indices are normalised by division with the maximum value of the index. Qualitative values are first quantified by applying AHP across all sources to compare them on the basis of the qualitative index in question, and then normalised by division by the maximum value. It must be noted that this normalisation is to ensure a uniform scale of values ranging from 0 to 1 before combining them using the weights obtained earlier. Also, a reverse scale is ensured during normalisation, i.e., lower value denote more desirable quality. In the case of quality indices that do not follow a reverse scale (e.g., EROI), inverse of the indicator may be considered as the quality and normalised as above. Once the normalised values of both quantitative and qualitative indices are obtained, the overall sustainability index can be calculated as a simple linear combination of these values. This overall sustainability index is then supplied to the Pinch Algorithm to calculate the resource requirement and the network allocation. The detailed steps of targeting and network synthesis are well established in Process Integration literature and need not be described here.

### 4. Case Study

To demonstrate the applicability of the proposed methodology, sustainable electricity sector planning for India is considered. The present electrical demand of the country (181.56 GW) is met by electricity generated from coal, oil, natural gas, hydro, nuclear, and renewables sources. For the overall sustainability index, quantitative indices such as carbon footprint (kT CO<sub>2</sub>-e/GWh), EROI (dimensionless), land footprint (m<sup>2</sup>/MW), water footprint (m<sup>3</sup>/MWh) and a qualitative index (risk to human lives), are considered. Detailed values of the existing power plants and corresponding qualities are given in Table 1. Assuming a 7 % growth over next 5 years, the electricity demand of Indian is going to be 254.65 GW. Targeted qualities for the demand are also tabulated in

Table 1. It may be noted that actual values of these indices should be decided by the Indian Government based on the economic and societal development considerations. It is assumed, for simplicity, that the enhanced demand will be met from the renewable sources while satisfying overall sustainability index.

Based on the opinions of the expert, a pair-wise comparison matrix between different quality indices (also known as the judgment matrix) is prepared and shown in Table 2. Applying the methodology of AHP, relative weights for different indices are calculated and shown in Table 3. The sustainability quality index can now be defined as the weighed sum of the five qualities using the weights given in Table 3. However, to calculate the numerical value of the overall sustainability index, *Risk to humans* should be quantified. AHP is applied to quantify this quality in a similar way (detailed calculations are not shown for brevity). Based on the normalised weights, the quantitative values for different attributes of *Risk to humans* are obtained as follows: very high risk is 1; high risk is 0.629; medium risk is 0.206; and low risk is 0.085. To take care of the different numerical values, all quality indices are normalized to obtain a value within the range [0, 1]. Furthermore, all quality indices should follow the inverse scale (lower numerical value denotes better quality). Quality indices such as carbon footprint, land footprint, and water footprint, already follow an inverse scale, and hence they are normalised with respect to the corresponding maximum value. It should be noted that EROI does not follow the inverse scale, and hence  $1/EROI$  is considered as the quality index and it is normalised with respect to its maximum value. These normalized indices and the overall sustainability indices for different sources and demand are presented in Table 4.

Table 1: Existing distribution of power plants and corresponding quality indices

	Current capacity (GW)	Carbon footprint (kT CO <sub>2</sub> -e/GWh)	EROI	Land footprint (m <sup>2</sup> a/kWh)	Water footprint (m <sup>3</sup> /MWh)	Risk to humans (qualitative)
Coal	99.50	0.990	25.00	72.00	27.04	Very high
Oil	1.19	0.700	16.00	43.16	2.18	High
Natural Gas	17.71	0.611	35.00	37.51	5.72	Medium
Hydro	38.20	0.013	41.00	0.04	113.26	Medium
Nuclear	4.78	0.026	8.00	0.40	11.34	High
Renewables	20.18	0.096	37.96	0.004	0.004	Low
Demand	254.65	0.400	15.00	0.350	1.50	Low

Table 2: Pair-wise comparison matrix between various quality indices

	Carbon footprint	EROI	Land footprint	Water footprint	Risk to humans
Carbon footprint	1	2	7	7	9
EROI	1/2	1	6	6	8
Land footprint	1/7	1/6	1	1	2
Water footprint	1/7	1/6	1	1	2
Risk to humans	1/9	1/8	1/2	1/2	1

Table 3: Weights assigned to qualities to calculate overall sustainability index using AHP

	Carbon footprint (kT CO <sub>2</sub> -e/GWh)	EROI	Land footprint (m <sup>2</sup> a/kWh)	Water footprint (m <sup>3</sup> /MWh)	Risk to humans (qualitative)
Weights	0.4836	0.3381	0.0687	0.0687	0.0409

Using the overall sustainability indicators as the quality index for the overall problem, procedures for Pinch Analysis may be applied to determine the minimum requirement of the renewables. By applying graphical or algebraic methodologies of Pinch Analysis, it may be concluded that 75.81 GW of renewables should be installed and 2.72 GW of coal based power plants should be shut down to achieve the targeted sustainability.

Table 4: Normalized quality indices and overall quality index

	Carbon footprint (kT CO <sub>2</sub> -e/GWh)	1/EROI	Land footprint (m <sup>2</sup> a/kWh)	Water footprint (m <sup>3</sup> /MWh)	Risk to humans (qualitative)	Overall sustainability index
Coal	1.000	0.320	1.000	0.239	1.000	0.718
Oil	0.707	0.500	0.599	0.019	0.629	0.579
Natural Gas	0.617	0.229	0.521	0.051	0.206	0.423
Hydro	0.013	0.195	0.001	1.000	0.206	0.149
Nuclear	0.026	1.000	0.006	0.100	0.629	0.384
Renewables	0.097	0.211	0.000	0.000	0.085	0.122
Demand	0.404	0.533	0.005	0.013	0.085	0.380

## 5. Conclusions

A multiple-index pinch analysis method has been developed in this paper. This approach uses AHP to determine a composite quality index and thus take into account multiple quality indices within the Pinch Analysis framework; doing so overcomes the key limitation of previously developed Pinch Analysis approaches to sustainable energy system planning. Furthermore, the use of AHP allows subjective or qualitative aspects to be approximately quantified and integrated into the Pinch Analysis framework. An illustrative case study has been solved to demonstrate this method. Future work may consider other method such as principal component analysis.

## References

- Alves J.J., Towler G.P., 2002. Analysis of refinery hydrogen distribution systems. *Industrial & Engineering Chemistry Research* 41, 5759-5769.
- Bandyopadhyay S., 2006. Source composite curve for waste reduction. *Chemical Engineering Journal* 45, 5287-5297.
- Bandyopadhyay S., Sahu G.C., Foo D.C.Y., Tan R.R., 2010. Segregated Targeting for Multiple Resource Networks Using Decomposition Algorithm. *AIChE Journal* 56, 1235-1248.
- Bandyopadhyay S. 2015. Mathematical foundation of pinch analysis. *Chemical Engineering Transactions* 45, 1753-1759.
- Čuček L., Klemeš J.J., Kravanja Z., 2012. A review of footprint analysis tools for monitoring impacts on sustainability. *Journal of Cleaner Production* 34, 9-20.
- De Benedetto L., Klemeš J.J., 2009. The Environmental Performance Strategy Map: an integrated LCA approach to support the strategic decision-making process. *Journal of Cleaner Production* 17, 900-906.
- El-Halwagi M.M., Manousiathakis V., 1989. Synthesis of Mass-Exchange Networks. *AIChE Journal* 35, 1233-1244.
- Foo D.C.Y., 2009. A State-of-the-art Review of Pinch Analysis Techniques for Water Network Synthesis. *Industrial & Engineering Chemistry Research* 48(11), 5125-5159.
- Foo D.C.Y., 2012. *Process Integration for Resource Conservation*. CRC Press, Boca Raton, FL, USA.
- Foo D.C.Y., Hallale N., Tan R.R. 2010. Optimize shift scheduling using pinch analysis. *Chemical Engineering* 117, 48-52.
- Foo D.C.Y., Tan R.R., 2016. A review on process integration techniques for carbon emissions and environmental footprint problems. *Process Safety and Environmental Protection*, in press, doi:10.1016/j.psep.2015.11.007).
- Geldermann J., Treitz M., Schollenberger H., Rentz O., 2006. Evaluation of VOC recovery strategies: Multi-objective pinch analysis (MOPA) for the evaluation of VOC recovery strategies. *OR Spectrum* 28, 3-20.
- Ho W., 2008. Integrated analytic hierarchy process and its applications – a literature review. *European Journal of Operational Research* 186, 211 – 228.
- Jia X., Li Z. Wang F., Foo D.C.Y., Tan R.R., 2016. Multi-dimensional pinch analysis for sustainable power generation sector planning in China. *Journal of Cleaner Production* 112, 2756-2771.
- Kazantzi V., El-Halwagi M.M., 2005. Targeting material reuse via property integration. *Chemical Engineering Progress* 101, 28-37.
- Klemeš J.J., Friedler F., Bulatov I., Varbanov P., 2011. *Sustainability in the Process Industry – Integration and Optimization*. McGraw-Hill, New York, USA.
- Klemeš J.J., ed. 2013. *Handbook of Process Integration*. Elsevier/Woodhead Publishing, Cambridge, UK.

- Klemeš J.J., Kravanja Z., 2013. Forty years of heat integration: pinch analysis (PA) and mathematical programming (MP). *Current Opinion in Chemical Engineering* 2, 461-474.
- Klemeš J.J., Varbanov P.S., Kravanja Z., 2013. Recent developments in Process Integration. *Chemical Engineering Research and Design* 91, 2037-2053.
- Krishna Priya G.S., Bandyopadhyay S., 2016. Multiple Objectives Pinch Analysis. Resources, Conservation and Recycling, in press, DOI:10.1016/j.resconrec.2016.02.005.
- Lim J.S.H., Foo D.C.Y., Ng D.K.S., Abdul Aziz R., Tan R.R., 2014. Graphical tools for production planning in small medium industries (SMIs) based on pinch analysis. *Journal of Manufacturing Systems* 33, 639-646.
- Linnhoff B., Townsend D.W., Boland D., Hewitt G.F., Thomas B.E.A., Guy A.R., Marshall R.H., 1982. *A User Guide on Process Integration for the Efficient Use of Energy*. Institute of Chemical Engineers, Rugby, UK.
- Linnhoff B. 1993. Pinch Analysis: A State-of-Art Overview. *Chemical Engineering Research and Design*. 71, 503-522.
- Manan Z.A., Tan Y.L., Foo D.C.Y., 2004. Targeting the minimum water flowrate using water cascade analysis technique. *AIChE Journal* 50, 3169-3183.
- Rockström J., Steffen W., Noone K., Persson A., Chapin F.S., Lambin E.F., Lenton T.M., Scheffer M., Folke C., Schellnhuber H.J., Nykvist B., De Wit C.A., Hughes T., Van der Leeuw S., Rodhe H., Sorlin S., Snyder P.K., Constanza R., Svedin U., Falkenmark M., Karlberg L., Corell R.W., Fabry V.J., Hansen J., Walker B., Liverman D., Richardson K., Crutzen P., Foley J.A., 2009. A safe operating space for humanity. *Nature* 461, 472-475.
- Saaty T.L., 1977. A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology* 15, 234 – 281.
- Saaty T.L., 1980. *The analytic hierarchy process*. McGraw-Hill, New York, USA.
- Shenoy U.V., 2011. Unified targeting algorithm for diverse process integration problems of resource conservation networks. *Chemical Engineering Research and Design* 89, 2686-2705.
- Shenoy A.U., Shenoy U.V., 2014. Designing optimal bioethanol networks with purification for integrated biorefineries. *Energy Conversion and Management* 88, 1271-1282.
- Sikdar S.K., 2003. Sustainable Development and Sustainability Metrics. *AIChE Journal* 49, 1928 – 1932.
- Sikdar S.K., 2009. On aggregating multiple indicators into a single metric for sustainability. *Clean Technologies and Environmental Policy* 11, 157 – 161.
- Singvhi A., Shenoy U.V., 2002. Aggregate planning in supply chains by pinch analysis. *Chemical Engineering Research and Design* 80, 597-605.
- Smith R., 2016. *Chemical Process: Design and Integration*, 2<sup>nd</sup> Edition. Wiley, Chichester, UK.
- Tan R.R., Foo D.C.Y., 2007. Pinch analysis approach to carbon-constrained energy sector planning. *Energy* 32, 1422-1429.
- Tan R.R., Foo D.C.Y., Aviso K.B., Ng D.K.S., 2009. The Use Of Graphical Pinch Analysis For Visualizing Water Footprint Constraints In Biofuel Production. *Applied Energy* 86, 605-609.
- Tan R.R., Foo D.C.Y., 2013. Pinch analysis for sustainable energy planning using diverse quality measures. In: Klemeš, J. J., ed. *Handbook of Process Integration*. Elsevier/Woodhead Publishing, Cambridge, UK.
- Tan R.R., Bandyopadhyay S., Foo D.C.Y., Ng D.K.S., 2015. Prospects for novel pinch analysis application domains in the 21st century. *Chemical Engineering Transactions* 45, 1741–1746.
- Walmsley M.R.W., Walmsley T.G., Atkins M.J., Kamp P.J.J., Neale J.R., 2014. Minimising carbon emissions and energy expended for electricity generation in New Zealand through to 2050. *Applied Energy* 135, 656-665.
- Wang Y.P., Smith R., 1994. Wastewater minimisation. *Chemical Engineering Science* 49, 981–1006.