Department of Energy Technology

Development and application of a multicriteria decision support framework for planning or retrofitting district heating systems

Haichao Wang

Aalto University

DOCTORAL DISSERTATIONS

Aalto University publication series
DOCTORAL DISSERTATIONS 212/2013

Development and application of a multicriteria decision support framework for planning or retrofitting district heating systems

Haichao Wang

A doctoral dissertation completed for the degree of Doctor of Science (Technology) (Doctor of Philosophy) to be defended, with the permission of the Aalto University School of Engineering, at a public examination held at the Auditorium M232 of the Mainbuilding (Otaniemi, Espoo) on 19 December 2013 at 12 noon.

Aalto University
School of Engineering
Department of Energy Technology

Supervising professor
Professor Risto Lahdelma, Aalto University

Thesis advisor
Professor Risto Lahdelma, Aalto University

Preliminary examiners
Simon Harvey, Professor, Chalmers University of Technology, Sweden
Agis M. Papadopoulos, Professor, Aristotle University Thessaloniki, Greece

Opponent
Miimu Airaksinen, Research Professor, VTT, Finland

Aalto University publication series
DOCTORAL DISSERTATIONS 212/2013

ISBN 978-952-60-5493-3
ISBN 978-952-60-5494-0 (pdf)
ISSN-L 1799-4934
ISSN 1799-4934 (printed)
ISSN 1799-4942 (pdf)
http://urn.fi/URN:ISBN:978-952-60-5494-0

Unigrafia Oy
Helsinki 2013

Finland

Publication orders (printed book):
The dissertation can be read at http://lib.tkk.fi/Diss/

441 697
Printed matter

Aalto University

Aalto University, P.O. Box 11000, FI-00076 Aalto www.aalto.fi

Abstract

Author
Haichao Wang

Name of the doctoral dissertation
Development and application of a multicriteria decision support framework for planning or retrofitting district heating systems

Publisher School of Engineering

Unit Department of Energy Technology

Series Aalto University publication series DOCTORAL DISSERTATIONS 212/2013

Field of research Energy Technology

Manuscript submitted 17 June 2013 **Date of the defence** 19 December 2013

Permission to publish granted (date) 26 November 2013 **Language** English

☐ **Monograph** ☒ **Article dissertation (summary + original articles)**

Abstract

CHP-based, combined district heating (DH) systems with gas-fired boilers for peak heating load compensation have several advantages compared to traditional DH systems. They have a relatively high level of energy and environmental efficiency. However, there is a lack of a decision support system aiding in the planning or retrofitting of them. Therefore, the aim of this dissertation is to demonstrate how these kinds of DH systems are designed and operated as well as to develop a decision support framework not only from an economic viewpoint, but also in relation to energy, technology, and environment issues.

First, the excessive heat supply rate (EHSR), which indicates the thermal maladjustment extent of heat substations, is presented to determine the installation strategy of peak shaving gas-fired boilers. On this basis, the combined heating alternatives to be addressed are constructed with a different basic heat load ratio; moreover, the design and operation of the system is discussed extensively. Then, the dissertation presents an application-oriented, multi-criteria decision support framework for evaluating different combined heating alternatives in a real-life DH system in Daqing, China. Before doing the multicriteria decision analysis (MCDA), a corresponding criteria aggregation system is developed, based on which criteria weights can be elicited using fuzzy AHP in combination with the concept of a 'complementary judgment matrix' (CJM) and hypothesis test. A feasible weight space instead of a deterministic weight vector is then proposed and utilized in the MCDA. Subsequently, the techno-economic performance, atmospheric environmental impact, reliability, and energy efficiency of the systems are modeled respectively in order to obtain the criteria measurements needed for decision support. Stochastic multicriteria acceptability analysis (SMAA) is implemented to synthetically handle the problem.

The results indicate that combined district heating systems consisting of CHP and gas-fired boilers can be economically more feasible and sustainable, and it is environmentally efficient to use gas-fired boilers for peak heating load compensation. The most preferred basic heat load ratio in the demonstration case should be between 0.66 and 0.77, with relatively high confidence factors. In all, the present decision support system can be useful for planning or retrofitting and operating the combined district heating system. Nevertheless, it can be extended and applied to other energy supply systems as well.

Keywords combined district heating, CHP, gas-fired boiler, peak shaving heating, environmental impact, SMAA

ISBN (printed) 978-952-60-5493-3 **ISBN (pdf)** 978-952-60-5494-0

ISSN-L 1799-4934 **ISSN (printed)** 1799-4934 **ISSN (pdf)** 1799-4942

Location of publisher Helsinki **Location of printing** Helsinki **Year** 2013

Pages 150 **urn** http://urn.fi/URN:ISBN:978-952-60-5494-0

Aalto-yliopisto

Tiivistelmä

Aalto-yliopisto, PL 11000, 00076 Aalto www.aalto.fi

Tekijä
Haichao Wang

Väitöskirjan nimi
Monikriteerimenetelmien kehittäminen ja soveltaminen kaukolämpöjärjestelmien suunnittelussa ja laajentamisessa

Julkaisija Insinööritieteiden korkeakoulu

Yksikkö Energiatekniikan laitos

Sarja Aalto University publication series DOCTORAL DISSERTATIONS 212/2013

Tutkimusala Energiatekniikka

Käsikirjoituksen pvm 17.06.2013 **Väitöspäivä** 19.12.2013

Julkaisuluvan myöntämispäivä 26.11.2013 **Kieli** Englanti

☐ **Monografia** ☒ **Yhdistelmäväitöskirja (yhteenveto-osa + erillisartikkelit)**

Tiivistelmä

Yhteistuotantoon perustuvissa kaukolämpöjärjestelmissä, joissa käytetään kaasukäyttöisiä huippulämpökattiloita, saavutetaan useita hyötyjä perinteisiin kaukolämpöjärjestelmiin verrattuna. Erityisesti energiatehokkuutta ja ympäristötehokkuutta voidaan parantaa. Kyseisten yhdistettyjen kaukolämpöjärjestelmien suunnittelun tai laajentamisen tueksi ei ole olemassa riittäviä päätöksenteon tukijärjestelmiä Tämän työn tavoitteena on esittää kuinka kyseisiä kaukolämpöjärjestelmiä suunnitellaan ja ajetaan, sekä kehittää tämän avuksi monikriteerisen päätöksenteon tukimenetelmiä, joilla voidaan huomioida taloudellisten näkökulmien lisäksi myös energiaan, teknologiaan ja ympäristöön liittyvät näkökulmat.

Aluksi työssä esitetään huippulämpökattiloiden asennusstrategia pohjautuen yhteistuotannon ja lämmön kulutuksen epätasapainoon lämmönjakokeskuksissa. Tämän perusteella luodaan erilaisiin perustuotannon osuuksiin perustuen vaihtoehtoisia yhdistettyjä kaukolämpöjärjestelmiä. Näiden järjestelmien suunnittelua ja käyttöä tarkastellaan laajasti. Tämän jälkeen työssä esitetään sovelluslähtöinen monikriteerisen päätöksenteon tukijärjestelmä vaihtoehtoisten yhdistettyjen kaukolämpöjärjestelmien evaluoimiseksi todellisessa Daqingin (Kiina) kaukolämpöjärjestelmässä. Monikriteerianalyysiä varten kehitetään AHP-menetelmään perustuva variaatio, jossa sovelletaan CJM (complementary judgment matrix) menetelmää ja hypoteesin testausta. Monikriteerianalyysia sovelletaan mallittamaan kaukolämpöjärjestelmän teknistaloudellista suorituskykyä, ilmastovaikutuksia, luotettavuutta ja energiatehokkuutta. Epävarman, epätarkan ja osittain puuttuvan informaation käsittelemiseksi sovelletaan stokastista monikriteeristä arvostusanalyysimenetelmää (SMAA).

Tulosten perusteella yhdistetyt kaukolämpöjärjestelmät voivat olla paitsi taloudellisesti edullisia, myös ympäristövaikutusten kannalta tehokkaampia. Paras perustuotannon osuus oli esimerkkitapauksissa suurella varmuudella välillä 0.66 and 0.77. Esitettyä monikriteerinen päätöksenteon tukijärjestelmää voidaan pitää hyödyllisenä yhdistettyjen kaukolämpöjärjestelmien suunnittelussa ja ajotavan määrittämisessä. Järjestelmää voidaan laajentaa ja soveltaa myös muihin energiantuotantojärjestelmiin.

Avainsanat yhdistetty kaukolämpöjärjestelmä, sähkön ja lämmön yhteistuotanto (CHP), kaasukäyttöinen huippulämpökattila, kulutushuipun leikkaus, ympäristövaikutukset, stokastinen monikriteerinen arvostusanalyysi (SMAA)

ISBN (painettu) 978-952-60-5493-3 **ISBN (pdf)** 978-952-60-5494-0

ISSN-L 1799-4934 **ISSN (painettu)** 1799-4934 **ISSN (pdf)** 1799-4942

Julkaisupaikka Helsinki **Painopaikka** Helsinki **Vuosi** 2013

Sivumäärä 150 **urn** http://urn.fi/URN:ISBN:978-952-60-5494-0

Preface

The work leading up to this dissertation has been carried out in the School of Municipal and Environmental Engineering, Harbin Institute of Technology and the Department of Energy Technology, Aalto University. I want to express my thanks to Professors Pinghua Zou and Wenling Jiao for their support and encouragement when completing the dissertation. Special thanks must be addressed to the author's supervisor, Professor Risto Lahdelma, for his inspiring and supportive instructions to me during my work in Finland. I would also like to acknowledge Professors Pekka Ahtila and Sanna Syri for their help in completing the theoretical study plan and publishing journal papers.

I cherish the working experience in the two universities, which have different cultures and which have broadened my horizon both in science and everyday life. I have enjoyed the time spent with my colleagues. Specifically, I am grateful to Helena Eklund, Seija Erander-Luukkanen, and Mika Pantsu for helping me to attend scientific conferences and leisure activities.

I also want to express my great appreciations to the pre-examiners, professor Simon Harvey from Charmers University of Technology and professor Agis M. Papadopoulos from Aristotle University Thessaloniki, for their invaluable comments and recommendations on the thesis.

My work has mainly been funded by the Chinese Eleventh and Twelfth Five-Year-Plans. I also thank the Research Foundation of Helsinki University of Technology. Without their support, this work would have never been possible.

Espoo, September 2013

Haichao Wang

Table of Contents

List of publications

I. Haichao Wang, Wenling Jiao, Pinghua Zou, & Jingcheng Liu. (2010). Analysis of an effective solution to excessive heat supply in a city primary heating network using gas-fired boilers for peak load compensation. *Energy and Buildings 42*(11), 2090–2097.

II. Haichao Wang, Wenling Jiao, Risto Lahdelma, & Pinghua Zou. (2011). Techno-economic analysis of a coal-fired CHP based combined district heating system with gas-fired boilers for peak load compensation. *Energy Policy 39*(12), 7950–7962.

III. Haichao Wang, Wenling Jiao, Risto Lahdelma, Pinghua Zou, & Shuhui Zhan. (2013). Atmospheric environmental impact assessment of a combined district heating system. *Building and Environment 64*(6), 200–212.

IV. Haichao Wang, Pinghua Zou, & Wenling Jiao. (2011). Reliability assessment of combined district heating system using quota heating coefficient. *Advanced Materials Research, 243–249*, 5017–5020, special issue for selected papers from proceedings of *the 1st International Conference on Civil Engineering, Architecture and Building Materials,* Haikou, China.

V. Haichao Wang, Wenling Jiao, Risto Lahdelma, & Pinghua Zou. (2011). Development of multicriteria index system and weighting optimization for a district heating system. In proceedings of *the 1st International Symposium & 10th Balkan Conference on Operational Research*, Thessaloniki, Greece , volume 1, 365–372.

Author's contribution

Haichao Wang has been the main researcher and author of all of the papers. Paper [I] took advantage of M.Sc. Jingcheng Liu's survey of Daqing's combined district heating system in China. Professor Risto Lahdelma provided useful suggestions for papers [II], [III] and [V]; he also carried out some editing work on the early draft of these papers. Paper [III] was improved thanks to Professor Sanna Syri's invaluable comments.

Nomenclature

Abbreviations

ADMS	Atmospheric Dispersion Model System
AERMOD	**A**MS/**E**PA **R**egulatory **MOD**el
AHP	Analytic Hierarchy Process
AMS	American Meteorological Society
BCHP	Building Combined Heat and Power
CALPUFF	CALifornia PUFF model
CFB	Circulating Fluidized Bed
CHP	Combined Heat and Power
CJM	Complementary Judgment Matrix
COP	Coefficient Of Performance
DEM	Digital Elevation Model
DH	District Heating
DM	Decision Maker
DSS	Decision Support System
ECOP	Equivalent Coefficient Of Performance
EE	Equivalent Electricity
EHSR	Excessive Heat Supply Rate
EPA	US Environmental Protection Agency
FAHP	Fuzzy Analytic Hierarchy Process
GHG	Green House Gas
GLC	Ground Level Concentration
HVAC	Heating, Ventilating & Air Conditioning
IEA	International Energy Agency
IRR	Internal Rate of Return
ISC	Industrial Source Complex
LCA	Life Cycle Assessment
LHV	Lower Heating Value
LP	Linear Programming
MCDA	MultiCritera Decision Analysis
MILP	Mixed Integer Linear Programming

MOO	Multi-Objective Optimization
MSD	Mean Spatial Distribution
NDRC	National Development and Reform Commission of China
NHC	Net Heating Cost
NPDW	Normalized Population Distribution Weight
NPV	Net Present Value
PM	Particulate Matter
PV	Present Value
SCADA	Supervisory Control And Data Acquisition
SMAA	Stochastic Multicriteria Acceptability Analysis
TMY	Typical Meteorological Year
WLSM	Weighted Least Square Method
ZEB	Zero Energy Building

Symbols

A_c	Annual cost
$\boldsymbol{A}$	Judgment matrix
a_{ij}	Element of a judgment matrix
a_i^h	Holistic acceptability index of alternative i
B	Coal consumption or gas consumption
B^*	Coal consumption of a typical condensing power plant
b_i^r	Rank acceptability index of alternative i
$b^*_{es,c}$	Coal consumption rate of a typical condensing power plant
$b^*_{es,g}$	Gas consumption rate of a typical gas power plant
C_{inv}	Initial investment
C_{ope}	Operating cost
C_{msd}	MSD concentration
c	AERMOD simulated concentration
g_2	Flow rate in a substation
I	IRR
J_{dw}	Electricity price
N	Cumulative heating time
p_{ij}	Allowable deviation in decision making regarding to a_{ij}
p_i^c	Confidence factor of alternative i
p_{ik}^c	Cross confidence factor for alternative i regarding target alternative k

Q	Heat provision
Q_{load}	Heat load
$\bar{Q}$	Relative heat load factor
Q_d^y	Lower heating value
t_g	Supply water temperature of heat user
t_h	Return water temperature of heat user
t_w	Outdoor temperature
t_n	Design indoor temperature
W	Electric power generation or weight space in SMAA
W^*	Electric power generation of a typical condensing power plant
W_{tp}^*	Electricity consumption of the typical condensing power plant itself
w	Weight
$\boldsymbol{w}$	Weight vector
$\tilde{w}$	Normalized population distribution weight
$\boldsymbol{w}_i^c$	Central weight vector
W_i^r	Favorable ranking weights
x_i	Alternative i
x_{ij}	Criterion measurement on j^{th} criterion for alternative i
$\bar{X}$	Normalized criteria measurements
α	Meta-weights
β	Basic heat load ratio
ε	Available fuel-specific exergy
η_{es}^*	Power supply efficiency of a typical power plant
η_b	Boiler efficiency in CHP plant
η_p	Gas-fired boiler efficiency
η_N	Distribution efficiency of heating network
τ_g	Supply water temperature of primary heating network
τ_h	Return water temperature of primary heating network
ω	Peak heating flow ratio in a substation
ω_{ij}	Errors of the elements in a judgment matrix

Subscripts

load	heating load
k	begin

hr	heat exchanger
g	gas
c	coal
p	peak
b	basic

1 Introduction

1.1 Motivation

Energy savings, environmental concerns, and the concept of eco-sustainability are widespread in the energy sector, for example in residential energy supply systems, and they have remarkable influences on the sustainable development of society and national economies. In addition, since the effects of climate change must also be taken into account in the energy sector as a whole, international climate policy nowadays requires strong actions within industrial and community sectors and emission control actions should be focused on reducing energy consumption and improving energy efficiency. Recent years have witnessed a fundamental change in the way governments approach energy-related environmental issues. Promoting sustainable development and combating climate change have become integral aspects of energy planning, analysis, and policy making in many countries, including all of the IEA member states (International Energy Agency, 2010a).

More and more energy is required to maintain comfortable conditions and services in buildings. This means that building energy demands are growing faster than ever before, for example building energy consumption in China accounted for 20.7% with respect to the total energy consumption in 2006 and it amounted to approximately 27% at the end of 2009 (Jiang, 2009a). Moreover, more than 36% of the total building energy demand is consumed for residential heating purposes (Jiang, 2009b).

In 1950s, a few scattered district heating (DH) systems emerged in some big cities of China during the first ‘Five-Year-Plan’. However, the central heating rate was extremely low at that time, and the development of DH was slow afterwards. Nevertheless, DH area grew faster since 1990s, as can be seen from figure 1.1 and table 1.1.

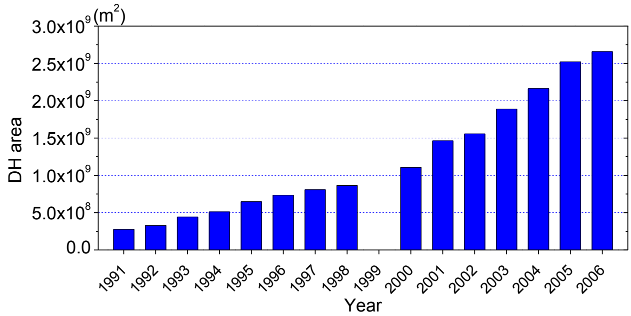


Figure 1.1. Development of DH area in China (1991–1998 and 2000–2006) (Xu, 2006 and Huang, 2008).

Table 1.1. Historical development of DH in China (2000–2006) (Huang, 2008).

Year	Heating capacity		Heat provision		Heating pipeline length	
	Steam (t/h)	Hot water (MW)	Steam (PJ)	Hot water (PJ)	Steam (km)	Hot water (km)
2000	74148	97417	238280	833210	7963	35819
2001	72242	126249	376550	1001920	9183	43926
2002	83346	148579	574380	1227280	10139	48601
2003	92590	171472	591360	1289500	11939	58028
2004	98262	174442	694470	1251940	12775	64263
2005	106723	197976	714930	1395420	14772	71338
2006	95204	217699	677940	1480110	14012	79943

Note: 1PJ=10^{12}J.

At present, the main heat production technologies in China are combined heat and power (CHP), heat-only boiler including district boiler and decentralized boiler. Other heating modes like electricity, solar heating with thermal storage and heat pump are still need developing in China because their total heat production accounted for less than 1.35% around 2008.

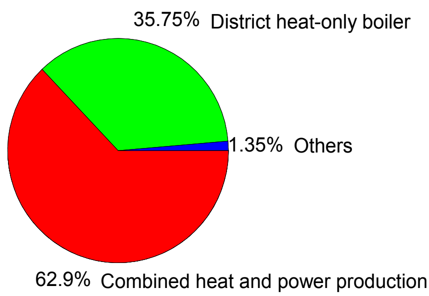


Figure 1.2. The main heat production technologies in China and the proportions, 2008 (Huang, 2008).

Fuel used in CHP for producing the 62.9% heat provisions (in figure 1.2) is mainly coal. This also can be indicated by the primary energy structure of China, which is shown in figure 1.3. Coal dominates the fuel market in heat and power production in China, with a projection share still more than 60% in 2015. Meanwhile, the proportions of oil and natural gas are increasing steadily since 1995. Nuclear contributes less than 1% till 2015.

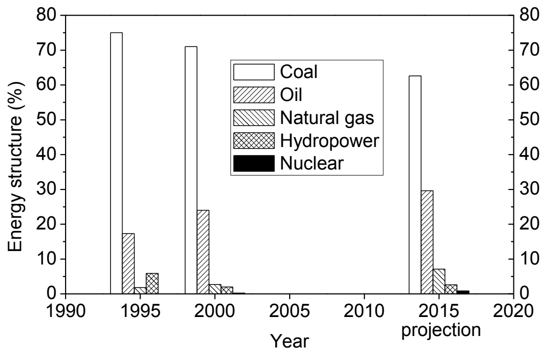
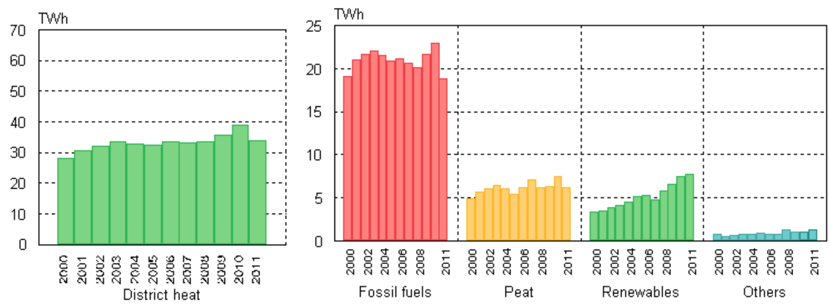


Figure 1.3. Primary energy structure of China, with year 2015 projected (Xu, 2006).

However, coal is the cheapest fossil fuel for heat production in China, and it is usually more than 2 times expensive using natural gas for heating compared to coal (Liu et al., 2002). Fuel price, fuel use by electric power generation mode and other related issues of district heating sector in China are discussed more extensively in papers [I]–[III].



(a) Heat production 2000–2011

(b) District heat production by fuels 2000–2011

Figure 1.4. The district heat production and district heat production by fuels 2000–2011 of Finland (Statistics Finland, 2012).

DH is also consuming more and more energy in Europe, for example the percentage of space heating in relation to the total end use of energy in Finland was 21% in 2005 and it gradually increased to 25% in 2012 (Statistics Finland, 2006; Statistics Finland, 2012), although the specific energy consumption of DH is reduced steadily. The district heat production and district heat production by fuels 2000–2011 of Finland are illustrated in figure 1.4. Unlike the situation in China, the district heat production increase slightly as a whole, and the fuel used for heat production are significantly different.

As can be seen in figure 1.5, CHP is also the main technology for heat and power production in Finland, but the fuel (see figure 1.6) is much more clean and renewable than that in China. Heat-only boilers using fuels such as fossil, biomass or waste and geothermal heat or solar heating are used in Finland for separate heat production.

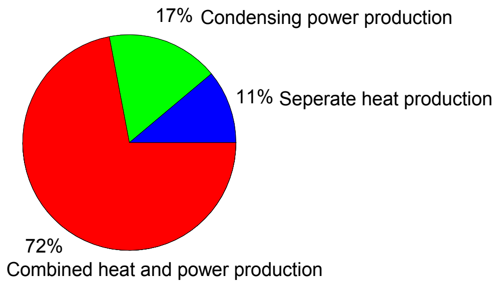


Figure 1.5. Fuel use by production mode in electricity and heat production 2011 (Statistics Finland, 2012).

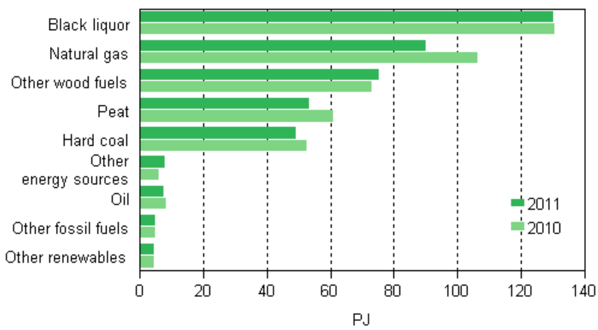


Figure 1.6. Fuel use in combined heat and power production 2010–2011 (Statistics Finland, 2012).

On the other hand, the supply of energy is becoming more challenging than ever, while the world still depends on fossil fuels (International Energy Agency, 2010b) and conventional practices and technologies (Alanne, 2007). In order to improve energy utilization efficiencies and reduce the external costs (Egeskog et al., 2009; Karlssona & Gustavsson, 2003; Holmgren & Amiri, 2007; Fahlén & Ahlgren, 2011) of DH systems, many sustainable technologies, such as 100% renewable energy systems (Lund, 2007) and/or revolutionary combinations of conventional systems, have emerged; these include solar thermal heating, zero energy building (ZEB) or nearly ZEB (Kurnitski et al., 2011) technologies, and combined district heating systems consisting of several heat production facilities, such as CHP plants and boilers or micro cogeneration fueled by biomass and natural gas.

The dissertation mainly focuses on combined district heating systems since they are easier to use in developing countries, especially in China, because of the historical inheritance of a large existing heating infrastructure and a connatural energy structure with a projection share of coal that will still be greater than 50% by the year 2050 (Lin, 2002; Zhang et al., 2009). This kind of district heating systems have already been employed in Russian district heating systems since the 1960s. Afterwards, combined district heating systems consisting of CHP plants, waste incineration plants, and/or boilers fueled by heavy oil emerged in some Nordic countries. Different heat production facilities were operated in a combined heating network with the assistance of remote computer control and judicious operation and regulation support according to the heat load variation in order to save energy, to increase profits, and to reduce air pollution. Nowadays, combined district heating systems are widely used in counties having advanced heating technologies and sound industrial bases.

Recently, these kinds of hybrid heating systems have also been promoted in China to save primary energy and alleviate severe seasonal air pollution during the heating periods. It has been widely recognized in China that traditional DH systems using heat-only boilers for separate heat production are with low energy efficiency, thus the government promotes the construction or retrofit of DH systems based on coal-fired CHP. This is a long-term policy concerning DH in China due to the long range of energy structure reformation, which is another long-term national policy. That is to say, if coal has to be used extensively in DH, why not use it more efficiently? Besides, CO_2 emissions from coal combustion account for about 85% of the total CO_2 emissions in China (Chen, 2003). Nevertheless, China has launched an ambitious green house gas (GHG) control target in 2009 that CO_2 emission per unit GDP falls by 40–45% in 2020 compared to that in 2005. Therefore, how to reduce CO_2 emissions from DH is one of the key factors for achieving that target.

Since the ultimate way to improve the atmospheric environment is to change the energy structure (Marbe et al., 2006; Tromborg et al., 2007), and given the background of energy structure reformation in China, gas is penetrating into the fuel market of DH. Therefore, it is proposed that gas-fired boilers be deployed in underperforming heating substations as peak shaving heat production facilities; paper [I] discussed this in more detail. The situation of gas-fired heat production facilities for heating has been discussed in more detail in paper [II]. Gas-fired boilers can make it possible to effectively adapt to the regulation demands of heat load fluctuations and improve the energy efficiencies, and thus, to mitigate the environmental impacts of DH systems. In a word, combined district heating is an important development trend for DH systems.

To conclude, the main advantages of combined district heating systems are as following: 1) they increase the backup capacity of heat production facilities and also the reliability of DH, because if a heat source is shut down due to an accident, others can compensate partial heat load; 2) they can improve the energy efficiency and reduce the environmental impact simultaneously by judicious management and deployment of the heat sources and 3) the operating cost and economic performance of the systems can also be improved.

In order to make full use of these merits, comprehensive evaluation from the aforementioned perspectives of energy, economy, technology, and the environment should be carried out for planning or retrofitting combined district heating systems. However, there is lack of comprehensive evaluation/optimization models on this kind of DH system. In view of this, a rational multicriteria assessment model is to be developed in the study to guide the combined district heating system in achieving its multi-optimization in terms of the integrated performance.

1.2 Research problem

The planning or retrofitting and design of a DH system should be primarily based on its economic performance. But other influencing factors cannot be neglected, for example energy utilization and environmental impacts. Namely, the decision analysis for planning or retrofitting a DH system is a problem of multiple targets instead of a single objective. Multicriteria decision analysis (MCDA) is a general term for methods that provide a systematic quantitative approach to support decision-making in problems involving multiple criteria and alternatives (Clemen, 1996). The aim is to help the decision maker (DM) make consistent decisions by taking all of the important objective and subjective factors of the problem into account. The DM is usually not the same person as the one who applies the decision analysis. The concept of decision support is more extensive; it not only guides DMs to make decisions but also helps them to organize and interpret data as well as understand the problem (Seppälä, 2003). Generally speaking, decision support may occur in expert systems, optimization algorithms, the applications of decision analysis, or some combination of these three factors. Decision support tools may be either generic, stand-alone programs or they may interact with other procedures, such as simulations (Alanne, 2007).

Unfortunately, most commonly used decision support methods in Chinese DH systems are single objective assessments with evaluation criterion for techno-economic or energy performance. Moreover, current MCDA methods used for planning or retrofitting the DH systems are not convincing enough in essence, which implies that they are misused to some extent. For example, they can be misused in the following ways:

1) The selected criteria, based on which multicriteria optimization is to be implemented, does not reflect the key points of the problem and the MCDA methods do not match the problem to a certain extent, leading to a vague conclusion. For example the environmental criterion is sometimes missing in criteria systems for MCDA of DH systems in China.

2) Many conflicting and incommensurable objectives exist, including both cardinal and ordinal criteria for a single problem, but many of conventional MCDA methods fail to treat them rationally. Economy and reliability criteria are a pair of conflicting and incommensurable objectives in DH system evaluation. Both of these two criteria can be treated as cardinal, but sometimes they were deemed as ordinal criteria even a raw investigation database was available for analyzing the economy performance of different DH options.

3) Sometimes qualitative indicators are used instead of quantitative values, which can originally be obtained in a MCDA process. This problem also

exists in the examples stated above. On the other hand, it is usually not reasonable to interpret an ordinal preference as a cardinal measurement.

4) Few current MCDA methods can deal with uncertainties in criteria measurements and weight vectors; however, weight determination is of great importance in a MCDA problem.

A single objective optimization problem can be solved using linear programming (LP), mixed integer linear programming (MILP), or proper nonlinear algorithms (Keppo, 2009). However, it is extremely complicated to determine a relatively good (the most preferred) alternative against a host of criteria, especially when conflicting criteria exist (Espen, 2007). Therefore, the problem can become even more challenging than just synthetically evaluating different combined district heating scenarios for a DH system.

The dissertation details an application-oriented MCDA process, during which the techno-economic performance, atmospheric environmental impact, energy utilization coefficient, reliability, and other relevant qualitative criteria are studied and examined as the source of background information required for MCDA rather than as independent tools that directly assist decision-making.

1.3 Earlier studies

MCDA is applied to a DH system in order to provide theoretical and engineering foundations for system planning or retrofitting, design and operation, as well as scheme classifying or ranking in relation to all of the criteria in question. Therefore, the investigation, preparation, and interpretation of the source data for different criteria should be detailed or determined with the assistance of proper algorithms and mathematical models. Consequently, the literature review of decision support for planning or retrofitting DH systems is carried out first in relation to single objective optimization and then in relation to MCDA applications.

Techno-economic methods are widely used when analyzing DH systems (Dzenajavičienė et al., 2007; Badescu, 2007). A decision support system (DSS) based on optimizing the major investment-related variables to maximize the financial yield has been developed by Rentizelas et al. (2009). Additionally, with respect to the optimization for the economical operation and management of DH systems, LP (e.g., Lahdelma & Hakonen, 2003; Rong & Lahdelma, 2005, 2007) and MILP algorithms (e.g., Thorin et al., 2005; Casisi et al., 2009; Lozano et al., 2010) are widely used. Zheng et al. (2007a) employed a single objective MILP model to optimize the operating costs of a combined district heating system consisting of coal-fired district boilers and gas-fired boilers in Tianjin, China. Based on this, they discussed the economical basic heat load ratio, the critical peak heating temperature, and the operation strategy for peak shaving gas-fired boilers. In addition, they also considered the influences of heating regulations on the operating costs of the combined district heating system (Zheng et al., 2007b).

Total energy and energy efficiency analysis, for example exergy analysis, can be very helpful when selecting a DH alternative and system analysis performance evaluation or optimization from the standpoint of energy (see, for example, Ozgener et al., 2007; Zmeureanu & Xin, 2007). An exergy flow diagram of a DH system can be derived and used to determine the position where exergy destruction takes place and exergy loss, based on which measures can be proposed to improve the system's performance.

More and more studies take into account the 'external cost' posed by DH systems, since the eco-sustainability concept is widespread in the energy sector. 'External cost' refers to the adverse effects that heat production or electricity generation have on society and the environment, such as acidification, eutrophication, and global warming, as well as the direct impacts on human health arising from the emissions through energy conversion. The costs of these effects have to be borne by society now or in the future even though they are not always taken into account in the price of energy (Karlssona & Gustavsson, 2003). Holmgren and Amiri (2007) performed a monetary value analysis of the external costs of a municipal DH system using the EU's ExternE (Externalities of Energy) project data (e.g., http://www.externe.info/). They usually carried out the external cost analyses coupled with the MODEST (Model for Optimization of Dynamic Energy Systems with Time-Dependent Components and Boundary Conditions) model (see, for example, Henning, 1997; Sundberg & Henning, 2002). Alanne and Saari (2008) introduced a method for assessing environmental burdens resulting from the construction and operation of a residential energy supply system. They assessed natural resource consumption through material input factors, and they estimated global warming and acidification potentials by means of CO_2 and SO_2

equivalents. Carlson (2002) considered the monetary values of damage to the environment and health resulting from atmospheric emissions of CO_2, NO_x, SO_2, and particulates using an optimizing method based on LP. He also indicated that it is cost-effective to take externality costs into consideration during the planning stage instead of correcting the damage later. Other researchers have used life cycle analysis (LCA) to assess the environmental impacts from DH (see, for example, Pehnt, 2008; Oliver-Sola et al., 2009; Pa et al., 2011).

Besides, in many developed countries growing awareness of the importance of pollutant spatial variations when assessing atmospheric environmental impacts has caused many scholars to extensively apply air dispersion models in their studies. Relevant state of the art air dispersion models and techniques have also been utilized when assessing the environmental impacts of DH. They include Gaussian models (Genon et al., 2009; Torchio et al., 2009), the CALPUFF–California Puff Model (Zhou et al., 2003; Holmes & Morawska, 2006), the AERMOD–American Meteorological Society (AMS)/Environmental Protection Agency (EPA) Regulatory Model (U.S. EPA, 2004; Morra et al., 2009), the ADMS–Atmospheric Dispersion Model System (Cambridge Environmental Research Consultants, 2010), and some regional air pollution control and cost optimization models for European and East Asian regions (Syri et al., 2008; Rong and Lahdelma, 2007; Cofala et al., 2010; Xing et al., 2010).

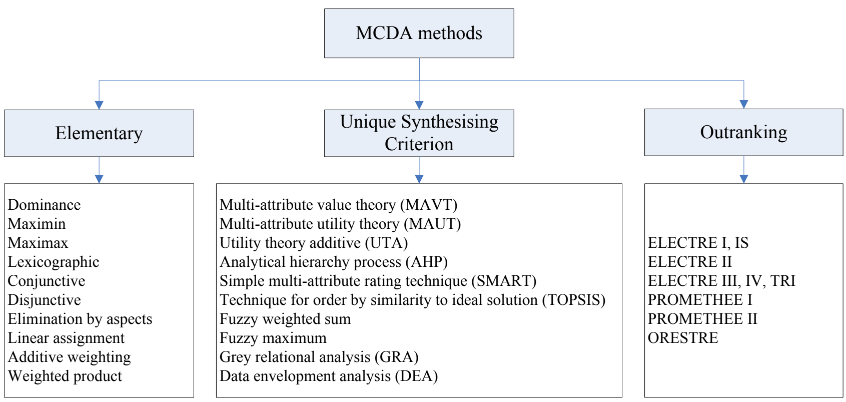


Figure 1.7. Classification of multicriteria decision analysis methods (Wang et al., 2009a).

Before the review of the MCDA applications for DH systems and some common MCDA methods are classified and illustrated in figure 1.7. In general, there are three types of MCDA methods: 'Elementary' is the basic method type; 'Unique Synthesizing Criterion' stands for a host of methods having a overall unique criterion for MCDA; while 'Outranking' methods are based on the 'outranking relation' (Benayoun et al., 1966). Most of these methods have been found in the applications for evaluating energy supply systems (Wang et al., 2009a, 2009b).

Mróz (2008) introduced ecology when planning community heating systems and created a database that was coupled with energy and economic materials for deciding upon a proper heating system in a community using ELECTRE. Ghafghazi et al. (2010) evaluated and ranked energy sources available for a DH system in Vancouver, Canada based on multiple criteria and the viewpoints of different stakeholders using PROMETHEE. In addition to these outranking methods, some other methods have also been introduced to the heating sector, such as a multiple objective optimization (MOO), analytic hierarchy process (AHP), multi-attribute utility theory (MAUT), pairwise comparison approaches, Novel Approach to Imprecise Assessment and Decision Environments (NAIADE), fuzzy methods, and grey system theory (e.g., Alanne et al., 2007; Huangfu et al., 2007; Wang et al., 2008a, 2008b, 2010; Browne et al., 2010; Xu et al., 2011). Li et al. (2004) studied a 'green heating system', which is characterized as an environmentally friendly heating system, such as CHP plus heat pumps in their case. Furthermore, they used an evolutionary, multi-objective algorithm to investigate the trade-off between the costs and environmental performances associated with such a system. Pilavachi et al. (2006) studied several CHP systems in Greece with respect to end user requirements and different criteria using an agglomeration function-based method to statistically evaluate the weight factors. Papadopoulos et al. (2008) pointed out that with the introduction of natural gas in the Greek energy market; the district heating options were broadened. He also presented empirical comparative results for a unitary gas-fired boiler in terms of energetic, environmental and economic considerations. Anastaselos et al. (2011) extended the use of LCA to an integrated assessment of a building's envelope and radiative heating system based on such criteria as energy, economic, and environmental performances as well as thermal comfort. In particular, Wei et al. (2010) evaluated seven DH systems in China using a fuzzy comprehensive evaluation, in which the economy, environment, and energy technology factors were synthetically taken into account. They indicated that CHP is the best choice among all the systems and that a gas-fired boiler system is the best fossil-fed solution compared to coal- and oil-fired boilers for heating purposes in China. This conclusion is quite consistent with the idea of combined district heating systems that will be addressed in the dissertation.

MCDA methods are now being more extensively used than ever before, and they indeed perform relatively well when planning or retrofitting an operation and conducting system optimization for energy systems, including DH. Although the above-mentioned models are appropriate for some specific real-life problems, they might not be very suitable for assessing combined district heating systems due to the coexistence of the four problems mentioned in section 1.2. To overcome these problems and also make full use of the preference information for the DMs, the dissertation takes advantage of the Stochastic Multicriteria Acceptability Analysis (SMAA) model (Lahdelma et al., 1998; Lahdelma & Salminen, 2001) to develop an application-oriented decision support system for planning or retrofitting CHP-based, combined district heating systems. Because SMAA is a family of methods developed and improved for aiding multicriteria decision making in problems with uncertain, imprecise, or partially missing information. The main characteristics of SMAA include: 1) it can be used in group decision making; 2) the need of preference from DMs are not mandatory any more, but any deterministic weight information undoubtedly will improve the accuracy and reliability of the result; 3) SMAA is inspired by so called inverse weight space analysis, which explore the available weight space in order to describe the preferences that make each alternative the most proffered one, or that would give a certain rank for a specific alternative; 4) the uncertainties of criteria measurements are better treated using distribution function in the model; 5) SMAA is very suitable to handle the problems with cardinal and ordinal criteria simultaneously.

2 Research subject and scope

2.1 Combined district heating with gas-fired boilers for peak load compensation

Generally speaking, in a combined district heating system, the CHP plant supplies the basic heat load for the whole heating season. However, if the outdoor temperature drops below the critical peak heating temperature, gas-fired boilers supply the corresponding peak shaving heat provisions. The connecting mode of gas-fired boilers and the heating network for a typical combined district heating system are illustrated in figure 2.1.

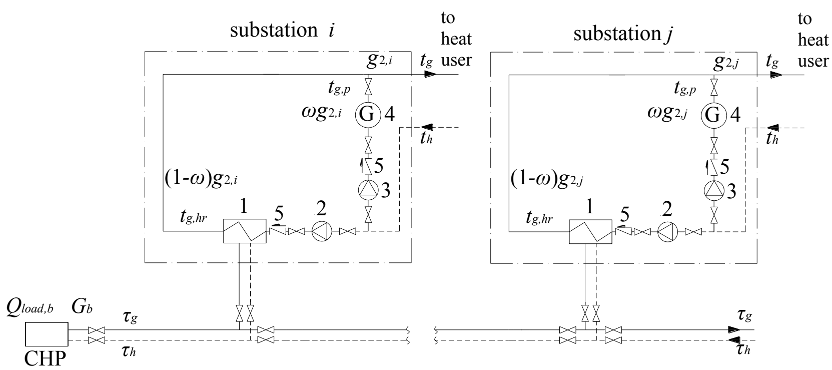


Figure 2.1. Connecting mode of gas-fired boilers and heating network. 1—heat exchanger; 2—circulating pump of substation; 3—peak heating circulating pump; 4—gas-fired boiler; 5—non-return valve; t_g, t_h—supply and return water temperatures of heat user; τ_g, τ_h—supply and return water temperatures of primary heating network; $t_{g,p}$—supply water temperature of gas-fired boiler; $t_{g,hr}$—supply water temperature of heat exchanger; ω—peak heating flow ratio of a substation, %; $g_{2,i}$—flow rate of a substation.

In a heating substation like the one shown in figure 2.1, return water from the secondary heating network is first heated by the heat exchanger, and then a portion of the flow rate ($\omega_{g2,i}$) will be sent to the gas-fired boiler to be heated up again; the rest of the return water will flow through a bypass pipe and finally be incorporated with the reheated water flow. Then, the mixed water will be sent to heat users according to the operation.

The heat load duration curve is quite helpful and is thus utilized to analyze the combined district heating system. Figure 2.2 is a representative heat load duration curve calculated by the method of non-dimensional comprehensive equations (Xu and He, 1986) which is a semi-empirical equation system developed based on the historical data from a lot of Chinese DH systems. Therefore it seems a little different from the real-life recorded heat duration loads.

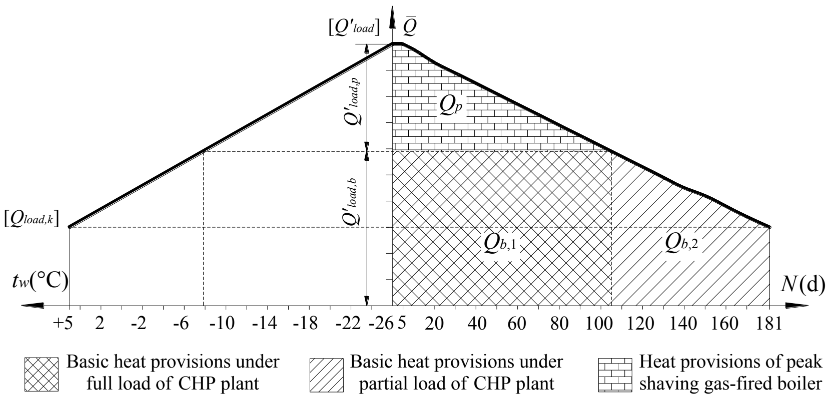


Figure 2.2. Heat load duration curve for a combined district heating system. The expressions in square brackets denote the relative position of the starting heat load and design heat load for the combined district heating system: t_w—outdoor temperature; N—cumulative heating time; $\overline{Q}$ — relative heat load factor. Cumulative heat provisions for producing domestic hot water are excluded from the analysis.

Figure 2.2 is a composite of two relationships. The left-hand part shows the variation in $\overline{Q}$ with a different t_w: it is recommended that DH starts when t_w falls below 5°C according to the handbook of regular-use data on Heating, Ventilation & Air Conditioning (HVAC) in China. However, this statement is not compulsory, which means that local authorities can make their own operating plan regarding the start time of DH. The cumulative heat provisions during a heating season (in this case, N=181 days) are graphically demonstrated in the right-hand panel. $Q_{b,1}$ and $Q_{b,2}$ are basic heat provisions under full load and partial load of CHP plant. $\overline{Q}$ indicates the ratio of actual heat load at a certain t_w and design heat load, which is demonstrated in equation (2-1):

$$\overline{Q}(t_w)=\frac{Q_{load,tw}}{Q'_{load}}=\frac{t_n-t_w}{t_n-t'_w}, \quad (2\text{-}1)$$

where t_n and t'_w are the design indoor and outdoor temperatures; Q'_{load} is the design heat load of the combined heating system and $Q_{load,tw}$ is the heat load at t_w. The interval for $\overline{Q}$ should be within [$\overline{Q}_k$, 1], where $\overline{Q}_k$=$Q_{load,k}/Q'_{load}$ and

$Q_{load,k}$ is the starting heat load for the heating system. $\bar{Q}_k$ is a function of t'_w, it is 0.295 in this case.

Figure 2.2 also shows that the total heat provisions comprise the heat provisions of the CHP plant ($Q_{b,1}$+$Q_{b,2}$) and the peak shaving gas-fired boilers (Q_p). Therefore, the design heat load of a combined district heating system is divided into two corresponding parts:

$$Q'_{load}=Q'_{load,b}+Q'_{load,p}\,, \tag{2-2}$$

where $Q'_{load,b}$ and $Q'_{load,p}$ refer to the design heat loads of CHPs and to the peak shaving gas-fired boilers, respectively. The basic heat load ratio, β, is then defined as,

$$\beta=\frac{Q'_{load,b}}{Q'_{load}}\,. \tag{2-3}$$

It can be seen from equations (2-1) and (2-3) that $\bar{Q}$ is a function of outdoor temperature, but β has no relation with t_w. When $Q'_{load,b}$ is somehow determined for a combined district heating system, the value of β is then fixed (design β) before the next large-scale retrofit due to the new connections to the heating network. However, the actual optimal β may change only a little based on many influencing factors, such as coal and gas prices; the sensitivity analyses of fuel prices can be found in paper [II]. It is assumed that β varies from 0.5 to 1.0 in the study, since CHP plants serve as the basic heat production facilities.

Combined district heating systems are preferred over traditional DH systems based on the following reasons. 1) They can regulate heat supplies on time and avoid excessive heating to some extent; because district heat can be produced on site by the gas-fired peak shaving boilers in substations, which make the operation more flexible and efficient. 2) They are able to optimize hydraulic conditions of the distribution network, because maladjustment of heat user in the worst hydraulic loop is relieved. 3) Peak shaving gas-fired boilers extend heating capacities, especially in urban areas. 4) They enhance the reliability of DH, which is discussed in the general characteristics in motivation section. 5) They prolong the high-efficiency running time of CHP plants due to the reduction of basic heat load. 6) They can alleviate environmental impacts thanks to the use of gas fuel.

2.2 Installation strategy of peak shaving gas-fired boilers

It is of great importance to judiciously install the peak shaving gas-fired boilers in a combined district heating system. The installation strategy decides which heating substations should be equipped with gas-fired boilers at a different β and their corresponding proper heating capacities as well as regulations; these factors consequently account for the combined heating alternatives assessed in the dissertation. A judicious installation also promotes the energy potential and investment savings of the combined district heating system. In a word, combined district heating alternatives at different β and with proper peak shaving heating capacities deployed in different substations according to the installation strategy form the decision problem to be addressed in the thesis.

There are mainly two types of combined district heating systems: Newly-built systems and retrofitted combined district heating systems. The latter systems are more popular in China due to the extensive existing heating infrastructure. But more and more DH system plans are in favor of these kinds of hybrid heating systems, too. With respect to the newly-built combined district heating systems, the installation of gas-fired boilers can be determined using the so-called 'proportional peak shaving' strategy, which suggests that gas-fired boilers could be deployed in all heating substations and that the capacities should be in proportion to the heat loads supplied by each substation. However, this is not the situation for the retrofitted combined district heating system. Instead of using the 'proportional peak shaving' strategy, it is proposed that the underperforming heating substations should be equipped with gas-fired boilers with proper heating capacities, according to the thermal conditions at a different β of a retrofitted combined district heating system. Excessive heat supply rate (EHSR) analysis provides a procedure for quantitatively determining the thermal conditions of a heating system, as detailed in papers [I] and [III]. EHSR indicates the excessive heat supply conditions of a heating substation over a given period of time. For a detailed discussion of how to calculate EHSRs, please refer also to paper [I]. The observed meteorological data and the typical meteorological yearly (TMY) data originating from a special weather data set for constructing a thermal environmental analysis of China (China Meteorological Administration, 2005) are used to conduct the EHSR analysis in this study, which can be found in paper [III]. Consequently, an installation strategy can be determined with the assistance of EHSR analysis, since it is a thermal condition indicator for a substation.

2.3 Criteria selection and aggregation for decision support

Criteria selection and aggregation is significant for decision support in planning or retrofitting a combined district heating system. It not only influences the way in which criteria weights are elicited, it also provides the basis upon which the reasonable multicriteria decision support occurs. When it comes to a simple decision-making problem, a parallel criteria aggregation system may be acceptable. However, in a complicated MCDA problem with many influencing factors, for example decision support for planning or retrofitting a combined district heating system, it is better to establish a hierarchical structure. The hierarchy consists of several different criteria levels: The first level should be the objective level and the rest of the levels should show the criteria meanings ranging from general to specific.

Principles exist for establishing a criteria aggregation system. In this dissertation, the following principles should be taken into account: 1) comprehensiveness, that is to say, the selected criteria should reflect the different properties of the DH systems; 2) objectivity, which means that each criterion should be scientifically determined; 3) maneuverability, that is to say, the selected criterion should be operational or convenient for real-life applications; 4) comparability, which indicates that the criteria should be fair in relation to all of the alternatives; 5) non-overlap between criteria, which means that one criterion should for the most part not cover the meaning of the other criteria; and 6) they should be consistent with the selected MCDA method. The procedure for developing a criteria aggregation system is illustrated in figure 2.3.

Subsequently, most evaluative criteria for DH systems have been selected based on the aforementioned literature review in section 1.3 and real-life experiences. According to principle 1, it is better to list a comprehensive package of criteria at the preliminary selection stage and refine them later. Moreover, a transparent multicriteria evaluation framework for better understanding and engineering applications for combined district heating systems is also required. In view of this, economy, technology, the environment, and energy have been chosen as first-level criteria. Each of them can be divided into corresponding second-level criteria with different properties, as shown in table 2.1.

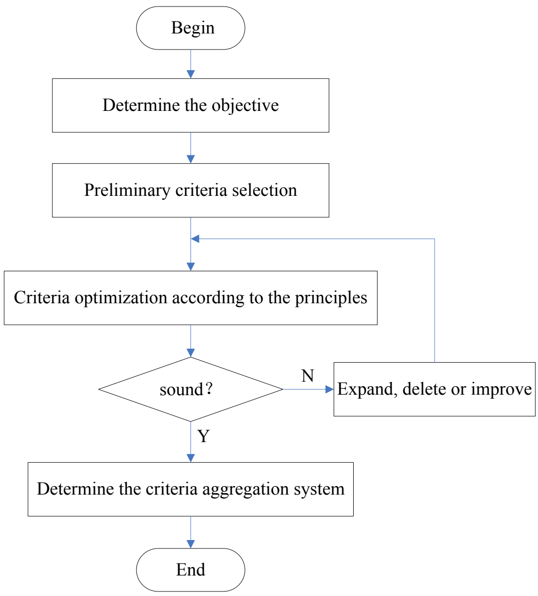


Figure 2.3. Procedure for developing a criteria aggregation system (Su, 2000).

Table 2.1 encompasses almost all the common criteria for assessing DH systems. It is clear that these criteria can be divided into positive and negative criteria or into quantitative and qualitative criteria according to different classification systems. Furthermore, this study refined the preliminary criteria based on six principles and aggregated them into a single hierarchical structure, which is shown in figure 2.4.

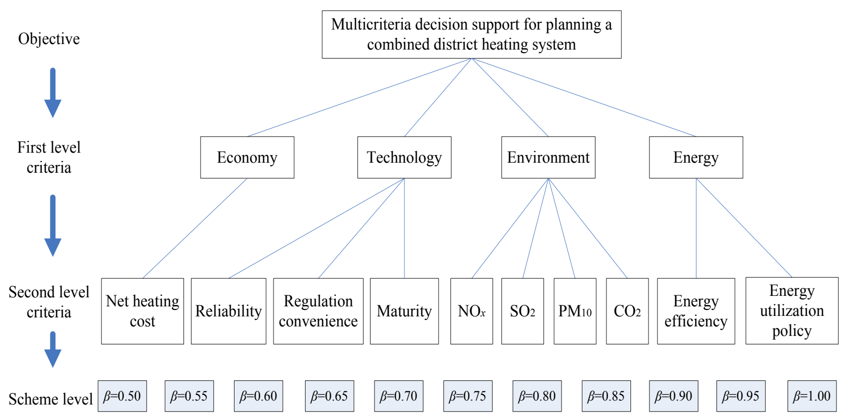


Figure 2.4. The criteria aggregation hierarchy of a combined district heating system.

Table 2.1. Preliminary criteria package for district heating systems.

First-level criteria	Second-level criteria	Description	Attribute
Economy (C_1)	Net heating cost (NHC) (C_{11})	An economic indicator indicating initial capital cost, operating cost, and revenue of power generation.	▼ quant.
	Annual cost (C_{12})	Cost per year over the entire service life.	▼ quant.
	Net present value (NPV) (C_{13})	NPV is defined as each cash inflow/outflow discounted to its present value (PV).	▲ quant.
	Investment recovery period (C_{14})	How long will it take to repay the investment?	▼ quant.
Technolog y (C_2)	Reliability (C_{21})	The district heating reliability.	▲ quant.
	Regulation convenience (C_{22})	Whether the system is easy to regulate and can be adjusted to account for the load fluctuations.	▲ qual.
	Maturity (C_{23})	Whether the technology is mature or not.	▲ qual.
	Maintenance (C_{24})	Whether the system is easy to maintain or not.	▲ qual.
	Automatic control level (C_{25})	Whether it is easy to apply remote automatic control for the system.	▲ qual.
	Technology level (C_{26})	Whether a technology is advanced and will be perfected in the future.	▲ qual.
	Footprint (C_{27})	System space requirements.	▼ quant.
Environm ent (C_3)	NO_x (C_{31})	It is a key ingredient in smog and it causes acid rain.	▼ quant.
	SO_2 (C_{32})	SO_2 is the dominant emission from coal-fired heat sources.	▼ quant.
	Particle matter (PM) (C_{33})	PM significantly influences people's health, especially proportions with aerodynamic diameters under 10 μm, i.e. PM_{10}.	▼ quant.
	CO_2 (C_{34})	It is the prominent greenhouse gas (GHG) emitted by heating system.	▼ quant.
	Solid waste (C_{35})	It will increase the public traffic load and treatment expenses.	▼ quant.
	Noise (C_{36})	Noise is not a direct factor that can harm the environment, but it can influence people's work or life.	▼ quant.
Energy (C_4)	Energy efficiency (C_{41})	It indicates the energy-saving potential of the system, or whether a system is energy efficient compared to other existing ones.	▲ quant.
	Energy utilization policy (C_{42})	It demonstrates the energy-utilizing preference from the authority's point of view.	▲ qual.
	Energy reservation (C_{43})	It implies the reservoir status of a certain kind of energy, especially fossil fuels.	▲ qual.

Note: 1. ▲=positive criterion (benefit criterion); ▼=negative criterion (cost criterion);
2. quant. =quantitative criterion; qual. =qualitative criterion.

In figure 2.4, other economic criteria are excluded in the case of too much overlap since net heating cost (NHC) is an integrated economic indicator. The three technological criteria selected for the hierarchy already reflect the technology aspect quite well, and the rest of the technological criteria can be interlinked with them. The footprint usually changes moderately in DH systems, and noise can be eliminated because a DH system usually has little influence on the people's living conditions in terms of noise. Solid waste, mainly coal residue, can be a byproduct that is recycled and utilized in civil engineering. Overall, the criteria aggregation system consists of four levels, including objective and scheme levels, and ten bottom-level criteria. The scheme level contains eleven alternatives, which are characterized by β (see section 2.2). The hierarchical structure is practical for the combined district heating systems with coal- and gas-fired heat production facilities. Nevertheless, the criteria can be expanded accordingly for some other DH technologies that are preferable for small-scale communities, for example heat pumps and building combined heat and power (BCHP). In the next chapter, the criteria measurement is determined using different models and the MCDA is conducted using the above-mentioned criteria aggregation system.

3 Methods

3.1 An overview

In this chapter, novel models or methods are summarized to determine the criteria measurements and weights. Subsequently, this study details how SMAA is implemented to provide multicriteria decision support for combined district heating systems. An overview of the information flow of the study is illustrated in figure 3.1.

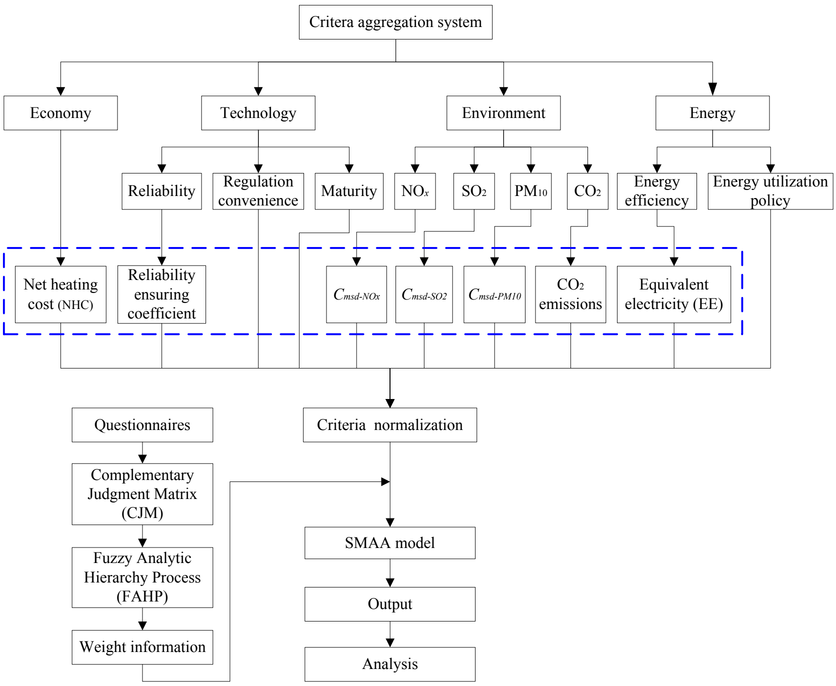


Figure 3.1. An overview of the information flow of the proposed decision support system.

The overview begins at the criteria aggregation system and all second level criteria are also listed. However, this chapter mainly focuses on the cardinal criteria measurements highlighted by a dashed rectangular; they are calculated or simulated using proposed sub-models in this chapter. Other criteria are treated as ordinal. All criteria measurements should be normalized before used in SMAA model. On the other hand, weight information is determined by carrying out the questionnaire survey and the method of CJM (Complementary Judgment Matrix) in combination with FAHP (Fuzzy Analytic Hierarchy Process).

3.2 Techno-economic analysis

As mentioned in chapter 2, the deployment of peak shaving gas-fired boilers promotes both energy efficiency and environmental sustainability. However, due to the relatively high price of natural gas in China, a techno-economic analysis is required for evaluating different heating scenarios, characterized by β, in order to determine the affordable economic boundaries in real-life applications. Moreover, the planning or retrofitting of a DH system is usually influenced to a large extent by its techno-economic performance.

This thesis employ the annual cost method to develop a model for computing the *net heating cost* (NHC) of the combined district heating system, while considering the current state of the art of cogeneration systems in China. NHC is defined as the investment costs and operating costs of the system subtracted by the revenues from power generation (see equation (3-3)). The model has been demonstrated in a combined district heating system in Daqing, China in paper [II].

According to time value theory, the initial investment cost of a project can be discounted equally for each year of the n-year life cycle using a capital recovery equation, and the annual cost is then derived from the summation of this discounted value and the operating costs, as shown in equation (3-1) (Thomas and Peter, 2001):

$$A_c = \left[\frac{I(1+I)^n}{(1+I)^n - 1}\right] C_{inv} + C_{ope} , \tag{3-1}$$

where A_c is the annual cost, C_{inv} denotes the initial investment cost, C_{ope} represents the operating costs excluding the revenue from electricity sales, I is the discount rate that equals to internal rate of return (IRR), and n is the service life. However, service lives may vary with different infrastructures and types of equipment, which may introduce problems into the analysis. Even still, the economic performances of the systems can be compared on a yearly basis regardless of how many years of service life there are for different infrastructures and equipment. Namely, the annual cost should be written as,

$$A_c = \sum_{j=1} \left[\frac{I(1+I)^{n(j)}}{(1+I)^{n(j)}-1} \right] C_{inv,j} + C_{ope}\,, \tag{3-2}$$

where $n(j)$ is the service life of the jth infrastructure or equipment in years. However, an assumption was made in the thesis that different infrastructures of the combined heating system have the same service life length according to the current situation in China. If the operating costs differ annually during the service life, then it is recommended that the present value be first calculated as part of the service life prior to computing the annual cost. But in this study, we assume that it will remain stable in the first stage of the project. However, without compromising the generality of the study, sensitivity analyses are implemented for the factors that have the most influence on the operating costs, which can be found in paper [II] in a more detailed manner.

In general, a CHP plant supplies heat and power commodities simultaneously at the expense of the initial investment cost and operating costs. Electricity sales usually form the majority of a CHP company's revenues in most cases in China. CHP companies prefer to generate more electricity due to its high retail price so that they can make more profits. This also makes combined district heating more feasible considering the fact that heat production is less profitable in China due to an immature pricing mechanism for heat supply and heat metering.

Moreover, the heat provisions of the combined district heating system are basically identical, while the electric energy production evidently varies due to different cogeneration units with a different β. Therefore, we propose taking into account the revenue obtained from power generation in combination with the annual costs, and then the NHC takes form:

$$Z = \sum_{j=1} \left[\frac{I(1+I)^{n(j)}}{(1+I)^{n(j)}-1} \right] C_{inv,j} + C_{ope} - WJ_{dw}\,, \tag{3-3}$$

where W is the estimated annual electric energy production of the combined district heating system and J_{dw} is the network power uploading price. The initial investment costs and operating costs should be investigated and interpreted in a very detailed manner, as shown in paper [II]. Fuel costs should be emphasized in order to make the modeling more accurate, since they are the major influencing factors on NHC.

3.3 Atmospheric environmental impact assessment

In this dissertation, a novel atmospheric environmental assessment model is presented. The model incorporates state-of-the-art AERMOD modeling and normalized population distribution weights (NPDWs) so that the mean spatial distribution (MSD) of pollutants can be computed in order to determine the atmospheric environmental impacts. The CO_2 reduction potential of the combined district heating systems on a city scale is also examined using the IPCC scenario.

3.3.1 AERMOD modeling

AERMOD replaced the industrial source complex (ISC) model as the new regulatory model in the U.S. (U.S. EPA, 2004). It has also been chosen as the recommended model for China's environmental impact assessment—atmospheric environment (HJ/T 2.2—2008) technical guideline. AERMOD consists of three interlinked components: An air dispersion model (AERMOD), a meteorological preprocessor (AERMET), and a terrain preprocessor (AERMAP). These are shown in figure 3.2.

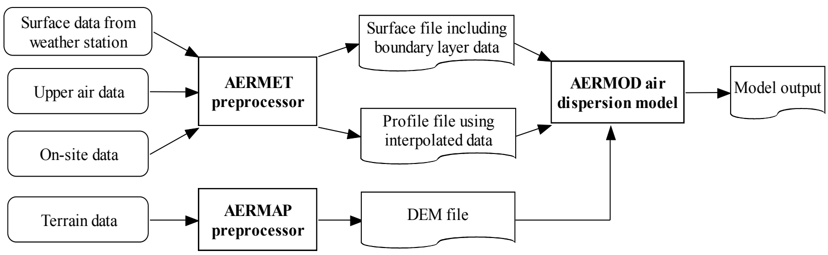


Figure 3.2. Structure of AERMOD model system.

3.3.2 Local impact assessment using MSD

It should be noted that even if the total emissions decrease, the atmospheric environmental impact can become more severe due to adverse meteorological conditions and/or some other influencing factors like population distribution. For example, the atmospheric environmental impact can be worse if the accompanying ambient air is stable; because the pollutant emissions are hard to be diffused or diluted. In view of this, traditional atmospheric environmental impact assessments without considerations of meteorology and population are not convincing enough. Therefore, we make full use of a state-of-the-art air dispersion model (AERMOD) to simulate the pollutant dispersion. In particular, AERMOD is suitable for computing pollutant concentrations at every simulation grid node (called a receptor) over given periods and for demonstrating the results in graphical forms. This feature favors calculating the MSD concentrations of the pollutants by considering population distribution (namely NPDWs), as follows:

$$C_{msd}=\frac{\int_{S_{dom}} c(x,y)\tilde{w}(x,y)dxdy}{S_{dom}}\ , \tag{3-4}$$

where C_{msd} is the MSD concentration of a pollutant, μg/m^3; S_{dom} stands for the study area, c is the simulated concentration at a receptor, μg/m^3, and $\tilde{w}$ represents the NPDWs of the study area. In fact, NPDWs are the elements of the matrix that stand for the population percentage of each corresponding grid cell over the study area. The simulated concentrations and NPDWs are influenced by the spatial resolution of the grid cells, as are the MSD concentrations. The choice of spatial resolution is ultimately a compromise between computational burden and accuracy of results. For a large area, a spatial resolution of 3km × 3km has previously been used (Beckx et al., 2009). However, the accuracy of the simulated results could be improved by using a finer resolution. Thus, a spatial resolution of 1km × 1km is used in this study since the computational burden is still affordable. Another reason for introducing MSD here is that it can quantify the atmospheric environmental impact with a relatively good level of reliability because it does not directly compare a host of AERMOD-exported concentration maps. An overview of the aforementioned model design is presented in figure 3.3. The required data inputs in figure 3.3 are detailed in paper [III].

Note that the AERMOD simulation grid is different from the population distribution grid, which is shown in figure 3.4. In particular, to make the AERMOD-simulated concentrations completely consistent with the population grid, that is, to align the receptors at the center of each population grid, the AERMOD simulation grid must be constructed as the inner grid (shown in figure 3.4), whereas the grid with a peripheral border is the population distribution. In this way, simulated concentrations at all receptors overlap exactly at the centers of corresponding population grid cells. For example, the first node of the AERMOD simulation grid (point B) coincides exactly with the center of the first grid cell of the population grid.

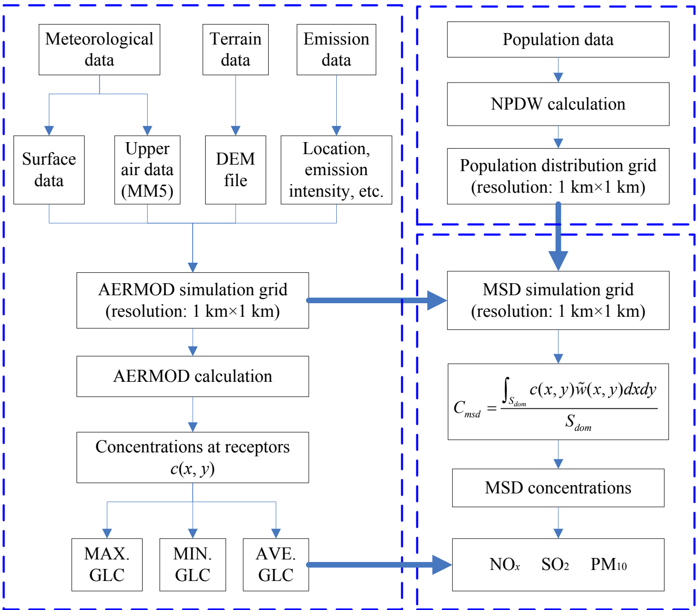


Figure 3.3. An overview of the AERMOD modeling and MSD calculation for NO_x, SO_2, and PM_{10}.

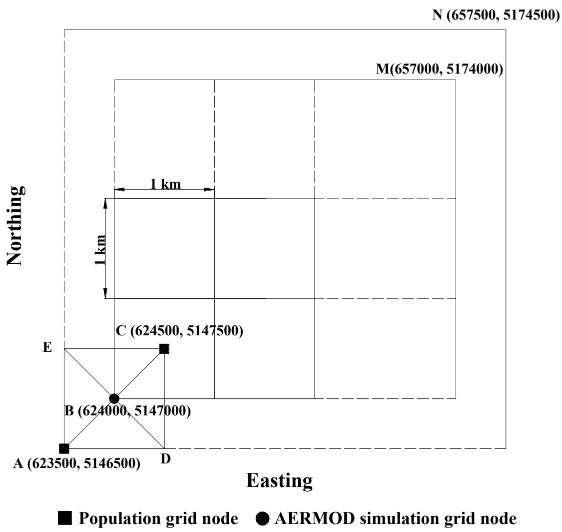


Figure 3.4. Relationship between AERMOD simulation and population distribution grids.

According to the AERMOD simulation results, equation (3-4) can take the following form:

$$C_{msd} = \sum_{i=1}^{n} \sum_{j=1}^{m} \left[c(x_i, y_j) \tilde{w}(x_i, y_j) \right], \qquad (3\text{-}5)$$

where $c(x_i, y_j)$ is the AERMOD-simulated concentration at a receptor in the ith row and jth column, $\mu g/m^3$, $\tilde{w}(x_i, y_j)$ is the NPDW of the population grid cell corresponding to the ith row and jth column, and m and n stand for the number of rows and columns in the AERMOD simulation grid. In this way, the MSD concentrations for NO_x, SO_2, and PM_{10} can be calculated.

3.3.3 Global impact based on IPCC scenario

However, the MSD is used to assess the impacts of local emissions, which influence only the local region without having substantial effects on global climate change. In addition to local emissions, global emissions account mainly for global climate change with limited local impacts. CO_2 from the burning of fossil fuels is the dominant cause of global warming (Intergovernmental Panel on Climate Change, 2001), and it is also the major GHG emission from DH systems. China has recently surpassed the United States as the largest CO_2 emitting country in the world. Therefore, it is very important to also consider the changes in CO_2 emissions induced by the local energy system retrofits.

The 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) have been adopted to calculate CO_2 emissions. Fuel characteristics are also taken into account. The total CO_2 emissions for a combined district heating system can be computed as:

$$CO_2\ \textit{emission amount} = \textit{fuel consumption} \times \textit{discharge coefficient} \qquad (3\text{-}6)$$

where the discharge coefficient is the specific CO_2 emissions from 1kg of coal or 1m^3 of natural gas. It doesn't include upstream emissions from extraction and distribution of the fuel and it can take the following form:

$$\textit{Discharge coefficient} = \textit{LHV} \times \textit{carbon emission factor} \times \textit{carbon oxidation rate} \times \textit{carbon transfer coefficient} \qquad (3\text{-}7)$$

where LHV is the lower heating value of fuel. The carbon emission factors have been obtained from the IPCC (2006). The carbon oxidation rates are 92.2% and 99% for coal and natural gas, respectively, based on calculations by China Energy Net (2010). Generally speaking, the carbon in coal cannot thoroughly participate in the chemical reactions of the combustion process; therefore, this study also takes into account the carbon transfer coefficient. Because Circulating Fluidized Bed (CFB) boilers are widely used in CHP plants, the carbon transfer coefficient of coal is assumed to be 97%, while it is basically equal to 1 for natural gas.

The carbon emission factors or discharge coefficients for different scenarios are also compared and shown in table 3.1. This study adopts the IPCC scenario because it provides a more detailed calculation process and technical support, and it also gives 95% confidence intervals for carbon emission factors. The carbon emission factors obtained from China Energy Net fall in the 95% confidence interval for the IPCC scenario. On this basis, the CO_2 emissions for combined district heating alternatives with different β and CO_2 reduction rates can subsequently be determined.

In addition, we notice that power generation for the combined district heating system also decreases once the β drops, which means that this part of the electricity should be compensated for by other power plants, for example coal-fired power plants, hydroelectric power stations, nuclear power plants, and other clean energy sources. Therefore, the CO_2 emissions from the combined district heating system are also influenced by the mix of power generation sources.

Table 3.1. Carbon emission factors or discharge coefficients for different scenarios.

Fuel	IPCC [1]	Energy Research Institute NDRC [2]	China Energy Net [3]
Coal	94.52 g/MJ	2.4567 tCO_2/tce	100.36 g/MJ
Natural gas	56.20 g/MJ	—	56.22 g/MJ

Note:
1. Carbon emission factors are calculated according to the original emission factors in the IPCC (2006); the 95% confidence intervals for coal and the natural gas emission factor are (−7.7%, 6.8%) and (−3.2%, 3.9%), respectively.
2. NDRC is the National Development and Reform Commission of China: ‘tce’ means ton of coal equivalent. This figure shows the CO_2 discharge coefficient when already considering the carbon oxidation rate and carbon transfer coefficient (Energy research Institute NDRC, 2010). It is within the 95% confidence interval of the IPCC scenario.
3. These figures are calculated using the departmental weighted average carbon oxidation rate and carbon transfer coefficient in China.

3.4 Reliability evaluation

DH systems represent important infrastructures within a city and their operational reliability is always of great importance to civil departments and all heat users. Therefore, reliability interacts with the planning or retrofitting of a DH system and becomes more critical when selecting combined district heating alternatives.

A reliability evaluation is usually carried out using some reliability indices by means of, for example, a 'state space method' (Wang, 2005), 'failure parameters' (Zheng et al., 2008), and 'failure spectra' (Zhang et al., 2004). However, when conducting a reliability evaluation on a combined district heating system with peak load compensation in a secondary heating network, it is suggested to use a *reliability ensuring coefficient* (presented in paper [IV]), which is based on a quota heating coefficient rather than traditional reliability indices, to describe the critical back-up heating capability under the most disadvantageous type of hydraulic failure of the heating network.

Combined district heating systems with peak shaving heating in a secondary network will improve the reliability of DH systems because peak shaving gas-fired boilers not only collaborate well with basic heat production facilities under regular operating conditions, but also can work independently with high efficiencies in a quota heating period in case of a failure. Peak shaving gas-fired boilers in secondary heating network serve as back-up boilers for the primary heating network and augment the reliability to a certain extent.

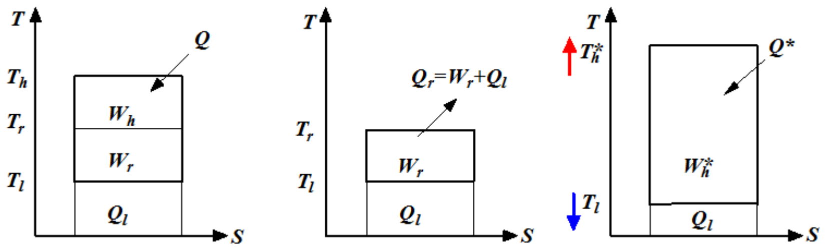
3.5 Energy utilization assessment

Total energy consumption has already been considered in section 3.1 for calculating the fuel cost of a combined district heating system. However, the energy conversion characteristics, or energy qualities, of different fuels and heat production facilities are overlooked to some extent when using a techno-economic analysis alone. Therefore, the energy utilization coefficient should also be assessed.

3.5.1 The fundamental way to improve the energy efficiency of CHP

It is believed that the energy saving potential of an energy conversion system varies according to the constant improvement of the energy utilization coefficient for heat production facilities and the rapid development of heating technologies. Namely, an advanced energy conversion system may become trivial or even unable to save energy due to the prevalence and promotion of this kind of energy conversion, that is to say, energy utilization assessment is a dynamic approach rather than a static process.

The fundamental way to improve the energy utilization coefficient for cogeneration is analyzed here. CHP can be seen as a combination of a Carnot heat engine and a heat pump, as shown in figure 3.5(a)–(b). Figure 3.5(a) assumes that an ideal Carnot heat engine will absorb the heat of Q from a high temperature heat source (T_h), generate the electricity of W=W_h+W_r, and accompany the heat release of Q_l to the low temperature heat source (T_l). In figure 3.5(b), it is assumed that an ideal heat pimp will absorb the heat of Q_l from the low temperature heat source and supply the heat of Q_r=W_r+Q_l to the high temperature heat source with an electricity consumption of W_r. Then, the integrated effect of the two processes will constitute an ideal cogeneration with a heat supply temperature of T_r.



(a) Carnot cycle

(b) Heating cycle with ideal heat pump

(c) Enhancing energy efficiency of CHP

Figure 3.5. Ideal thermodynamic cycles and fundamental way to enhance the energy efficiency of CHP (Zhou & Hu, 2001).

Furthermore, it can be concluded that the dominant factors influencing the energy utilization coefficient of CHP plants are W and W_r, which are determined by the heat engine characteristics and heat supply parameters.

Irreversible losses cannot be avoided in any energy conversion system and real-life thermodynamic cycles will never reach the ultimate limit of quasi-static processes, but the assumption that a reversible ideal cogeneration cycle exists will provide a theoretical basis for guiding the direction of energy saving in a CHP. As can be seen in figure 3.5(c), the fundamental way to improve energy efficiency is to enhance the initial vapor parameters, to reduce the vapor parameters for heat supply, or to do both at the same time.

3.5.2 Energy utilization assessment based on equivalent electricity

There should be a common uniform base for evaluating the energy utilization coefficient, no matter how complicated the energy conversion processes are.

Energy can be divided into exergy and anergy according to the second law of thermodynamics. Exergy cannot be totally converted into work output due to the irreversibility of any real-life energy systems, and the capacity to convert exergy into work output even differs according to the parameters of exergy. That is to say, exergy and work output are different; even exergy with different parameters are not equivalent. Work output has the highest energy quality and conversion capability compared to energy and exergy. Besides, any work output can be seen as equivalent, which is essential to be an evaluating base (Zhou and Hu, 2001). Because electricity is basically equivalent to work output as well as to the energy quality and conversion capability, and because electricity is more preferred for transmissions and metering, it is thus reasonable to establish an energy utilization assessment model using *equivalent electricity* (EE) as the benchmark. This is done as follows:

$$EE = EE_b + EE_p + E_{pump,t} + E_{acc} \tag{3-8}$$

where EE_b, EE_p, $E_{pump,t}$, and E_{acc} stand for the equivalent electricity consumption of the CHP plants, peak shaving gas-fired boilers, circulating pumps, and accessories, respectively, in kWh.

A majority of the electricity is generated from coal-fired condensing power plants in China. Therefore, it is necessary to analyze the current energy efficiencies of the typical condensing power plants before calculating the EE for the CHP plants. By typical power plants, we mean major plants that have a pressure level representing the most current developments in technology and that generate the majority of online electricity. At present, the parameters of typical power plants have already reached a supercritical level in China, shown in table 3.2.

The coal consumption rate ($b^*_{es,c}$) and power supply efficiency ($\eta^*_{es,c}$) of a typical condensing power plant are of great importance and can take the following form:

$$b^*_{es,c} = \frac{B^*}{W^* - W^*_{tp}}, \tag{3-9}$$

$$\eta^*_{es,c} = \frac{W^* - W^*_{tp}}{B^* Q^y_{low,c}}, \tag{3-10}$$

where W^* is the electric power generation, kWh, W^*_{tp} represents the electricity consumption of the power plant itself, kWh, B^* is the total coal consumption, t, and $Q^y_{low,c}$ is the low heating value of coal, MJ/kg.

Table 3.2. Parameters of the condensing power plants in China (Zhou and Hu, 2001).

Pressure level	Initial pressure (MPa)	Boiler efficiency η_b (%)	Relative internal efficiency (%)	Power supply efficiency $\eta^*_{es,c}$ (%)	Coal consumption rate $b^*_{es,c}$ (g/kWh)	Available fuel specific exergy ε_c (kWh/kg)
Low	1.27	88	78	17.1	720	1.39
Sub-medium	2.35	88	80	20.8	595	1.68
Medium	3.43	90	82	23.4	525	1.90
Sub-high	5.88	90	83	29.6	415	2.41
High	8.83	90	86	31.5	390	2.56
Super high	12.75	91	87	35.7	345	2.90
Subcritical	16.18	92	89	37.3	330	3.03
Supercritical	—			39.7	310	3.23
Ultra supercritical	—			47	262	3.82
Advanced combined cycle		—		50	246	4.07
1994 average level					414.1	2.41
Present [1]					**310**	**3.23**

Note: 1. Although the numbers were collected in 2001, the current typical major condensing power plants are still within the supercritical level; power plants with higher pressure levels are still a long ways away from becoming major plants.

In addition, exergy can be partially converted into electricity according to the different energy systems and the second law of thermodynamics. Furthermore, since the typical power plants represent the current development level of the power industry, the electricity generation per unit of fuel at a typical condensing power plant can be called the available fuel specific exergy,

$$\varepsilon_c=\frac{1}{b^*_{es,c}}=\frac{\eta^*_{es,c}}{0.123}, \tag{3-11}$$

where ε_c is the available fuel-specific exergy of coal, kWh/kg, and 0.123kgce/kWh is the minimum standard coal equivalent consumption for generating 1kWh of electricity with a theoretical energy conversion efficiency of 100%. Table 3.2 shows that ε_c gradually increases along with the development of the power industry technology. Consequently, the EE for CHP plants can be written as follows:

$$EE_b=\varepsilon_c B_b=\frac{1}{b^*_{es,c}}\frac{Q_b}{Q^y_{low,c}\eta_b\eta_N}=\frac{Q_b}{ECOP_b}, \tag{3-12}$$

$$ECOP_b=\eta_b\eta_N Q^y_{low,c} b^*_{es,c}, \tag{3-13}$$

where $ECOP_b$ is the equivalent coefficient of the performance (COP) of CHP plants, η_b is boiler efficiency in CHP plants, and η_N is the transmission efficiency of the network.

The process is similar for analyzing the energy utilization of natural gas, but the typical power plants that use a gas turbine are assumed to have a power supply efficiency of 45% at present. Nevertheless, state-of-the-art, gas-fueled power plants that use a combined cycle can even reach a higher level of power supply efficiency, for example 55%. However, this technology is not widespread at present. The available fuel-specific exergy of natural gas takes the form:

$$\varepsilon_g = \frac{1}{b^*_{es,g}} = \frac{\eta^*_{es,g}}{0.1012}, \tag{3-14}$$

where $b^*_{es,c}$ is the gas consumption rate, m3/kWh, $\eta^*_{es,c}$ is the power supply rate when using gas, and 0.1012Nm3/kWh is the minimum rate of gas consumption for generating 1kWh of electricity with a theoretical energy conversion efficiency of 100%. Therefore, the EE of natural gas can be written as follows:

$$EE_p = \varepsilon_g B_p = \frac{1}{b^*_{es,g}} \frac{Q_p}{Q^y_{low,g}\eta_p\eta_N} = \frac{Q_p}{ECOP_p}, \tag{3-15}$$

$$ECOP_p = \eta_p\eta_N Q^y_{low,g} b^*_{es,g}, \tag{3-16}$$

where $ECOP_p$ is the equivalent COP of peak shaving gas-fired boilers, η_p is the gas-fired boiler's efficiency, and $Q^y_{low,g}$ is the low heating value of gas, MJ/m3.

The electrical equipment of a combined district heating system mainly consists of water pumps for various purposes and accessories, such as ventilation, dust catching, fuel supplying, and automatic controlling equipment. The pumps and accessories for a combined district heating system are driven by so-called typical condensing power plants. The electricity consumption can be obtained directly from the techno-economic analysis implemented in section 3.1, and detail information can be found in paper [II].

3.6 Weighting methods using Fuzzy AHP

Criteria weights directly influence the ranking of alternatives. Accordingly, the rationality and veracity of criteria weights determine the reliability of the evaluation results (Wang et al., 2009a). This has led to a variety of suggestions and methods (shown in figure 3.6) regarding how to assess weights for multicriteria evaluation. A detailed review of the weighting methods can be found in a study by Wang et al. (2009a).

The criteria weights for the aggregation system illustrated in figure 2.4 vary for different cities. Moreover, they are changing constantly in accordance with the development of DH, the promotion of heating technologies, and more stringent environmental regulations. For this reason, the study introduces the concept of '*feasible weight space*'. Feasible weight space is a union of all weight vectors derived from fuzzy AHP, which is described in the following section. It is much more reasonable than having a deterministic weight vector for the purpose of MCDA because it can reflect all of the DMs' preferences without losing too much of the judgment information.

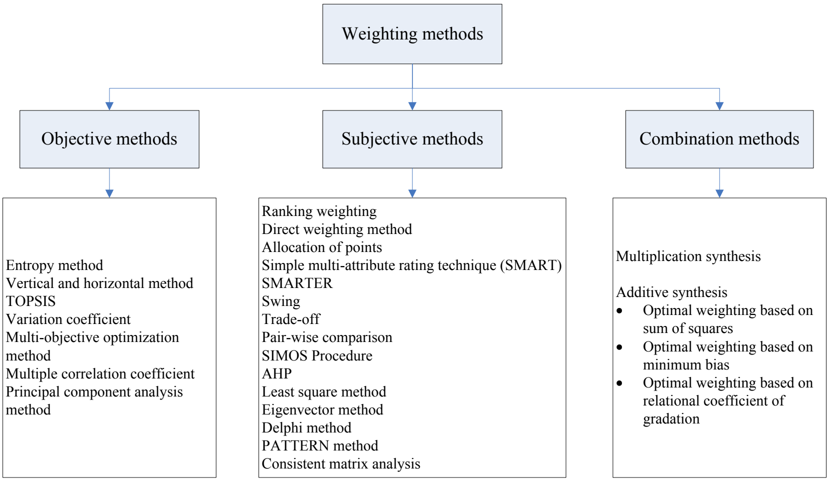


Figure 3.6. Weighting methods classification in MCDA (Wang et al., 2009a).

3.6.1 Fuzzy AHP based on the complementary judgment matrix

AHP is widely used to elicit the DMs' preferences and to compute the weight vectors. AHP has been updated constantly since it was first introduced. Currently, the '*complementary judgment matrix*' has been introduced to AHP; it constitutes the theoretical basis of the so-called fuzzy AHP method (Lv, 2002). Complementary judgment means that two related pairwise comparison elements in the judgment matrix add up to 1, that is, they add up to a complementary relationship rather than a reciprocal one because the essence of the weights constitutes the preference proportion of the criteria.

The main procedure for fuzzy AHP is similar to that for AHP. First, a complementary judgment matrix, ***A***, should be constructed via consultation and/or a questionnaire using the binary grading value shown in table 3.3.

Table 3.3. Binary grading value of complementary judgment matrix.

Description	a_{ij}	a_{ji}
*i*th criterion is identical compared with *j*th	0.5	0.5
*i*th criterion is a little more important compared with *j*th	0.6	0.4
*i*th criterion is important compared with *j*th	0.7	0.3
*i*th criterion is very important compared with *j*th	0.8	0.2
*i*th criterion is extremely important compared with *j*th	0.9	0.1

Then, a consistency check should be performed for all matrices. Generally, only the judgment matrices that pass the consistency check can be used to calculate weight vectors. A complementary judgment matrix with n criteria can be written as follows:

$$A=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, \tag{3-17}$$

where a_{ij} is the preference proportion of the ith criterion compared with the jth criterion. Assume that the weights of the ith and jth criteria are w_i and w_j, respectively. Then a_{ij} would take the following form:

$$a_{ij}=\frac{w_i}{w_i+w_j}. \tag{3-18}$$

It is clear that a_{ij} has the following two properties: a_{ii}=0.5 and a_{ij}=1-a_{ji}, $\forall$ i, j=1, 2, ..., n. In addition, the following definitions are quite important for the use of fuzzy AHP.

Definition 1. A complementary judgment matrix, $\boldsymbol{A}=(a_{ij})_{n\times n}$, has ordinal consistency if any one of the following relationships hold true:

$$a_{ik}>0.5,\ a_{kj}>0.5 \Rightarrow a_{ij}>0.5 \text{ or } a_{ik}>0.5,\ a_{kj}>0.5 \Rightarrow a_{ij}>0.5. \tag{3-19}$$

Equation (3-19) means that if criterion i is decided to be more important than k and criterion k is more important than j for an alternative, then criterion i should be more important than j to reach the ordinal consistency.

Definition 2. A complementary judgment matrix, $\boldsymbol{A}=(a_{ij})_{n\times n}$, has complementary consistency if the following relationship holds true:

$$a_{ik}a_{kj}a_{ji}=a_{ki}a_{jk}a_{ij}. \tag{3-20}$$

This complementary consistency of a CJM is based on the definition and properties of a_{ij}.

Definition 3. Although a judgment matrix, $\boldsymbol{A}=(a_{ij})_{n\times n}$, is not complementarily consistent, it still can be satisfactorily consistent if the following judgment matrix, $\boldsymbol{A'}$, is complementarily consistent, where p_{ij} is the allowable deviation in decision making:

$$\boldsymbol{A'}=(a'_{ij})_{n\times n},\ a'_{ij}=a_{ij}\pm p_{ij}. \quad (3\text{-}21)$$

Generally speaking, it is difficult to keep the complementary judgment matrices consistent. Therefore, a consistency check is necessary prior to eliciting the weight vectors. However, if the inconsistency only varies slightly and can be deemed 'satisfactorily consistent', then the judgment matrix is still acceptable and can be used to calculate the weight vector by means of the weighted least square method (WLSM).

If the judgment matrix is complementarily consistent, then $a_{ij}=w_i/(w_i+w_j)$. But this cannot be achieved easily; therefore, we assume that,

$$\omega_{ij}=a_{ij}-\frac{w_i}{w_i+w_j}, \quad (3\text{-}22)$$

where ω_{ij} is the errors of the elements in the judgment matrix. They can be seen as statistically random variables with mean value expectations of zero. Basically, the more important a criterion is, the lower its error should be. Following this reasoning, the objective function of WLSM is to compute the weight vectors, which are defined as:

$$min\ \ T=\sum_{i=1}^{n}\sum_{j=1}^{n}\left[\left(w_i+w_j\right)\omega_{ij}\right]^2=\sum_{i=1}^{n}\sum_{j=1}^{n}\left(a_{ij}w_i+a_{ij}w_j-w_i\right)^2 \quad (3\text{-}23)$$

s.t. $\qquad w_i>0\ and\ \sum_{i=1}^{n}w_i=1,\ i,j=1,2,\ldots,n.$

The solution to this problem can be found in paper [V]. Additionally, in this dissertation a consistency check is conducted with the assistance of a hypothesis test; however, if p_{ij} is known, then the consistency check becomes more trivial according to Definition 3. Subsequently, the weight vectors are calculated using WLSM. The weight vectors have also been discussed in more detail in paper [V].

3.6.2 The feasible weight space

The questionnaire concerning the criteria aggregation system shown in figure 2.4 has been made to obtain the complementary judgment matrices for a combined district heating system in Daqing, China. The questionnaire respondents include scholars at universities, the operation and management staff of the heating system, and even heat users. Although it is quite difficult to make all respondents understand the objective and procedure of giving a complementary judgment matrix, valid feedback has still been received and collected, as illustrated in tables 3.4–3.7. So far, twelve valid judgment matrices have been obtained as a part of this survey for each level of the criteria aggregation system.

Subsequently, these matrices will be used to compute the weight vectors in the order of the first to the second level, figuring they pass the consistency check. The weights of the bottom-level criteria will then be obtained according to the hierarchy structure of the criteria aggregation system. Finally, a feasible weight space will be constructed using the union of the bottom-level criteria weights derived from each 'consistent' judgment matrix. In this way, the feasible weight space can make full use of the 'consistent' preferences without too much loss of a DM's useful judgment information.

Table 3.4. Complementary judgment matrices for the first-level criteria.

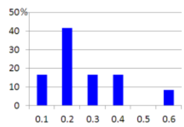
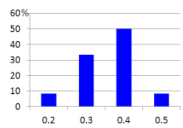
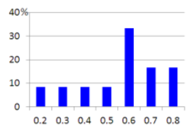
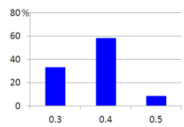
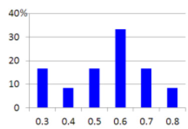
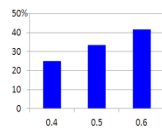
First level criteria	Economy	Technology	Environment	Energy
Economy	0.5			
Technology		0.5		
Environment			0.5	
Energy				0.5

Table 3.5. Complementary judgment matrices for the second-level criteria concerning technology.

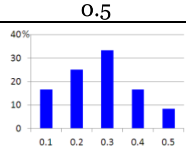
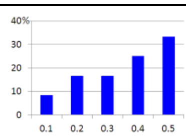
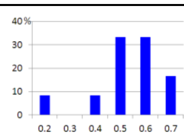
Second level criteria	Reliability	Regulation convenience	maturity
Reliability	0.5		
Regulation convenience		0.5	
maturity			0.5

Table 3.6. Complementary judgment matrices for the second-level criteria concerning the environment.

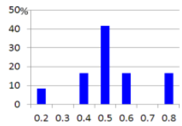
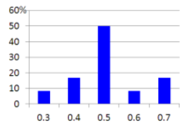
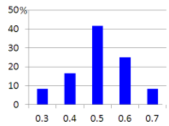
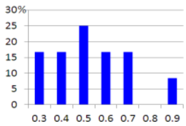
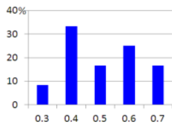
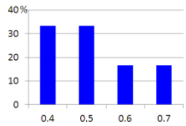
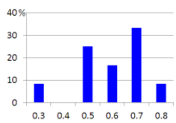
Second level criteria	NO_x	SO_2	PM_{10}	CO_2
NO_x	0.5			
SO_2		0.5		
PM_{10}			0.5	
CO_2				0.5

Table 3.7. Complementary judgment matrices for the second-level criteria concerning energy.

Second level criteria	Energy efficiency	Energy utilization policy
Energy efficiency	0.5	
Energy utilization policy		0.5

It can be concluded that the upper triangle elements of the complementary matrices have the same distributions as the lower triangle elements. That is why tables 3.4–3.7 only illustrate the judgment distribution of the lower triangle elements. In these distributions, the horizontal coordinate shows the judgment of the DMs according to table 3.3, while the vertical coordinate stands for the preference distribution in percentages among the twelve respondents. It seems that many of the distributions are similar to a normal distribution while others are likely to be uniform. It would be better to obtain more judgment matrices to determine the distribution with a greater degree of accuracy.

This study assumes a uniform distribution when using the SMAA model to generate criteria weights within a feasible weight space, since the distribution for generating criteria weights has little effect on the statistic variables when using the SMAA model (Lahdelma & Salminen, 2001). However, the idea presented here still provides the possibility to better understand and improve the preference distribution and weight elicitation in further weighting and MCDA studies. On the other hand, some scholars have introduced a triangle fuzzy number into the complementary judgment matrix and presented new methods for deriving weight vectors (Liu, et al., 2011).

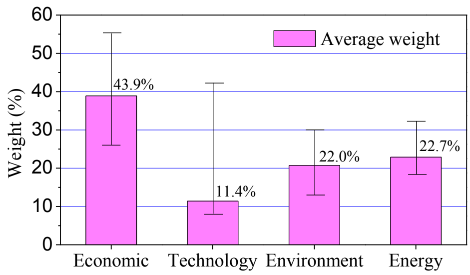
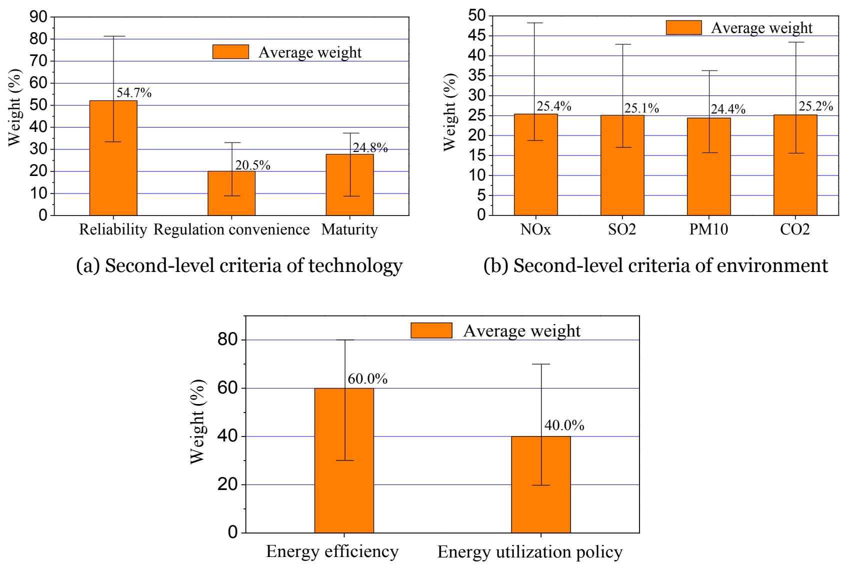


Figure 3.7. Feasible weight space for the first-level criteria.



(a) Second-level criteria of technology
(b) Second-level criteria of environment
(c) Second-level criteria of energy

Figure 3.8. Local feasible weight analyses of the second-level criteria.

Complementarily consistent judgment matrices are used to figure out the criteria weights when using WLSM. Besides, weight analysis can be divided into two categories: Local and global weight analyses. The former examines the weight percentages of second-level criteria in relation to their respective parent criterion, while the latter examines the weight percentages of second-level criteria with respect to the optimization objective. Figures 3.7 and 3.8 illustrate the local weight analyses of the first- and second-level criteria, while the global weight analysis of the bottom-level criteria is demonstrated in figure 3.9.

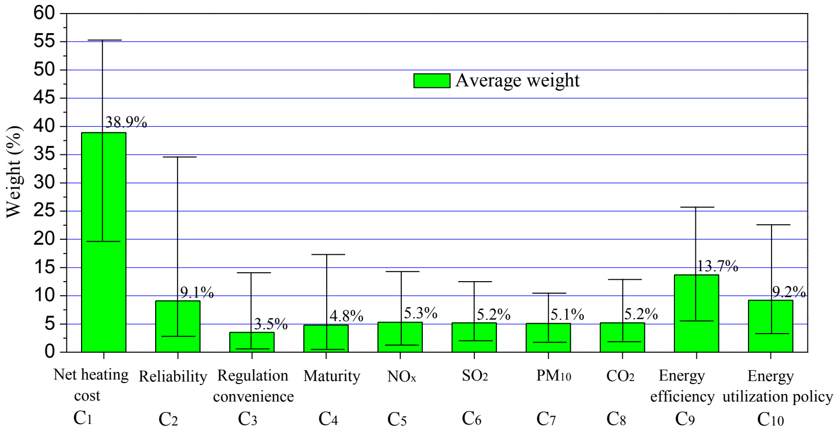


Figure 3.9. Global feasible weight analysis of the bottom-level criteria.

Figure 3.9 shows that the net heating cost is the dominant factor, with an average weight of 38.9%, followed by the energy efficiency criterion, which has a weight percentage of 13.7%. In addition, the rest of the criteria have weight percentages lower than 10%; of these criteria, the energy utilization policy and reliability are of greatest importance, environmental second-level criteria are of second-most importance with similar priorities, while the others' weights are relatively small. Up until now, it has been difficult to give a complete ordinal sequence for these bottom-level criteria; however, the feasible weight space constructed using the present weight intervals fits better with the SMAA model.

4 Multicriteria decision support based on SMAA

The decision support for planning or retrofitting combined district heating systems is a typical MCDA problem with uncertain or imprecise information both in terms of criteria measurements and weighting. In the dissertation, stochastic multicriteria acceptability analysis (SMAA) is adopted to handle this problem; for more details on the original SMAA model, please refer to Lahdelma et al. (1998). SMAA is a family of models that aid in multicriteria decision making for problems with uncertain, imprecise, or partially missing information. They explore the weight space to describe the preferences that make each alternative the most preferred one, or that would give a certain rank for an alternative, rather than make decisions directly according to a decision model with particular criteria measurements and deterministic weight vectors.

4.1 Implementation of SMAA

SMAA family of models encompasses many different variants (Tervonen and Figueira, 2008), among which the SMAA-2 and SMAA-O models have been used most widely until now. They are developed based on the utility function theory for quantitative and qualitative problems, respectively. In addition, the combination of the two methods collaborate well (see, for example, Lahdelma et al., 2001; Tervonen et al., 2008) for problems having both quantitative and qualitative criteria, and therefore they have been adopted for this study.

4.1.1 The SMAA-2 model

The SMAA-2 method extends the original SMAA model by considering all ranks in the analysis based on a holistic acceptability index. There are also some other reasons that the original SMAA model should be extended; these reasons have been discussed extensively in a study by Lahdelma and Salminen, (2001). Consider a MCDA problem having m alternatives $A=\{x_1, x_2, x_3, \ldots, x_m\}$, which needs to be evaluated in terms of n criteria. Let's assume that the DM's preference structure can be represented by a utility function, which maps the different alternatives to the utility values for $u(x_i,\boldsymbol{w})$. With the SMAA-2 method, the decision model is a general utility or value function of this type. The SMAA-2 method introduces a rank acceptability index to describe the overall acceptability of each alternative. A ranking function is presented to compute the rank of each alternative as an integer from the best rank (1) to the worst rank (m), following the suggestions of Lahdelma and Salminen (2001):

$$rank(\xi_i,w)=1+\sum_k \rho\left[u(\xi_k,w)>u(\xi_i,w)\right], \tag{4-1}$$

where ρ(true)=1 and ρ(false)=0, $u(\bullet)$ is the utility function, SMAA uses $\boldsymbol{\xi}$ to denote criteria measurements with a stochastic distribution of $f_X(\boldsymbol{\xi})$, and $\boldsymbol{w}$ has a stochastic distribution of $f_W(\boldsymbol{w})$. The SMAA-2 method is based on analyzing the sets of favorable rank weights, $W_i^r(\boldsymbol{\xi})$, which are defined as:

$$W_i^r(\xi)=\left\{w\in W : rank(\xi_i,w)=r\right\}, \tag{4-2}$$

where

$$W=\left\{w\in R^n : w_j\geq 0, \sum_{j=1}^n w_j=1\right\}. \tag{4-3}$$

A weight vector, $\boldsymbol{w}\in W_i^r(\boldsymbol{\xi})$, assigns utilities for the alternatives so that alternative x_i obtains rank r. The rank acceptability index, b_i^r, is then defined as the expected volume of the set of favorable rank weights for each alternative. This is done as follows:

$$b_i^r=\int_X f_X(\xi)\int_{W_i^r(\xi)} f_W(w)dwd\xi. \tag{4-4}$$

The rank acceptability index is a measure of the variety of different valuations that assign alternative x_i with a rank r. In order to examine the overall acceptability of each alternative, a holistic acceptability index that combines all of the rank acceptability indices is presented:

$$a_i^h=\sum_{r=1}^m \alpha_r b_i^r, \tag{4-5}$$

where α_r are the meta-weights, which indicate the contribution of each rank acceptability index to the evaluation of an alternative. In this respect, $\boldsymbol{\alpha}$ can be obtained as follows:

$$\alpha=\left\{\alpha\in R^m, 1\geq\alpha_1\geq\alpha_2\geq\cdots\geq\alpha_m\geq 0\right\}. \tag{4-6}$$

The central weight vector, $\boldsymbol{w}_i^c$, is defined as the expected center of gravity of the favorable weight space. The central weight vector is computed as an integral of the weight vector over the criteria and weight distributions by,

$$w_i^c = \frac{\int_X f_X(\xi)\int_{W_i^1(\xi)} f_W(w)w dw d\xi}{b_i^1}. \tag{4-7}$$

The central weight vector is the best single vector representation of the preferences of a typical DM supporting x_i, given the assumed weight distribution.

The confidence factor, p_i^c, is defined as the probability that a particular alternative is the most preferred alternative when a particular central weight vector is chosen. The confidence factor is computed as an integral over the criteria distributions by,

$$p_i^c = \int_{\xi \in X : rank(\xi, w_i^c)=1} f_X(\xi) d\xi . \tag{4-8}$$

The confidence factor measures whether the criteria data are accurate enough to discern the alternatives using central weight vector. It can be described as the proportion of stochastic criterion space that determines the best alternative for the given weight vector.

The confidence factor can be calculated for any given weight vector and alternative. On this basis, SMAA-2 calculates the confidence factors for alternatives using each others' central weight vectors, and these are called cross confidence factors; based on these cross confidence factors, more detailed analyses can be done to improve the discrimination capability of SMAA. In particular, the cross confidence factor for alternative x_i with respect to target alternative x_k is computed as follows:

$$p_{ik}^c = \int_{\xi \in X, b_k^1 \neq 0 : w_k^c \in W_i^1(\xi)} f_X(\xi) d\xi . \tag{4-9}$$

The cross confidence factor is the probability that an alternative will obtain the first rank when the central weight vector of the target alternative is used. Therefore, the nonzero cross confidence factors identify the alternative x_i that compete for the first rank with a given central weight vector of alternative x_k and how strongly they do it. Note that the target alternative has to be efficient; otherwise its central weight vector is undefined. It is clear that the cross confidence factor p_{ii}^c is equal to the confidence factor p_i^c.

4.1.2 The SMAA-O model

The SMAA-O model was developed and described in a study by Lahdelma et al. (2003); they designed it for problems with ordinal criteria. The SMAA-O model uses a rank level number, r_j=1, 2, ..., j^{max}, to describe how the alternatives are evaluated for each criterion, where 1 is the best and j^{max} is the worst rank level. Alternatives that are considered equally good are placed on the same rank level and the rank levels are numbered consecutively; thus, $j^{max} \leq m$. The ordinal measurements should be mapped onto the cardinal values in advance. All consistent mappings between the ordinal and cardinal scales are taken into account so that the ordinal criteria are modeled correctly. The idea is to simulate such mappings numerically by generating random cardinal values that correspond to the known ordinal values.

Let γ_j represent the unknown cardinal values corresponding to the known rank levels, r_j. The ordinal-to-cardinal mapping is (David & Nagaraja, 2003):

$$\gamma_j = v_j(r_j). \qquad (4\text{-}10)$$

Because lower ranks are preferred to higher ranks, $v(\bullet)$ must be a monotone decreasing mapping process. Without the loss of generality, a linear cardinal scale for γ_j in the interval [0, 1] is selected, where 1 is the best value. The mapping processes are illustrated graphically in figure 4.1. With this choice, the sum of the lengths of the scale intervals satisfies the following equation:

$$\sum_{r=1}^{j^{max}-1} \Delta\gamma_{j,r} = \sum_{r=1}^{j^{max}-1} \left(\gamma_{j,r+1} - \gamma_{j,r}\right) = 1. \qquad (4\text{-}11)$$

Now the problem turns to simulating all scales whose intervals belong to the valid scale interval space, which is done as follows:

$$\Gamma_j = \left\{ \Delta\gamma_j \in R^{j^{max}-1} : \Delta\gamma_{j,r} > 0, \sum_{r=1}^{j^{max}-1} \Delta\gamma_{j,r} = 1 \right\}. \qquad (4\text{-}12)$$

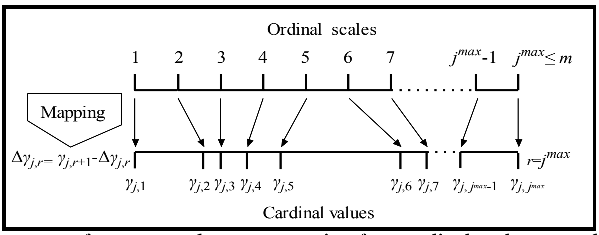
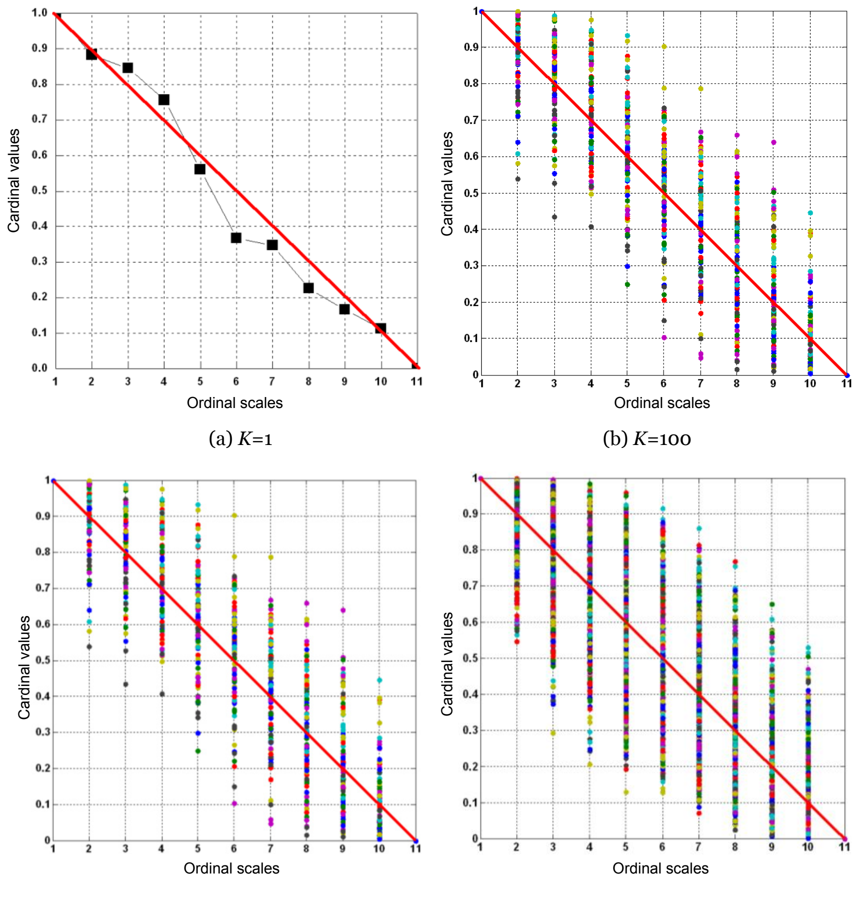


Figure 4.1. Process of monotone decrease mapping from ordinal scales to cardinal values in SMAA-O.

Figure 4.1 just shows an example of the possible mapping process. In fact, as the numbers used in the mapping process increase rapidly, the valid interval space that is being searched for will expand to the greatest possible extent, which can be concluded in figure 4.2 with the assumption that $j^{max}=m=11$. The simulation of moving from ordinal scales to cardinal values in figure 4.2 can cover an increasingly large interval space along with the iterations.



(a) K=1

(b) K=100

(c) K=500

(d) K=1000

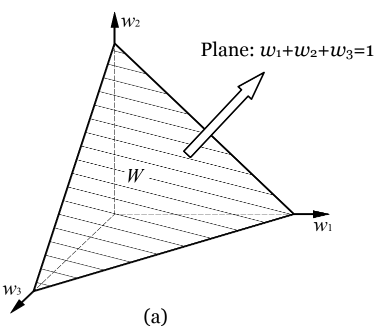
Figure 4.2. Variation of Γ_j, which maps ordinal scales onto cardinal values with simulation iterations from 1 to 1000 in SMAA-O when $j^{max}=m=11$.

Without any additional knowledge about the scale intervals, a uniform distribution can be presumed in the simulation. The simulation is implemented by generating $j^{max}-2$ distinct random numbers from the uniform distribution in the interval [0, 1] and sorting them in decreasing order to get $1=\gamma_{j,1}>\gamma_{j,2}>\ldots>\gamma_{j,j^{max}}=0$. These numbers are then used as a sample of stochastic cardinal criteria measurements such that for each alternative, x_i, ξ_{ij} is equal to γ_{jr}. The statistic variables of rank acceptability indices, the central weight vectors, and the confidence factors can be calculated using the SMAA-O model in a similar way as with the SMAA-2 model. These multidimensional integrals for the most part cannot be calculated directly, but they can be computed using numerical techniques; for example, the Monte-Carlo simulation is quite suitable.

4.1.3 Handling the uncertainties

The uncertainties of cardinal criteria can be expressed, for example, as a specific probability distribution around the expected value. The most commonly used distributions are uniform and normal distributions (Lahdelma et al., 1998). The SMAA-O model can handle the uncertainties of ordinal criteria measurements when mapping the ordinal scales, and therefore no further distributions are needed. In the following section, the focus is on illustrating the way to handle weight information uncertainties using 3-criterion cases. However, the same technique can be extended for modeling the uncertainties in higher dimensions. There are also some other uncertainty patterns in addition to the three important cases shown in figures 4.3–4.5.

In the most extreme case, no weight information is available. However, a uniform or normal distribution can be assumed. In this case, the feasible weight space is a $(n-1)$-dimensional simplex (see equation (4-3)). Figure 4.3 illustrates the feasible weight space in the 3-criterion problems. It is assumed that a uniform weight distribution represents the missing weight information.



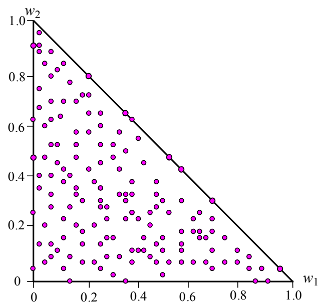


Figure 4.3. Feasible weight space (a) and projection onto w_1-w_2 plane (b) of 3-criterion problems with the missing weight information represented by a uniform distribution.

The weight intervals can be expressed as $w_j \in [w_j^{\min}, w_j^{\max}]$. They may result from direct preference statements of the DMs or from the CJMs using fuzzy

AHP. The intervals can be represented as a distribution by restricting the uniform weight distribution with linear inequality constraints based on the intervals. The restricted distribution weights can easily be generated by modifying the above procedure to reject weights that do not satisfy the interval constraints. Figure 4.4 illustrates the resulting weight distribution.

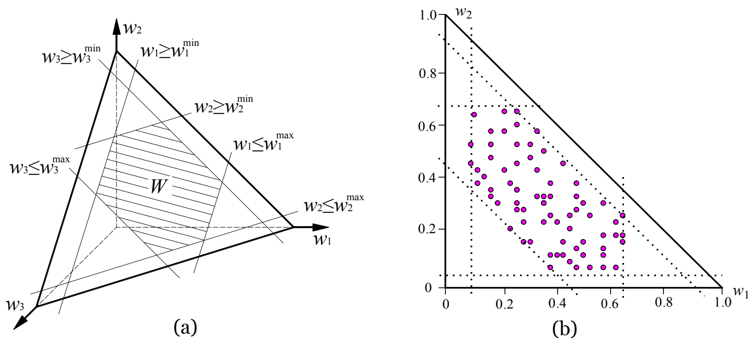


Figure 4.4. Feasible weight space (a) and projection onto w_1-w_2 plane (b) of 3-criterion problems with the weight interval constraints represented by a uniform distribution.

Ordinal preference information can be expressed as linear constraints: $w_1 \geq w_2 \geq \ldots \geq w_n$. It is also possible to allow an unspecified importance ranking for some criteria ($w_j ? w_k$) or else an equal importance ranking. For example, in figure 4.5, if the relationship between w_2 and w_3 is uncertain, then the weight space can be illustrated as the shadow only with constraint of $w_1 \geq w_2$, which means the weight space becomes larger. In general, ordinal preference information means that the preference statements of the DMs correspond to a partial importance ranking of the criteria.

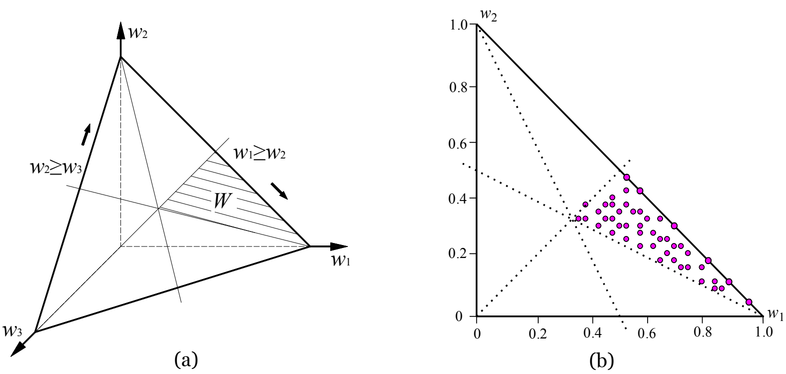


Figure 4.5. Feasible weight space (a) and projection onto w_1-w_2 plane (b) of 3-criterion problems with the ordinal preference information, $w_1 \geq w_2 \geq w_3$, represented by a uniform distribution.

4.2 Case study in Daqing, China

In the dissertation, a combined district heating system that serves as a case study for the National Eleventh Five-year Project of China has been adopted to demonstrate the framework of decision support elaborated on in this study. The heating system is located in the city of Daqing, which had a population of 2.7 million at the end of 2007. Daqing has a long, cold winter with low humidity. Daqing's combined district heating system supplies heat for a floor area of 8.6 million square meters, and CHP plants A and B supply its 50 heating substations with heat. The position and topology of the combined district heating network is shown in figure 4.6.

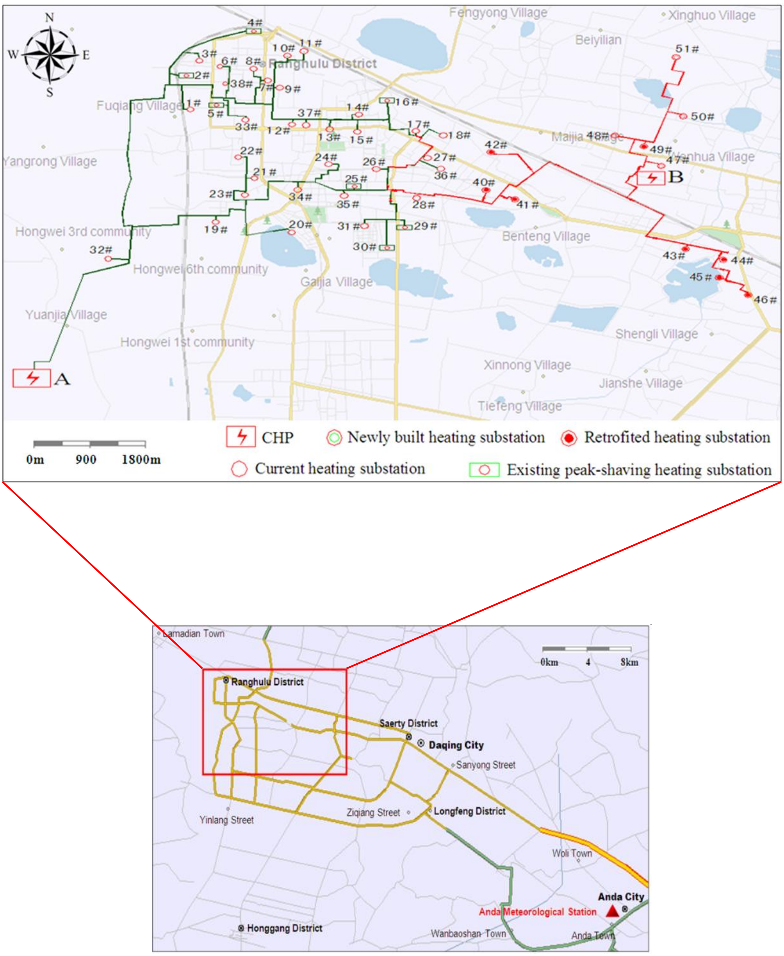


Figure 4.6. The position and topology of Daqing's combined district heating system. Anda Meteorological Station is also labeled at the bottom using a solid triangle.

At the beginning of a heating season, CHP A is firstly put into service; CHP B operates when CHP A is at full load but still insufficient. CHP B serves as peak heat load provider only for a period, not for the whole heating season. In this way, CHP plants A and B as a whole supply the basic heat load; afterwards, peak shaving gas-fired boilers in substations supply the peak heat load to guarantee the heat needed. The design heat load of CHP A is 300 mega-watts (MW), but the design heat load of CHP B is determined by β. Different configurations of basic and peak shaving heat sources constitute the combined district heating alternatives to be addressed in the study. The heating network has been equipped with a supervisory control and data acquisition (SCADA) system. Some relevant design parameters of the combined district heating system are shown in table 4.1.

Table 4.1. Design parameters of the combined district heating system in Daqing.

Item	Value	Unit
Heat load	616	MW
Specific fractional resistance of main pipelines	30–70	Pa/m
Local resistance rate	30	%
Design supply and return water temperature	130/80	°C
Design outdoor temperature [1]	−26	°C
Design indoor temperature [1]	18	°C
Heating period [1]	181	d

Note: 1. Referred to in the Handbook of Regular-Use Data in HV&AC of China, 2002.

Table 4.2. Parameters of the heat production facilities that are a part of Daqing's combined district heating system with different β.

β	Peak heat load $Q'_{load,tf}$ (MW)	Critical peak heating temperature $t'_{w,tf}$ (°C)	Cumulative peak heating time (d)	Basic heat provisions $Q_{jb,1}+Q_{jb,2}$ (GJ)	Peak heat provisions Q_{tf} (GJ)	Percentage of peak provisions (%)
0.50	308.0	−4.0	128.1	4,504,100	1,713,800	27.6
0.55	277.2	−6.2	115.3	4,823,400	1,394,500	22.4
0.60	246.4	−8.4	102.6	5,109,200	1,108,700	17.8
0.65	215.6	−10.6	89.9	5,361,700	856,200	13.8
0.70	184.8	−12.8	77.3	5,581,100	636,800	10.2
0.75	154.0	−15.0	64.8	5,767,600	450,300	7.2
0.80	123.2	−17.2	52.4	5,921,300	296,600	4.8
0.85	92.4	−19.4	40.1	6,042,800	175,100	2.8
0.90	61.6	−21.6	28.0	6,132,200	85,700	1.4
0.95	30.8	−23.8	16.2	6,190,300	27,600	0.4
1.00	0.0	—	0.0	6,217,900	0	0.0

Additionally, the heat loads and provisions of the basic and peak shaving gas-fired boilers clearly vary once the basic heat load changes. These heat provisions, combined with some other important parameters, are listed in table

4.2. More detailed information about this demonstration case can be found in papers [II] and [III].

In the following paragraphs, the dissertation shows how to determine the criteria measurements and their uncertainties. Among the bottom-level criteria shown in figure 2.4, there are seven quantitative criteria, while others are deemed qualitative and should be evaluated using the SMAA-O model. The criteria measurements for Daqing's combined district heating system are shown in table 4.3.

Table 4.3. Criteria measurements and uncertainties of Daqing's combined district heating system at different β.

First level criteria	Economy	Technology			Evironment				Energy	
Second level criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
	▼,quant.	▲, quant.	▲, qual.	▲, qual.	▼, quant.	▼, quant.	▼, quant.	▼, quant.	▼, quant.	▲, qual.
	Net heating cost (10^8 RMB)	Reliability ensuring coefficient (%)	Regulation convenience	Maturity	$C_{msd\text{-}NOx}$ ($\mu g/m^3$)	$C_{msd\text{-}SO_2}$ ($\mu g/m^3$)	$C_{msd\text{-}PM_{10}}$ ($\mu g/m^3$)	CO_2 emissions (Mt)	Equivalent electricity (10^8 kWh)	Energy utilization policy
β=0.50	2.923	61.11	1	11	0.3601	0.1283	0.0371	2.025	25.215	11
β=0.55	2.657	55.00	2	10	0.4255	0.1553	0.0436	2.035	25.570	10
β=0.60	2.439	48.89	3	9	0.4801	0.1795	0.0495	2.044	25.888	9
β=0.65	2.269	42.78	4	8	0.5334	0.2008	0.0543	2.052	26.169	8
β=0.70	2.157	36.67	5	7	0.5349	0.2027	0.0543	2.059	26.413	7
β=0.75	2.085	30.56	6	6	0.5583	0.2137	0.0566	2.066	26.620	6
β=0.80	2.086	24.44	7	5	0.5760	0.2221	0.0583	2.071	26.792	5
β=0.85	2.115	18.33	8	4	0.5890	0.2282	0.0595	2.074	26.927	4
β=0.90	2.195	12.22	9	3	0.6008	0.2340	0.0607	2.077	27.026	3
β=0.95	2.333	6.11	10	2	0.5986	0.2377	0.0611	2.079	27.091	2
β=1.00	2.507	0	11	1	0.5986	0.2394	0.0601	2.080	27.122	1
Uncertainty	±10%	±20%	–		±50%			±10%		–

The uncertainty of techno-economic analysis is usually considered to be within 10% (Hokkanen et al., 2000). This study adopts an uncertainty of ±20% for the reliability criterion because it is complicated to evaluate the reliability according to many different factors that influence it. An uncertainty of ±50% has been used for NO_x, SO_2, and PM_{10} criteria. Other quantitative criteria are deemed to be within ±10% in the dissertation.

The original criteria measurements should be normalized before being using the SMAA model. If the criterion is positive, the measurements can be normalized as follows:

$$\overline{x}_{ij} = \frac{x_{ij} - x_{ij}^-}{x_{ij}^+ - x_{ij}^-}, \tag{4-13}$$

where $\overline{x}_{ij}$ is the normalized measurement of alternative x_i in relation to criterion j, and x_{ij}^+ and x_{ij}^- are the maximum and minimum value of alternative x_i corresponding to criterion j.

If the criterion is a negative one, the original measurements can be normalized using equations (4-14) and (4-15).

$$\bar{x}_{ij}=\frac{x_{ij}^{+}-x_{ij}}{x_{ij}^{+}-x_{ij}^{-}}, \tag{4-14}$$

$$\bar{X}=\left[\bar{x}_{ij}\right]_{m?}=\begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} x_1 \\ x_2 \\ \vdots \\ x_m \end{array} & \begin{bmatrix} \bar{x}_{11} & \bar{x}_{12} & \cdots & \bar{x}_{1n} \\ \bar{x}_{21} & \bar{x}_{22} & \cdots & \bar{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \bar{x}_{m2} & \cdots & \bar{x}_{mn} \end{bmatrix} \end{array}. \tag{4-15}$$

Subsequently, the normalized criteria measurements used in the SMAA model can be calculated according to equations (4-13)–(4-15) and shown in table 4.4.

Table 4.4. Normalized criteria measurements and uncertainties of Daqing's combined district heating systems at different β.

Criterion	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
β=0.50	0	1	1	11	1	1	1	1	1	11
β=0.55	0.317	0.9	2	10	0.728	0.757	0.729	0.815	0.820	10
β=0.60	0.578	0.8	3	9	0.501	0.539	0.483	0.649	0.652	9
β=0.65	0.780	0.7	4	8	0.280	0.347	0.283	0.500	0.503	8
β=0.70	0.914	0.6	5	7	0.274	0.330	0.283	0.374	0.373	7
β=0.75	1	0.5	6	6	0.177	0.231	0.188	0.261	0.263	6
β=0.80	0.999	0.4	7	5	0.103	0.156	0.117	0.171	0.172	5
β=0.85	0.964	0.3	8	4	0.049	0.101	0.067	0.104	0.101	4
β=0.90	0.869	0.2	9	3	0	0.049	0.017	0.050	0.048	3
β=0.95	0.704	0.1	10	2	0.009	0.015	0	0.014	0.014	2
β=1.00	0.496	0.0	11	1	0.009	0	0.042	0	0	1
Uncertainty	±10%	±20%	—		±50%			±10%		—

4.3 Results

In real-life MCDA problems, criteria weights are always difficult to obtain. Moreover, sometimes the consultation or preparing the questionnaire on the DMs' preferences is time consuming. However, we elicited the criteria weights using the concept of feasible weight space based on the discussion in section 3.5. We took into account three different kinds of criteria weights in the SMAA model; they are shown in table 4.5. These weight types are labeled (a), (b), and (c), respectively, in the following analyses.

Table 4.5. Weight bounds used in SMAA for Daqing's combined heating alternatives.

Weight type	No.	Description
Ordinal weight information partially known	(a)	$w_1>w_9>w_{10}?w_2>w_5?w_6?w_7?w_8>w_4>w_3$
Weight intervals partially known	(b)	The intervals of w_1, w_2, w_9 and w_{10} are known.
All weight intervals known	(c)	All weight intervals are known.

4.3.1 Rank acceptability analysis

Because the problem in question encompasses both quantitative and qualitative criteria, we performed the MCDA for Daqing's combined heating alternatives using SMAA-2 in combination with SMAA-O. We used 100,000 Monte-Carlo iterations in the simulation, which gives error limits of less than 0.01(Tervonen & Lahdelma, 2007). The confidence factors, holistic acceptability, and rank acceptability indices using the three types of weight bounds (see table 4.5) are presented in tables 4.6–4.8. In these tables, the alternatives with a^h>30%, p^c>20%, or b^1>10% appear in boldface for better discrimination. B050 stands for the combined heating alternative at β=0.50, and so on. In addition, all acceptability indices are also illustrated graphically in figure 4.7, while the first rank and holistic acceptability indices are highlighted in figure 4.8. Figure 4.9 demonstrates the central weight vectors as stacked columns. Notice that the central weight vector is not defined for an alternative B100 using a type (a) weight bound because it has a confidence factor of zero.

Table 4.6. Confidence factors (p^c) and holistic (a^h) and rank acceptability indices (b^r) in percentages using a type (a) weight bound and sorted in decreasing order with respect to the confidence factors.

Alt.	a^h	p^c	b^1	b^2	b^3	b^4	b^5	b^6	b^7	b^8	b^9	b^{10}	b^{11}
B050	**53.65**	**55.85**	**30.23**	15.71	9.93	7.39	6.42	6.03	6.00	6.26	6.09	4.22	1.71
B070	**47.50**	**31.35**	**14.84**	14.64	15.91	17.51	16.77	11.95	5.97	2.00	0.38	0.03	0
B075	**40.33**	**29.38**	**11.14**	10.80	11.48	13.50	15.93	19.21	12.04	4.75	1.02	0.12	0.01
B055	**50.68**	**27.39**	**18.01**	22.26	15.22	11.15	9.11	7.90	7.01	5.89	2.92	0.51	0.02
B060	**47.51**	18.96	**12.38**	17.06	20.94	16.61	13.30	10.16	6.40	2.52	0.57	0.05	0
B065	**42.45**	16.75	9.06	12.44	16.47	19.74	18.34	13.34	7.16	2.77	0.61	0.06	0
B080	27.22	11.88	3.57	5.34	6.92	8.82	11.48	16.66	26.82	15.20	4.45	0.68	0.07
B085	17.55	3.16	0.74	1.63	2.82	4.50	6.86	10.55	18.76	36.05	14.84	2.89	0.36
B090	9.52	0.32	0.03	0.11	0.31	0.76	1.73	3.95	8.60	19.18	48.77	14.25	2.31
B095	4.20	0.07	0	0	0	0.02	0.06	0.25	1.17	4.95	17.62	61.30	14.63
B100	0.80	0	0	0	0	0	0	0.01	0.07	0.44	2.73	15.88	80.88

Table 4.7. Confidence factors (p^c) and holistic (a^h) and rank acceptability indices (b^r) in percentages using a type (b) weight bound and sorted in decreasing order with respect to the confidence factors.

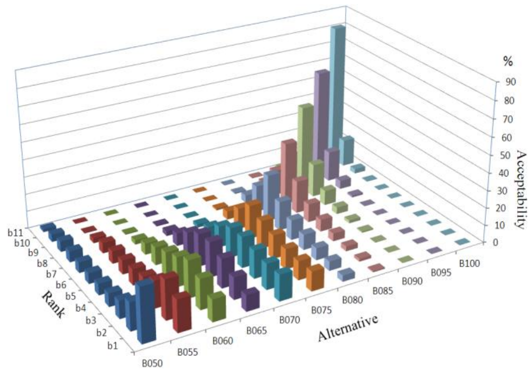
Alt.	a^h	p^c	b^1	b^2	b^3	b^4	b^5	b^6	b^7	b^8	b^9	b^{10}	b^{11}
B050	**34.73**	**39.27**	**14.02**	9.97	8.45	7.79	7.47	7.63	8.02	8.73	9.29	8.47	10.16
B070	**52.06**	**32.58**	**20.07**	17.67	16.09	14.58	12.72	9.43	5.63	2.61	0.91	0.24	0.05
B075	**48.55**	**32.14**	**18.15**	15.69	14.19	13.07	12.42	12.49	8.28	3.97	1.36	0.33	0.05
B055	**38.26**	**24.81**	**12.26**	12.39	11.09	10.41	10.07	9.90	9.87	9.51	7.43	5.86	1.20
B060	**41.25**	18.76	**11.46**	13.26	14.01	13.49	12.92	12.04	10.07	6.84	4.24	1.33	0.32
B065	**36.03**	17.85	8.66	10.39	11.20	11.60	11.93	13.10	17.53	10.53	3.93	0.98	0.16
B080	**41.49**	15.80	**10.32**	13.08	14.73	15.56	15.10	12.91	9.15	5.63	2.46	0.86	0.22
B085	25.50	10.94	3.83	5.42	6.94	8.51	9.83	11.41	14.91	24.81	11.02	2.83	0.49
B090	14.75	6.05	0.99	1.70	2.59	3.78	5.54	7.66	10.58	16.55	36.56	11.70	2.34
B095	6.84	3.46	0.20	0.35	0.59	0.98	1.63	2.77	4.68	8.29	17.10	50.44	12.97
B100	1.98	2.23	0.04	0.08	0.13	0.23	0.36	0.67	1.28	2.54	5.69	16.97	72.03

Table 4.8. Confidence factors (p^c) and holistic (a^h) and rank acceptability indices (b^r) in percentages using a type (c) weight bound and sorted in decreasing order with respect to the confidence factors.

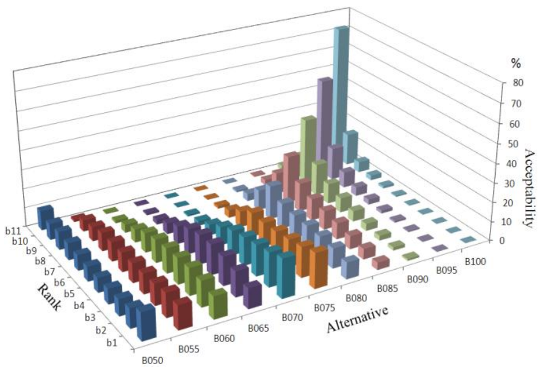
Alt.	a^h	p^c	b^1	b^2	b^3	b^4	b^5	b^6	b^7	b^8	b^9	b^{10}	b^{11}
B050	**32.13**	**32.33**	**11.38**	9.03	8.08	7.76	7.91	8.38	9.27	10.42	11.10	9.32	7.35
B070	**54.60**	**32.29**	**22.43**	18.90	16.37	14.30	11.87	8.57	4.81	2.01	0.60	0.12	0.02
B075	**50.71**	**31.20**	**19.89**	16.77	14.62	13.08	12.08	11.71	7.59	3.24	0.86	0.15	0.02
B055	**37.32**	**22.67**	**11.24**	11.53	10.94	10.55	10.63	10.92	11.18	10.63	7.52	3.92	0.93
B060	**41.58**	18.24	**11.43**	13.13	14.07	13.93	13.67	12.70	10.32	6.48	3.05	0.99	0.22
B065	**36.78**	16.26	8.87	10.72	11.58	11.94	12.18	13.36	17.43	10.21	3.13	0.52	0.06
B080	**42.29**	15.25	**10.61**	13.35	15.12	15.97	15.56	13.09	8.89	4.80	1.92	0.57	0.13
B085	25.16	8.32	3.41	5.14	6.81	8.58	9.99	11.75	15.62	25.86	10.68	1.96	0.20
B090	13.77	3.25	0.65	1.26	2.07	3.25	4.97	7.35	10.67	17.64	39.77	11.02	1.36
B095	5.86	1.18	0.07	0.16	0.32	0.57	1.02	1.91	3.65	7.35	17.48	55.81	11.68
B100	1.22	0.47	0.01	0.01	0.03	0.07	0.14	0.27	0.57	1.36	3.90	15.61	78.02

The emphasis was on analyzing the MCDA results using the weight interval bounds presented here. When inspecting the SMAA results in table 4.6, the last three alternatives (B090, B095, and B100) can be rejected as feasible alternatives because of their near-zero confidence factors. The rest have confidence factors in the range of 10.94–39.27%.

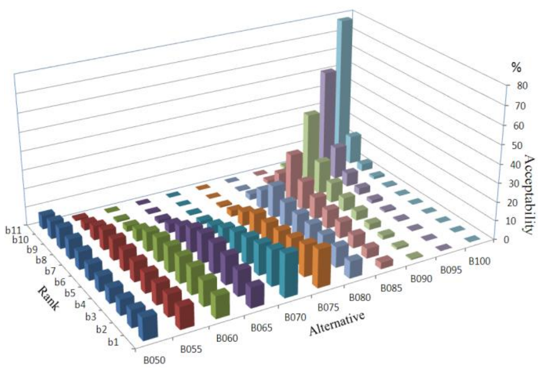
Next, we examined the rank acceptability indices. The rank acceptability indices of B085 are quite small for the best ranks (3.83% for rank 1, 5.42% for rank 2), but relatively large for the worst ranks (after rank 8 here); nevertheless, the confidence factor and holistic acceptability of this alternative are also small compared to the rest of the alternatives. Therefore, B085 can be eliminated from the possible compromise alternatives. Alternative B070 has the highest first-rank and holistic acceptability indices with a high confidence factor and has small rank acceptability indices for the worst ranks; it thus can be selected as the optimal alternative.



(a) Ordinal weight information partially known



(b) Weight intervals partially known



(c) All weight intervals known

Figure 4.7. Rank acceptability indices (b^r) with different types of weight bounds for Daqing's combined district heating alternatives.

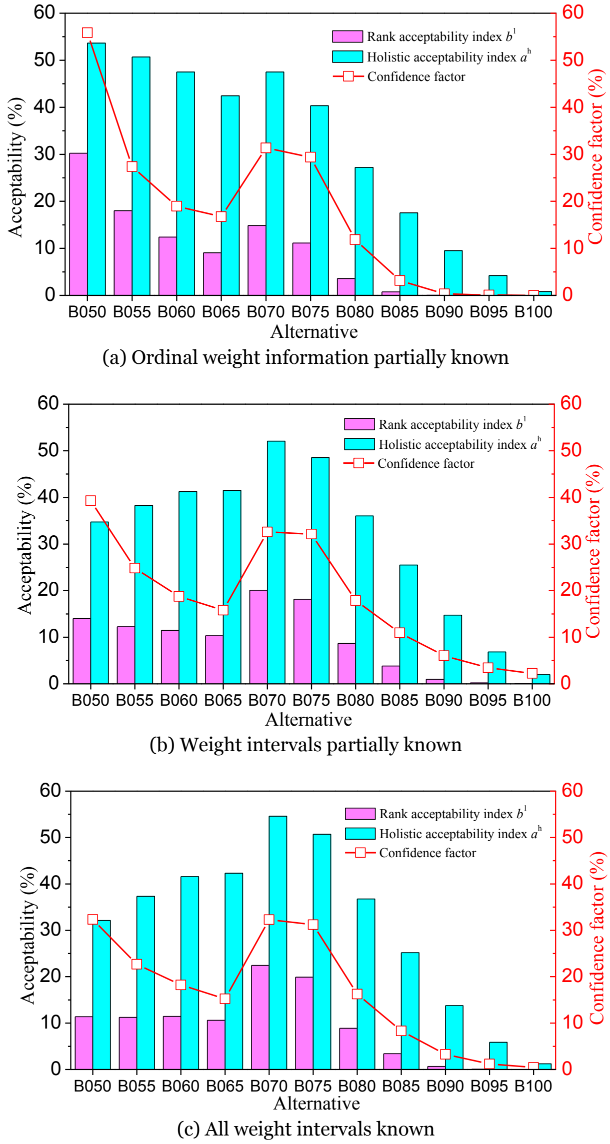
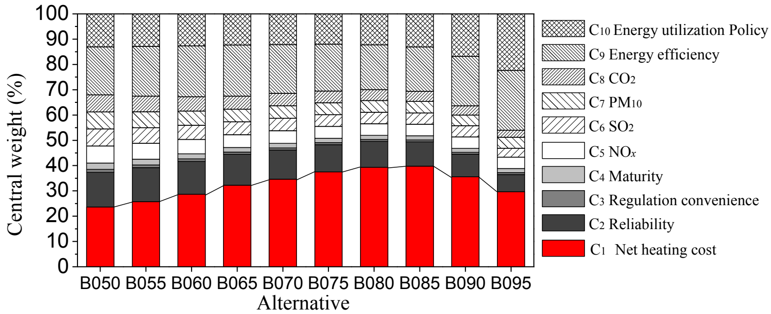
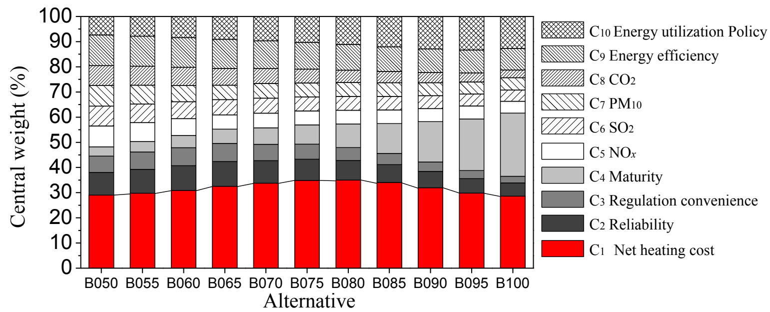


Figure 4.8. First-rank acceptability indices (b^1) and confidence factors (p^c) with different types of weight bounds for Daqing's combined district heating alternatives.

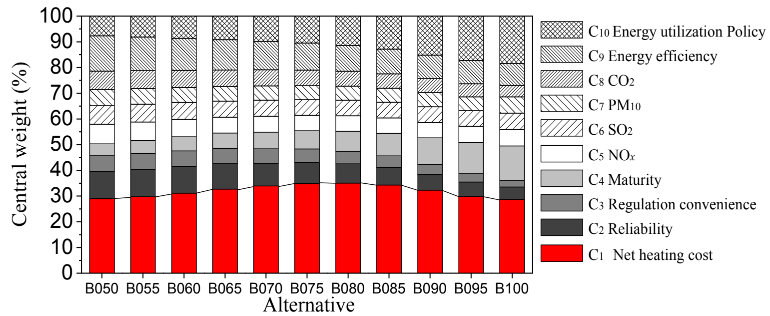
By looking at the central weights in figure 4.9(b), B070 favors the economy and energy criteria. Alternative B075 is quite similar to B070, and it can also reach the most preferred weight if more weights are assigned to the economy and energy criteria by the DMs. In terms of the other five alternatives, even though B050 has the largest confidence factor and first rank acceptability, it cannot become a compromise alternative because of the very large acceptabilities for worst ranks. Namely, B050 is very likely to be the worst alternative even if the DMs' weights are slightly different than its central weights. The situation is basically the same for alternative B055. Finally, B060, B065, and B080 are possible compromise alternatives; in particular, the DMs' preferences are close to their central weights, as shown in figure 4.9(b).



(a) Ordinal weight information partially known



(b) Weight intervals partially known



(c) All weight intervals known

Figure 4.9. Central weights with different weight bounds for Daqing's combined district heating alternatives.

Subsequently, the SMAA results corresponding to the type (c) weight bound are detailed in the same way as for the type (a) weight bound. First, B085, B080, B095, and B100 are not chosen as possible compromise alternatives according to table 4.8 and figure 4.8(c). B070 and B075 are also the most preferred alternatives on the same basis as that of the type (a) weight bound; moreover, the central weights are more or less the same for the two alternatives in figure 4.9(b) and figure 4.9(c). The compromise alternatives are also B060, B065, and B080 for the weight bound. The SMAA results for weight bound (a) can be performed in the same way; the final SMAA results are shown in table 4.9.

Table 4.9. The most preferred and the compromise alternatives using different weight bounds in the SMAA-based MCDA for Daqing's combined district heating alternatives. The alternatives are sorted based on their possibilities of being the most preferred alternative when considering the holistic acceptability indices that use the respective central weight vectors. Alternatives that appear in boldface are the most preferred.

Weight type	No.	Most preferred and compromise alternatives
Ordinal weight information partially known	(a)	**B070**, **B075**, B050, B055, B060, B065
Weight intervals partially known	(b)	**B070**, **B075**, B060, B065, B080
All weight intervals known	(c)	**B070**, **B075**, B060, B065, B080

Table 4.9 indicates that the most preferred alternatives that the DMs should choose are B070 or B075, even though different types of weight bounds are used. Besides, it is clear that the SMAA results for weight bounds (b) and (c) provide the same recommendations when choosing the most preferred and the compromise alternatives. The statistic variables are basically identical with only small differences, which imply that when using the weight interval bound in SMAA, it can be precise enough to adopt several of the most important criteria weights that add up to more than, for example, 70%, like in the case study of Daqing's combined district heating system.

4.3.2 Cross confidence factor analysis

The discrimination of the above-mentioned SMAA results can be improved with the assistance of a cross confidence factor (detailed in section 4.1). Therefore, the dissertation also performs cross confidence factor analyses for each weight bound, shown in tables 4.10–4.12. In these tables, alternatives with cross confidence factors larger than 10% are highlighted in boldface. The results are also illustrated graphically in figure 4.10 to make the analysis more explicit.

Table 4.10. Cross confidence factors (p_{ik}^c) in percentages using a type (a) weight bound. B100 never reached the optimal alternative, therefore the cross confidence factors are not defined.

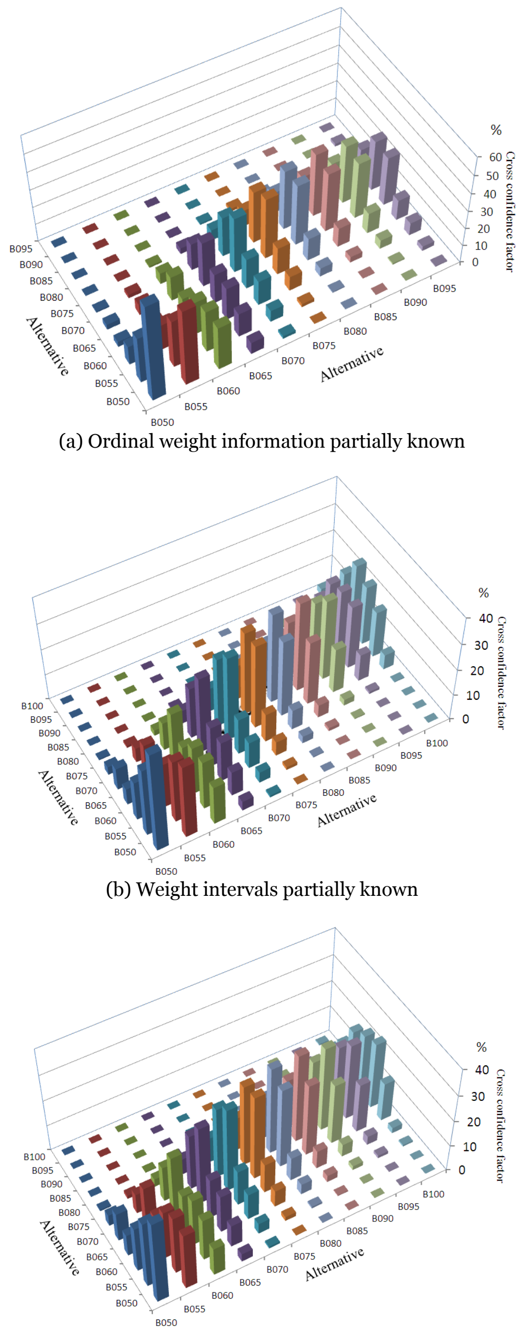
	B050	B055	B060	B065	B070	B075	B080	B085	B090	B095
B050	**55.85**	**26.73**	**10.71**	3.02	2.90	0.73	0.06	0	0	0
B055	**43.97**	**27.39**	**14.60**	5.67	6.11	2.04	0.21	0.01	0	0
B060	**25.04**	**23.98**	**18.96**	**10.99**	**13.80**	6.22	0.95	0.07	0	0
B065	6.75	**13.64**	**18.50**	**16.75**	**25.48**	**15.24**	3.29	0.35	0	0
B070	1.52	6.53	**14.06**	**17.20**	**31.35**	**22.50**	6.00	0.83	0.01	0
B075	0.10	1.81	8.16	**15.37**	**34.39**	**29.38**	9.22	1.55	0.03	0
B080	0	0.52	4.78	**12.75**	**34.26**	**33.48**	**11.88**	2.28	0.05	0
B085	0	0.22	3.21	**10.77**	**33.19**	**35.45**	**13.89**	3.16	0.11	0
B090	0.02	0.76	4.89	**11.57**	**31.50**	**32.64**	**14.05**	4.23	0.32	0
B095	0.44	2.57	7.11	**11.36**	**27.15**	**27.95**	**14.80**	7.04	1.52	0.07

Table 4.11. Cross confidence factors (p_{ik}^c) in percentages using a type (b) weight bound.

	B050	B055	B060	B065	B070	B075	B080	B085	B090	B095	B100
B050	**39.27**	**26.78**	**15.48**	6.35	8.53	3.17	0.40	0.02	0	0	0
B055	**28.96**	**24.81**	**17.61**	9.08	**12.98**	5.64	0.87	0.05	0	0	0
B060	**15.24**	**19.20**	**18.76**	**12.95**	**20.57**	**10.96**	2.13	0.19	0	0	0
B065	3.67	9.65	**15.67**	**15.80**	**29.45**	**19.93**	5.15	0.68	0.01	0	0
B070	0.82	4.27	**10.47**	**13.96**	**32.58**	**26.65**	9.27	1.92	0.06	0	0
B075	0.06	1.16	5.55	**11.09**	**32.47**	**32.14**	**13.56**	3.77	0.21	0	0
B080	0	0.31	2.73	7.71	**29.45**	**34.58**	**17.85**	6.66	0.71	0.01	0
B085	0	0.08	1.19	4.90	**24.50**	**34.39**	**21.82**	**10.94**	2.11	0.07	0
B090	0	0.01	0.37	2.31	**17.21**	**30.78**	**24.99**	**17.53**	6.05	0.73	0.02
B095	0	0	0.08	0.89	**10.37**	**24.13**	**25.02**	**23.20**	**12.39**	3.46	0.46
B100	0	0	0.01	0.29	5.75	**17.64**	**22.49**	**25.90**	**17.94**	7.75	2.23

Table 4.12. Cross confidence factors (p_{ik}^c) in percentages using a type (c) weight bound.

	B050	B055	B060	B065	B070	B075	B080	B085	B090	B095	B100
B050	**32.33**	**26.04**	**17.50**	8.35	**10.96**	4.26	0.53	0.03	0	0	0
B055	**22.15**	**22.67**	**18.77**	**11.09**	**16.28**	7.69	1.27	0.09	0	0	0
B060	**10.94**	**16.36**	**18.24**	**14.04**	**23.40**	**13.67**	3.02	0.33	0	0	0
B065	3.08	8.64	**14.51**	**15.25**	**29.98**	**21.37**	6.17	0.99	0.02	0	0
B070	0.77	4.07	**10.10**	**13.58**	**32.29**	**27.17**	9.78	2.16	0.08	0	0
B075	0.13	1.63	6.38	**11.39**	**32.43**	**31.20**	**12.99**	3.64	0.21	0	0
B080	0.02	0.69	3.98	9.02	**30.53**	**33.41**	**16.26**	5.58	0.51	0	0
B085	0.01	0.32	2.53	6.93	**27.64**	**33.88**	**19.12**	8.32	1.23	0.02	0
B090	0	0.17	1.56	4.78	**23.22**	**32.21**	**21.92**	**12.65**	3.25	0.23	0
B095	0	0.13	1.04	3.28	**18.78**	**28.98**	**23.21**	**16.77**	6.55	1.18	0.07
B100	0	0.06	0.60	2.10	**14.72**	**25.14**	**23.37**	**20.09**	**10.38**	3.07	0.47



(a) Ordinal weight information partially known

(b) Weight intervals partially known

(c) All weight intervals known

Figure 4.10. Cross confidence factors (p_{ik}^{c}) with different weight bounds for Daqing's combined district heating alternatives.

It can be concluded that alternatives B070 and B075 basically have the largest cross confidence factors with respect to all of other target alternatives, except for alternatives B050 and B055. That is to say, alternatives B070 and B075 perform well and can be the most preferred alternative even if the central weights of the other alternatives are adopted. As can be seen in figure 4.10, they compete intensively for the first rank with the other alternatives. For example, Table 4.12 shows that B070's cross confidence factor with a target alternative of B060 is 23.40%, which is clearly larger than B060's own confidence factor (18.24%). Namely, even though B060's central weights are adopted, it should not be chosen as the most preferred alternative because it is dominated by alternative B070. This is why alternatives B060 and B065 have relatively small confidence factors, as shown in figure 4.10.

4.4 Discussion

In this section, we principally discuss the SMAA results, which are shown comprehensively in figure 4.11. This figure analyzes the sensitivity of holistic acceptability indices at different weight bounds while considering the confidence factors. In addition, we also examine the rank acceptabilities of the worst ranks (defined as b^8–b^{11} here) to determine possible compromise alternatives. Note that the definition of worst ranks is not deterministic; on the contrary, worst ranks can be changed for different problems only if they can be of good discrimination for the analysis. In general, one alternative should never be a compromise solution if it has large acceptabilities with respect to the worst ranks, no matter how large its first-rank or holistic acceptability indices are.

The bottom panel of figure 4.11 shows the variation of confidence factors with alternatives and weight bounds, while the upper panel illustrates the variation of holistic and worst rank acceptabilities. The line of p^c=20% divides the alternatives into four groups, namely I, II, III, and IV. These groups can also be extended into the upper panel and used to choose the most preferred and the compromise alternatives, coupled with the restriction of a^h=30%. We will find that groups II and IV have relatively small confidence factors that should be rejected in the following analysis. Among the rest of the groups, group I has slightly higher confidence factors, but it also has large acceptabilities in the worst ranks, which makes it unsatisfactory as a compromise alternative. However, the confidence factors in group III are relatively large and insensitive to the weight bounds; moreover, the acceptabilities of the worst ranks are very small compared to other alternatives. Therefore, the alternatives in group III should be chosen as the most preferred ones, namely β=0.66–0.77. But alternatives that are close to this group can also be the possible compromise solutions, for example B065, if the weight is close to their central weights.

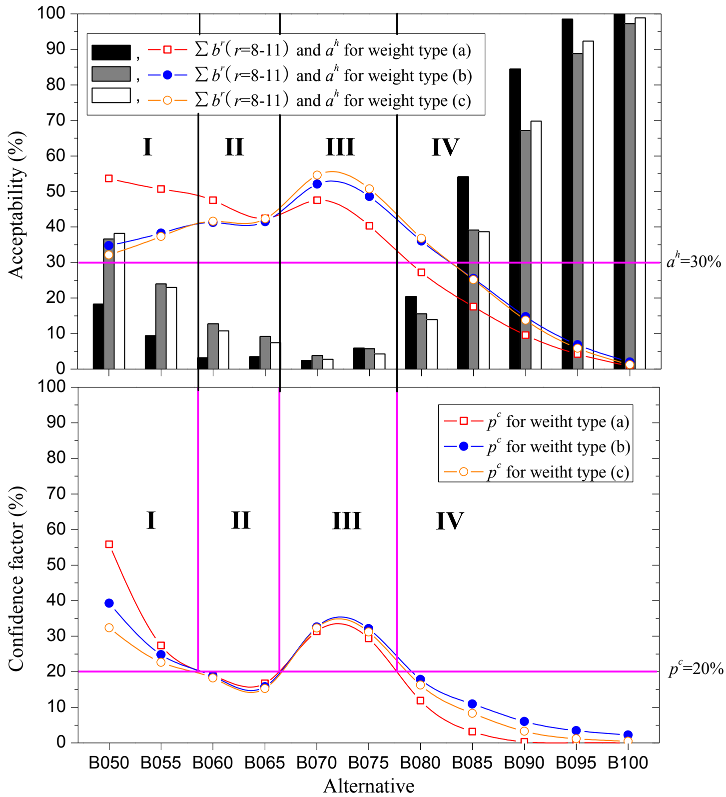


Figure 4.11. Sensitivity analysis of SMAA results for Daqing's combined district heating system.

In conclusion, the results from the sensitivity analysis and cross confidence factor analysis are consistent and they all favor combined heating alternatives with β=0.66–0.77, no matter what kind of weight bounds are adopted. This implies that the DMs should choose a basic heat load ratio in this range for planning or retrofitting Daqing's combined district heating system. Some measures regarding the design and operation of this kind of combined district heating system are also described in the published papers.

5 Concluding remarks and scientific contributions

In terms of DH, CHP-based, combined district heating systems with gas-fired boilers for peak heating load compensation are increasingly being built in developing countries such as China. They are preferred over traditional DH systems and thus promoted because they have relatively high energy and environmental efficiencies and are consistent with the energy structure reformation policy in China. However, a decision support framework is lacking when it comes to planning or retrofitting these kinds of DH systems not only from an economic standpoint, which has been taken into account in most previous applications, but also in relation to energy, technology, and environmental aspects.

The dissertation presents an application-oriented multicriteria decision support framework for evaluating different combined district heating alternatives, which is characterized by a basic heat load ratio (β) in a real-life combined district heating system in Daqing, China. Before using multicriteria decision analysis (MCDA), we developed a corresponding criteria aggregation system, based on which weights can be elicited using fuzzy AHP in combination with the concept of a 'complementary judgment matrix' and hypothesis test. Subsequently, the techno-economic performances, atmospheric environmental impacts, reliabilities, and energy efficiencies of these combined heating alternatives were modeled or simulated, respectively, in order to obtain the criteria measurements needed for decision support. We then implemented stochastic multicriteria acceptability analysis (SMAA) to synthetically handle this problem, which was characterized by incommensurable measurements, conflicting preferences, large uncertainties, and imprecise or incomplete information.

In a combined district heating system, we propose deploying gas-fired boilers in the underperforming heating substations with proper heating capacities according to thermal conditions at a different β. Excessive heat supply rate (EHSR) analysis provides a procedure to quantitatively determine the thermal conditions of a heating system because it can indicate the excessive heat supply conditions of a heating substation over a given period of time, based on which a strategy for installing peak shaving gas-fired boilers can be judiciously proposed. In this way, the operation and regulation measurements can be discussed further.

We developed a detailed techno-economic analysis model while considering current state-of-the-art cogeneration systems in China and the flexibility of gas-fired boilers. This study demonstrated that CHP-based, combined district heating systems can be economically more feasible and sustainable with an appropriate basic heat load ratio and corresponding reasonable regulations. The net heating cost (NHC) of a combined district heating system is more sensitive to coal prices, while the economically optimal basic heat load ratio is more easily influenced by gas prices.

We established a novel assessment model using state-of-the-art AERMOD modeling and normalized population distribution weights (NPDWs) to assess the atmospheric environmental burdens of the combined district heating system. In contrast to national level or regional level modeling efforts, it provides a detailed local-scale assessment of the impacts of energy policies on CO_2 and other air pollution problems. We proposed mean spatial distribution (MSD) concentrations that integrate the AERMOD simulation concentrations and NPDWs for assessing non-CO_2 emissions. The results suggest that it is environmentally efficient to use gas-fired boilers for peak heating load compensation. The combined district heating system can undertake a part of the CO_2 emission reduction burden in China in the DH sector at a city scale. Moreover, it can be concluded that the atmospheric environmental impact posed by DH systems may be more sensitive to population distribution than to pollutant dispersion. This conclusion also justifies the fact that the present model is superior to conventional models, which only measure the pollutant emissions per unit floor heating area or unit heat supply. Municipal authorities and decision makers (DMs) can take advantage of the present model when evaluating and controlling air quality. Nevertheless, we still encourage future researchers to propose new ideas and innovations for reducing the impacts of DH systems and even of other industries by appropriate planning and air pollution mitigation measurements based on this modeling framework.

We assessed the reliability of the model based on a quota heating coefficient to describe the critical back-up heating capability of DH systems under the most disadvantageous hydraulic failure of the heating network. It is clear that the use of peak shaving gas-fired boilers not only will prolong the high-efficiency running time of the CHP plants, but will also improve the reliability of DH and extend its heating capacities, especially in urban areas. In addition, the dissertation assessed their energy efficiency using the concept of available fuel-specific energy and electricity equivalent (EE) based on the fact that the energy utilization assessment is a dynamic approach rather than a static process.

The aforementioned analyses and modeling procedures help to determine the criteria measurements needed for the MCDA of the combined district heating system. We combined SMAA-2 and SMAA-O models to solve this problem. We adopted three types of weight bounds—(a) ordinal weight information partially known, (b) weight intervals partially known, and (c) all weight intervals known—in the dissertation to check the influence of weight information on the SMAA recommendations and statistic variables. The SMAA results demonstrate that combined heating alternatives with β=0.66–0.77 are the most preferred solutions, no matter what kind of weight bound is adopted, because this alternative group is insensitive to the weight bounds. This implies that DMs should choose a basic heat load ratio in this range when planning or retrofitting Daqing's combined district heating system.

The scientific contributions mainly lie in two directions. First, the dissertation introduces the concept of feasible weight space based on fuzzy AHP and a 'complementary judgment matrix' for weighting. The key point is that this feasible weight space encompasses preference information from different groups of DMs and thus can be more rational for use with MCDA; in particular, it can be integrated with SMAA perfectly. Second, a novel atmospheric environmental impact assessment model has been developed using a state-of-the-art AERMOD modeling system that considers network topology and population distribution. On this basis, we calculated the MSD and proposed using it when assessing the environmental burdens of non-CO_2 emissions.

This work demonstrates the decision support aided by MCDA for planning or retrofitting a combined district heating system consisting of CHP plants and gas-fired boilers, but it can be extended and applied to other DH systems and industries as well. For example, it can be used to determine judicious energy supply systems for a city or community based on a host of possible alternatives. Future studies may choose to concentrate on evaluating synthetic building energy supply systems in relation to many other considerations, for example climate policy and developing technologies, not only as a way of choosing proper alternatives, but also to obtain more insights into the systems and understand their impacts on society.

References

Alanne, K., 2007. Applications of the decision analysis in the assessment of energy technologies for buildings. System Analysis Laboratory Research Reports A98, Helsinki University of Technology .

Alanne, K., Salo, A., Saari, A., Gustafsson, S.I., 2007. Multicriteria evaluation of residential energy supply systems. Energy and Buildings 39(12): 1218–1226.

Alanne, K., Saari, A., 2008. Estimating the environmental burdens of residential energy supply systems through material input and emission factors. Building and Environment 43(10): 1734–1748.

Anastaselos, D., Theodoridou, I., Papadopoulos, A.M., Hegger, M., 2011. Integrated evaluation of radiative heating systems for residential buildings. Energy 36(7): 4207–4215.

Badescu, V., 2007. Economic aspects of using ground thermal energy for passive house heating. Renewable Energy 32(6): 895–903.

Beckx, C., Int Panis, L., Arentze, T., Janssens, D., Torfs, R., 2009. A dynamic activity based population modeling approach to evaluate exposure to air pollution: methods and application to a Dutch urban area. Environmental Impact Assessment Review 29(3): 179–185.

Benayoun, R., Roy, B., Sussman, N., 1966. Manual de Reference du Programme Electre. Pairs: Direction Scientifiques SEMA.

Browne, D., O' Regan, B., Moles, R., 2010. Use of multi-criteria decision analysis to explore alternative domestic energy and electricity policy scenarios in an Irish city-region. Energy 35(2): 518–528.

Carlson, A., 2002. Energy system analysis of the inclusion of monetary values of environmental damage. Biomass and Bioenergy 22(3): 169–177.

Casisi, M., Pinamonti, P., Reini, M., 2009. Optimal lay-out and operation of combined heat & power (CHP) distributed generation systems. Energy 34(12): 2175–2183.

CERC, 2013. http://www.cerc.co.uk/environmental-software/ADMS-model.html.

Chen, Q.R., 2003. The prevention and treatment of coal-smoke air pollution in China. Journal of University of Science and Technology, Suzhou (Engineering Technology Edition) 16(1): 1–7.

China Energy Net, 2010. http://www.china5e.com/show.php?contentid=77707.

China Meteorological Administration, 2005. The special weather data set for building thermal environmental analysis of China. Beijing: China Architecture & Building Press.

Clemen, R.T., 1996. Making hard decisions—an introduction to decision analysis, 2nd edition. Duxbury Press at Wadsworth Publishing Company, Belmont, CA.

Cofala, J., Amann, M., Asman, W., Bertok, I., Heyes, C., Hoeglund, I.L. et al., 2010. Integrated assessment of air pollution and greenhouse gases mitigation in Europe. Archives of Environmental Protection 36(1): 29–39.

David H.A., Nagaraja H. N., 2003. Order Statistics. Wiley Series in Probability and Statistics.

Dzenajavičienė, E.F., Kveselis, V., McNaught, C., Tamonis, M., 2007. Economic analysis of the renovation of small-scale district heating systems — 4 Lithuanian case studies. Energy Policy 35(4): 2569–2578.

Egeskog, A., Hansson, J., Berndes, G., Werner, S., 2009. Co-generation of biofuels for transportation and heat for district heating systems—an assessment of the national possibilities in the EU. Energy Policy 37(12): 5260–5272.

Energy Research Institute NDRC., 2010. http://www.eri.org.cn/index.php.

Espen, L., 2007. Use of multicriteria decision analysis methods for energy planning problems. Renewable and Sustainable Energy Reviews 11(7):1584–1595.

Fahlén, E., Ahlgren, E. O., 2011. Accounting for external environmental costs in a study of a Swedish district-heating system – an assessment of simplified approaches. Journal of Cleaner Production doi: 10.1016/j.jclepro.2011.12.017.

Genon, G., Torchio, M.F., Poggio, A., Poggio, M., 2009. Energy and environmental assessment of small district heating systems: Global and local effects in two case-studies. Energy Conversion and Management 50(3): 522–529.

Ghafghazi, S., Sowlati, T., Sokhansanj, S., Melin, S., 2010. A multicriteria approach to evaluate district heating system options. Applied Energy 87(4): 1134–1140.

Henning, D., 1997. MODEST—an energy-system optimization model applicable to local utilities and countries. Energy 22(12): 1135–1150.

Hokkanen, J., Lahdelma, R., Salminen, P., 2000. Multicriteria decision support in a technology competition for cleaning polluted soil in Helsinki. Journal of Environmental Management 60: 339–348.

Holmes, N.S., Morawska, L., 2006. A review of dispersion modeling and its application to the dispersion of particles: An overview of different dispersion models available. Atmospheric Environment 40(30): 5902–5928.

Holmgren. K., Amiri. S., 2007. Internalising external costs of electricity and heat production in a municipal energy system. Energy Policy 35(10): 5242–5253.

Huangfu, Y., Wu, J.Y., Wang, R.Z., Kong, X.Q., Wei, B.H., 2007. Evaluation and analysis of novel micro-scale combined cooling, heating and power (MCCHP) system. Energy Conversion and Management 48(5): 1703–1709.

Huang, J., 2008. Comprehensive evaluation for the setup of peak heating using gas fired boiler. Master thesis of Beijing University of Civil Engineering and Architecture.

IEA, 2010a. CO_2 emissions from fuel combustion (2010 edition). Available at: http://www.iea.org/ publications/free _new_ Desc.asp? PUBS_ID =1825.

IEA, 2010b. 2010 Key world energy statistics. Available at: http://www.iea.org /textbase/nppdf/free/2010/key_stats_2010.pdf.

IPCC, 2001. http://www.ipcc.ch/ipccreports/tar/wg1/pdf/TAR-02.PDF.

IPCC, 2006. http://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/2_Volume2 /V2_2_Ch2_Stationary_Combustion.pdf.

Jiang, Y., 2009a. Building energy conservation in China — current status, problems and solutions. Building Energy Research Center of Tsinghua University.

Jiang, Y., 2009b. Development trend of building energy conservation and key points. Available at: http://www.autooo.net/pv/htm/1/ 18053.html.

Karlssona, Å., Gustavsson, L., 2003. External costs and taxes in heat supply systems. Energy Policy 31(14): 1541–1560.

Keppo, I., 2009. On energy modeling for a range of spatial, temporal and technological scales. TKK Dissertations 198, Department of Energy Technology, Helsinki University of Technology.

Kurnitski, J., Saari, A., Kalamees, T., Vuolle, M., Niemelä, J., Tark, T., 2011. Cost optimal and nearly zero (nZEB) energy performance calculations for residential buildings with REHVA definition for nZEB national implementation. Energy and Buildings 43(11): 3279–3288.

Lahdelma, R., Hokkanen, J., Salminen, P., 1998. SMAA—stochastic multiobjective acceptability analysis. European Journal of Operational Research 106(1): 137–143.

Lahdelma, R., Salminen, P., 2001. SMAA-2: Stochastic multicriteria acceptability analysis for group decision making. Operations Research 49(3): 444–454.

Lahdelma, R., Salminen, P., Simonen, A., Hokkanen, J., 2001. Choosing a reparation method for a landfill using the SMAA-O multicriteria method. In Multiple Criteria Decision Making in the New Millennium, Lecture Notes in Economics and Mathematical Systems, volume 507, pages 380–389. Springer-Verlag, Berlin.

Lahdelma, R., Miettinen, K., Salminen, P., 2003. Ordinal criteria in stochastic multicriteria acceptability analysis (SMAA). European Journal of Operational Research, 147(1): 117–127.

Lahdelma, R., Hakonen, H., 2003. An efficient linear programming algorithm for combined heat and power production. European Journal of Operational Research 148(1): 141–151.

Li, H.T., Burer, M., Song, Z.P., Favrat, D., Marechal, F., 2004. Green heating system: characteristics and illustration with multi-criteria optimization of an integrated energy system. Energy 29(2): 225–244.

Lin, Z.H., 2002. Influences of the energy policy reformation of our country on developments of industrial boilers. Industrial Boiler (3): 4–7.

Liu, S., Zhang, Y.T., Yu, D.Y., 2011. Consistency improvement and priority of triangular fuzzy number complementary judgment matrix based on niche genetic algorithm. Systems Engineering Theory & Practice, 31(3): 522–529.

Liu, Y.F., Liu, J.P., Liu, Y., 2002. Comprehensive economic analysis for heating systems using gas-fired heat source. In proceedings of China HV&AC conference.

Lozano, M.A., Ramos, J.C., Serra, L.M., 2010. Cost optimization of the design of CHCP systems under legal constraints. Energy 35(2): 794–805.

Lund, H., 2007. Renewable energy strategies for sustainable development. Energy 32 (6) 912–919.

Lv, Y.J., 2002. Weight calculation method of fuzzy analytical hierarchy process. Fuzzy Systems and Mathematics, 16: 80–86.

Marbe, Â., Harvey, S., Berntsson, T., 2006. Technical, environmental and economic analysis of co-firing of gasified biofuel in a natural gas combined cycle combined heat and power plant. Energy 31(10): 1614–1619.

Morra, P., Lisi, R., Spadoni, G., Maschio, G., 2009. The assessment of human health impact caused by industrial and civil activities in the Pace Valley of Messina. Science of the Total Environment 407(12): 3712–3720.

Mróz, T.M., 2008. Planning of community heating systems modernization and development. Applied Thermal Engineering 28(14–15): 1844–1852.

Oliver-Sola, J., Gabarrell, X., Rieradevall, J., 2009. Environmental impacts of the infrastructure for district heating in urban neighbourhoods. Energy Policy 37(11): 4711–4719.

Ozgener, L., Hepbasli, A., Dincer, I., 2007. Exergy analysis of two geothermal district heating systems for building applications. Energy Conversion and Management 48(4): 1185–1192.

Pa, A.T., Bi, X.T., Sokhansanj, S., 2011. A life cycle evaluation of wood pellet gasification for district heating in British Columbia. Bioresource Technology 102(10): 6167–6177.

Papadopoulos, A.M., Oxizidis, S., Papandritsas, G., 2008. Energy, economic and environmental performance of heating systems in Greek buildings. Energy and Buildings 40 (2): 224–230.

Pehnt, M., 2008. Environmental impacts of distributed energy systems — The case of micro cogeneration. Environmental Science & Policy 11(1): 25–37.

Pilavachi, P.A., Roumpeas, C.P., Minett, S., Afgan, N.H., 2006. Multicriteria evaluation for CHP system options. Energy Conversion and Management 47(20): 3519–3529.

Rentizelas, A.A., Tatsiopoulos, I.P., Tolis, A., 2009. An optimization model for multi-biomass tri-generation energy supply. Biomass and Bioenergy 33(2): 223–233.

Rong, A.Y., Lahdelma, R., 2005. An efficient linear programming model and optimization algorithm for trigeneration. Applied Energy 82(1): 40–63.

Rong, A.Y., Lahdelma, R., 2007. Efficient algorithms for combined heat and power production planning under the deregulated electricity market. European Journal of Operational Research 176(2): 1219–1245.

Rong, A.Y., Lahdelma, R., 2007. CO_2 emissions trading planning in combined heat and power production via multi-period stochastic optimization. European Journal of Operational Research 176 (3): 1874–1895.

Seppälä, J., 2003. Life cycle impact assessment based on decision analysis (Doctoral Thesis). Finnish Environment Institute, Helsinki.

Statistics Finland, 2006. Final energy consumption by sector 2005. Available at: http://www.stat.fi/til/ekul/2005/ekul_2005_2006-12-08_kuv_003_en.html.

Statistics Finland, 2012. Energy. Available at: http://www.stat.fi/til/ene_en.html.

Su, W.H., 2000. Study on multicriteria comprehensive evaluation theories and methodologies. Doctoral dissertation of Xiamen University, Xiamen, China.

Sundberg, G., Henning, D., 2002. Investments in combined heat and power plants: influence of fuel price on cost minimised operation. Energy Conversion and Management 43(5): 639–650.

Syri, S., Lehtilä, A., Ekholm, T., Savolainen, I., 2008. Global energy and emissions scenarios for effective climate change mitigation — Deterministic and stochastic scenarios with the TIAM model. International Journal of Greenhouse Gas Control 2(2): 274–285.

Tervonen, T., Lahdelma, R., 2007. Implementing stochastic multicriteria acceptability analysis. European Journal of Operational Research 178(2): 500–513.

Tervonen, T., Figueira, J.R., 2008. A survey on stochastic multicriteria acceptability analysis methods. Journal of Multi-Criteria Decision Analysis 15(1–2): 1–14.

Tervonen, T., Hakonenb, H., Lahdelma, R., 2008. Elevator planning with stochastic multicriteria acceptability analysis. Omega 36(3): 352–362.

Thomas, N., Peter, N., 2000. A new method for an economic assessment of heat and power plants using dimensionless numbers. Biomass and Bioenergy 18 (3): 181–188.

Thorin, E., Brand, H., Weber, C., 2005. Long-term optimization of cogeneration systems in a competitive market environment. Applied Energy 81(2): 152–169.

Torchio, M.F., Genon, G., Poggio, A., Poggio, M., 2009. Merging of energy and environmental analyses for district heating systems. Energy 34(3): 220–227.

Tromborg, E., Bolkesjo, T.F., Solberg, B., 2007. Impacts of policy means for increased use of forest-based bio-energy in Norway. Energy Policy 35(12): 5980–5991.

US EPA, 2004. User's guide for the AMS/EPA regulatory model—AERMOD. EPA-454/B-03-001; September 2004.

Wang, J.J., Jing, Y.Y., Zhang, C.F., Shi, G.H., Zhang, X.T., 2008a. A fuzzy multi-criteria decision-making model for trigeneration system. Energy Policy 36(10): 3823–3832.

Wang, J.J., Jing, Y.Y., Zhang, C.F., Zhang, X.T., Shi, G.H., 2008b. Integrated evaluation of distributed triple-generation systems using improved grey incidence approach. Energy 33(9): 1427–1437.

Wang, J.J., Jing, Y.Y., Zhang, C.F., 2009a. Weighting methodologies in multi-criteria evaluations of combined heat and power systems. International Journal of Energy Research (33): 1023–1039.

Wang, J.J., Jing, Y.Y., Zhang, C.F., Zhao, J.H., 2009b. Review on multicriteria decision analysis aid in sustainable energy decision-making. Renewable and Sustainable Energy Reviews 13(9): 2263–2278.

Wang, J.J., Zhang, C.F., Jing, Y.Y., 2010. Multi-criteria analysis of combined cooling, heating and power systems in different climate zones in China. Applied Energy 87(4): 1247–1259.

Wang, X.X., 2005. Fault condition and reliability analysis of multi-heat source ring-shaped heat-supply network. PhD dissertation of Harbin Institute of Technology.

Wei, B., Song, L.W., Li, L., 2010. Fuzzy comprehensive evaluation of district heating systems. Energy Policy 38(10): 5947–5955.

Xing, J., Wang, S.X., Chatani, S., Zhang, C.Y., Wei, W., Hao, J.M. et al., 2010. Projections of air pollutant emissions and its impacts on regional air quality in China in 2020. Atmospheric Chemistry and Physics Discussions 10(11): 26891–26929.

Xu, G., Yang, Y.P., Lu, S.Y., Li, L., Song, X.N., 2011. Comprehensive evaluation of coal-fired power plants based on grey relational analysis and analytic hierarchy process. Energy Policy 39(5): 2343–2351.

Xu, M. Z., He, P., 1986. How to determine the non-dimensional comprehensive equations for district heating. District Heating (1): 4–11.

Xu Z T, Developing city district heating in China. Available at: http://wenku.baidu.com/ view/208a8afb941ea76e58fa0473.html.

Zhang, H.S., Wang, X.X., Zou, P.H., Wu, X., Wang, Y., Wang, K.J., et al., 2004. Failure rate statistics and spectrum analysis of heating network components based on an investigation. Journal of HV&AC 34(1): 15–18.

Zhang, M., Mu H.L., Ning, Y.D., 2009. Accounting for energy-related CO_2 emission in China, 1991–2006. Energy Policy 37(3): 767–773.

Zhang, X., 2005. Causes for the sluggish pace of development of energy saving building technology and some countermeasures, Journal of Xuzhou Institute of Architectural Technology 5(1): 55–57.

Zheng, X.J., You, S.J., Zhang, H., Jiang, N., 2007a. Optimal design of district heating system with gas-fired peak load regulating boiler in the secondary network. Journal of Tianjin University 40(8): 948–951.

Zheng, X.J., You, S.J., Jiang, N., 2007b. Operational regulation schedule of district heating system with peak-load boiler in the secondary network. Journal of Tianjin University 40(12): 1511–1516.

Zheng, X.J., You, S.J., Jiang, N., 2008. Reliability of heating networks with peak load regulating boiler in secondary networks. Journal of Tianjin University 41(2): 163–167.

Zhou, S.X., Hu S.G., 2001. Unified index system for evaluating energy utilization and total energy system. Power Engineering, 21, 2(1): 1069–1077.

Zhou, Y., Levy, J.I., Hammitt, J.K., Evans, J.S., 2003. Estimating population exposure to power plant emissions using CALPUFF: a case study in Beijing, China. Atmospheric Environment 37(6): 815–826.

Zmeureanu, R., Xin, Y.W., 2007. Energy and exergy performance of residential heating systems with separate mechanical ventilation. Energy 32(3): 187–195.

Aalto-DD 212/2013

Combined heat and power (CHP) is playing an indispensible role and thus far from out-of-date, especially in the district heating (DH) sector. CHP-based, combined district heating systems with gas-fired boilers for peak heating load compensation are proposed and studied in the dissertation. First, the design and operation of such DH systems are discussed. Then a multicriteria decision support framework for planning or retrofitting the combined district heating systems is developed and validated in terms of energy, economy, environment and technology, in a more integrated manner. Sub-models concerning energy efficiency, techno-economic analysis and atmospheric environmental simulation are established to facilitate the decision support. Stochastic multicriteria acceptability analysis (SMAA) in combination with the proposed 'feasible weight space' are used in the framework in order to increase the accuracy and reliability of the decision making.

9 789526 054933

ISBN 978-952-60-5493-3
ISBN 978-952-60-5494-0 (pdf)
ISSN-L 1799-4934
ISSN 1799-4934
ISSN 1799-4942 (pdf)

Aalto University
School of Engineering
Department of Energy Technology
www.aalto.fi

BUSINESS +
ECONOMY

ART +
DESIGN +
ARCHITECTURE

SCIENCE +
TECHNOLOGY

CROSSOVER

DOCTORAL
DISSERTATIONS