A HYBRID MULTI-CRITERIA ANALYSIS OF ENERGY EFFICIENT CO_2 IRON MAKING TECHNOLOGIES WITH CARBON CAPTURE AND STORAGE

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FACULTY OF ENGINEERING
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DISSERTATION SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING

DEPARTMENT OF MECHANICAL ENGINEERING
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ORIGINAL LITERARY WORK DECLARATION

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Field of Study: Energy and Environmental Technology

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ABSTRACT

An increase in CO_2 emissions to the atmosphere from the fossil fuel based industries has contributed serious global warming problems. Among several greenhouse gases (GHGs), CO_2 is the prime contributor and accounts for approximately 60% of the greenhouse effect due to its immense amount of discharges. The iron and steel industry is known as the largest energy consuming manufacturing sector, contributing 5% of the world's total energy consumption. Also, this industry is emitting about 6% of the total world anthropogenic CO_2. Therefore, investigation, development and deployment of alternative energy-efficient iron-making breakthrough technologies along with CO_2 capture technologies are receiving high priority to mitigate GHG emissions around 50% by 2050 compared to 2007 level. A new hybrid Multi-criteria Decision Making (MCDM) model was proposed to evaluate the CCS systems in the iron and steel making processes. This model successfully identifies the important optimal criteria and selects the best alternative iromaking technology by considering four prominent aspects (engineering, economic, environmental and social) of sustainability. Surveys questionnaire had been conducted with groups of experts having relevant experience. The model is aimed to transparently and comprehensively measure a wide variety of heterogeneous CCS interdisciplinary criteria to provide insights into aid decision makers in making CCS specific decisions in the iron and steel industry. This proposed MCDM model integrated four methods: Delphi, 2-tuple DEMATEL (Decision making trial and evaluation laboratory), AHP (Analytical hierarchy process) and EFAHP (Extent Analysis method on Fuzzy AHP). A case study was conducted in the iron and steel manufacturing industries in Malaysia to illustrate the application of the framework. This proposed model is flexible with a potential scope of application in similar kinds of energy-intensive industries for the implementation of CCS systems in terms of considered alternatives and criteria.

ABSTRAK

Peningkatan dalam pengeluaran CO_2 ke atmosfera daripada industri berasaskan bahan api fosil telah menyumbang masalah pemanasan global yang serius. Antara beberapa gas rumah hijau (GHG), CO_2 merupakan penyumbang utama dan mencakupi kira-kira 60% daripada kesan rumah hijau kerana jumlah yang besar iaitu pelepasan. The industri besi dan keluli yang dikenali sebagai terbesar sektor pembuatan memakan tenaga, menyumbang 5% daripada jumlah penggunaan tenaga dunia. Juga, industri ini mengeluarkan kira-kira 6% daripada jumlah CO_2 dunia antropogenik. Oleh itu, penyiasatan, pembangunan dan penggunaan tenaga alternatif yang cekap besi membuat teknologi kejayaan bersama-sama dengan teknologi pengumpulan CO_2 menerima keutamaan yang tinggi untuk mengurangkan pelepasan GHG sekitar 50% pada tahun 2050 berbanding dengan paras 2007. Model hibrid baru Multi-kriteria Membuat Keputusan (MCDM) telah dicadangkan untuk menilai sistem CCS dalam besi dan proses pembuatan keluli. Model ini berjaya mengenal pasti kriteria yang optimum penting dan memilih alternatif teknologi pembuatan besi yang terbaik dengan mengambil kira empat aspek penting (kejuruteraan, ekonomi, alam sekitar dan sosial) kemampanan. Ukur soal selidik telah dijalankan dengan kumpulan pakar-pakar yang mempunyai pengalaman yang berkaitan. Model ini bertujuan untuk mengukur secara telus dan menyeluruh pelbagai heterogen CCS kriteria antara disiplin untuk memberi maklumat kepada pembuat keputusan bantuan dalam membuat CCS keputusan tertentu dalam besi dan keluli industri. Model MCDM dicadangkan bersepadu empat kaedah: Delphi, 2-tuple DEMATEL, AHP dan EFAHP. Satu kajian kes telah dijalankan dalam industri besi dan pembuatan keluli di Malaysia untuk menggambarkan penggunaan rangka kerja tersebut. Model yang dicadangkan adalah fleksibel dengan skop yang berpotensi permohonan dalam jenis yang sama industri berintensif tenaga bagi pelaksanaan sistem CCS dari segi dianggap alternatif dan kriteria.

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In the beginning, all praises to the Almighty Lord (Allah) for everything in my life.

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LIST OF SYMBOLS AND ABBREVIATIONS

AHP	:	Analytical hierarchy process
AISI	:	American Iron and Steel Institute
AP	:	Acidification potential
BFG	:	Blast furnace gas
BF	:	Blast Furnace
BOF	:	Basic oxygen furnace
CH_4	:	Methane
CO_2	:	Carbon dioxide
CO	:	Carbon monoxide
CO_2CRC	:	Cooperative Research Centre for Greenhouse Gas Technologies
CCS	:	Carbon Capture & Storage
COURSE50	:	CO_2 Ultimate Reduction in Steelmaking Process by Innovative Technology for Cool Earth 50
COG	:	Coke oven gas
CI	:	Consistency index
DEMATEL	:	Decision-making trial and evaluation laboratory
DM	:	Decision makers
EU	:	European Union
EAF	:	Electric arc furnace
EFAHP	:	Extent analysis method on fuzzy AHP
EP	:	Eutrophication Potential
EU ETS	:	EU Emission Trading Scheme
FHDM	:	Fuzzy hierarchical decision making
GHG	:	Greenhouse gas

GWP	:	Global warming potential
H_2	:	Hydrogen
HTP	:	Human toxicity potential
IEA	:	International Energy Agency
IEAGHG	:	IEA Greenhouse Gas Program
IRM	:	Influential Relation Map
IGCC	:	Integrated gasification combined cycle
IPCC	:	Intergovernmental Panel on Climate Change
ISM	:	Iron and Steel Mill
JISF	:	Japan Iron and Steel Federation
MEA	:	Monoethanolamine
MCDM	:	Multi-criteria decision making
MCDA	:	Multi-criteria decision analysis
MOF	:	Metal Organic Framework
OPEX	:	Operating costs/expenses
PSA	:	Pressure swing absorption
POSCO	:	Pohang Iron and Steel Company
TGRBF	:	Top gas recycling blast furnace
ULCOS	:	Ultra-Low CO_2 Steelmaking
VPSA	:	Vacuum pressure swing adsorption

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

1.1 Background

Increase in atmospheric concentration of CO_2 emissions from fossil based industries has contributed to the serious global warming problems. Among several GHGs, CO_2 is the prime provider and accounts for around 60% of the greenhouse effect due to its huge amount emissions (Han et al., 2014). Iron and steel industry is known as the largest energy consuming manufacturing sector, consuming 5% of the world's total energy consumption and emitting about 6% of the total world anthropogenic CO_2. It shows that one ton of steel manufacturing process emits about 1.8 tons of CO_2 gas (Patel & Seetharaman, 2013) and that the specific energy consumption per ton of crude steel production is 16.0–21.0 GJ (Burchart-Korol, 2013). According to the International Energy Agency (IEA)'s report, steel manufacturing industry produces the biggest share of CO_2 emission that is around 31% of the global manufacturing sectors share see in Figure 1.1 (IEA, 2013 ; Mandil, 2007).

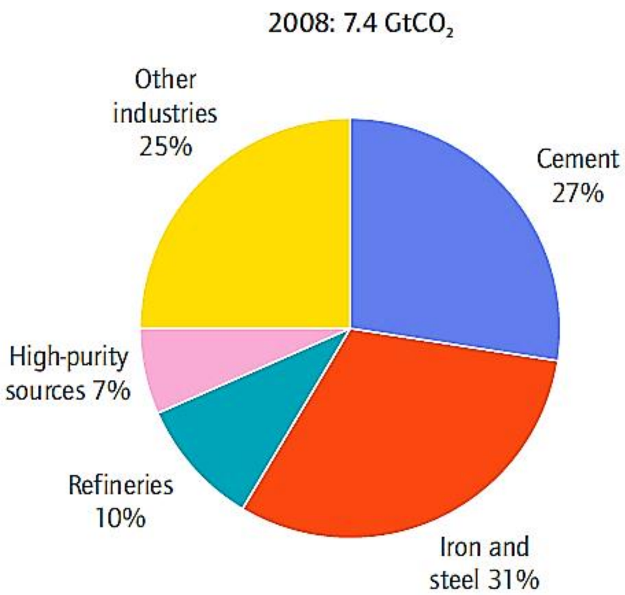


Figure 1.1: Breakdown of the CO_2 emission from industrial sector (IEA, 2013)

However, steel is considered to be one of the most important and useful metals in the world and it continue to be the dominant global metal production (Gupta & Kapur, 2014). According to the World Steel Association's statistics, total steel production and consumption in the world amounted 1,606 million tonnes (Mt) in 2013 and 1,559 Mt in 2012 and has accelerated rapidly since 2002 (Wårell, 2014). In 2013, world steel demand increased by 3.6% with an average annual growth rate of around 5% (W. S. Association, 2013). It implies that the significant rise of CO_2 emission for iron and steel production is unpreventable if not any actions do not measure to mitigate CO_2 emission seen in Figure 1.2.

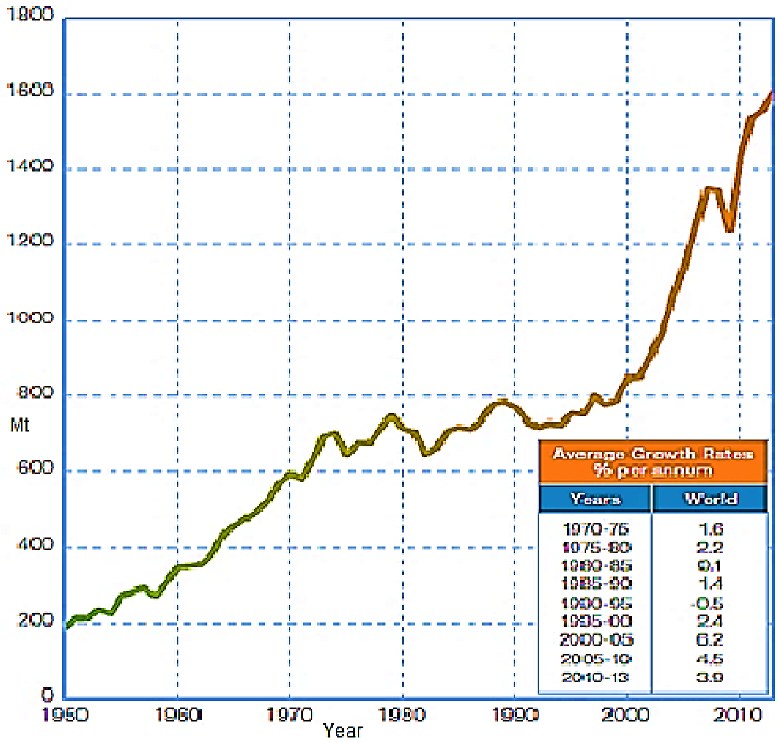


Figure 1.2: Global crude steel production from 1950-2013 (W. S. Association, 2014)

To reduce CO_2 emission from steel industry , there are several options such as reducing steel demand, increasing steel recycling, energy efficiency improvement, innovation in steel manufacturing technologies, and carbon capture and storage (CCS) systems. But IEA has estimated that, in the BLUE Map Scenario of cutting 50% CO_2 emission by 2050 compared to 2007 level, substantial deployment of CCS in industrial applications is necessary (IEA, 2013). The main reason is that CCS contributes significantly a least-cost route of reducing and stabilizing CO_2 emissions in the atmosphere compared to other mitigation alternatives like renewable energy technologies, nuclear energy and greater energy efficiency (Birol, 2010). In addition, according to the International Energy Agency (IEA) (Tanaka, 2008) strategic assessment, called Energy Technologies Perspectives BLUE Map scenario, for reducing GHG emissions by 50% by 2050 compared to 2007 level, concluded that CCS will need to contribute one-fifth of the necessary emissions reductions to achieve stabilization of GHG concentrations in the most cost-effective manner. Otherwise, if CCS technologies are not available, the overall cost to achieve a 50% reduction in CO_2 emissions by 2050 would increase by 70% (IEA, 2013). Moreover, the IPCC Special Report on CCS assessed that CCS could provide 15% to 55% of the cumulative mitigation effort up to 2100 (Coninck, et. al. 2005). To achieve deeper CO_2 emission reduction, hence, CCS has been considered as one of the most promising options to utilize fossil fuels continuously without the significant influence to the climate change (IEA, 2011; Kuramochi et al., 2011).

On the other hand, reduction of CO_2 emissions from the steel mill can be achieved in three areas: (1) reduced steel demand, (2) increased steel recycling, and (3) innovation in steel manufacturing technologies (Pauliuk et al., 2013). Due to the consistent growth in steel production (still mostly coal-based and highly dependent on fossil fuels) for human need and shortage of available high-quality and low price steel scraps (less than 30%) to meet the demand, development and implementation of CO_2 breakthrough technologies with CCS technology might be the only way to reduce substantial emissions (Milford et al., 2013; Pardo & Moya, 2013).

In the iron and steel industry, diverse research projects in several countries under the 'CO_2 breakthrough Programs' have been implemented to enable drastic reduction in CO_2 emission during iron and steel manufacturing processes. For instant, ULCOS

(Ultra-Low CO_2 Steelmaking) project in Europe (ULCOS, 2013), COURSE50 (CO_2 Ultimate Reduction in Steelmaking Process by Innovative Technology for Cool Earth 50) project in Japan (COURSE50, 2013), AISI (American Iron and Steel Institute) CO_2 Breakthrough Program in the USA (Steel Recycling Institute, 2013), and CO_2 Breakthrough Framework of POSCO (Pohang Iron and Steel Company) in Republic of Korea (POSCO,2013). Among these, the EU ULCOS program is the most comprehensive and ambitious program. For the CCS implementation in steel industry, researchers are facing lots of barrier and challenges of engineering, economic and environmental. So it is highly significant to study the impact of CCS application in various iron and steel manufacturing processes.

1.2 Research problem statements

CCS is the only technology capable of directly abating 50% of CO_2 emissions from the steel industry. Even though the CCS technology reduces the high amount of direct CO_2 emission from the iron and steel-making process, it has its own disadvantages such as the high energy requirement, safety (Wilday & Bilio, 2014), additional chemicals and infrastructure (Kenarsari et al., 2013; Spigarelli & Kawatra, 2013; Sreenivasulu et al., 2015). In addition, the collection method of CO_2 from flow gases requires a series of systematic technical process such as pretreatment, separation, and compression shown in Figure 1.3. However, there are various emerging iron and steel-making technologies like 'CO_2 breakthrough technologies' that are still at different stages of the demonstration in the laboratory or small pilot plants. As a result, there are lots of pertinent uncertainties and barriers that create different challenges for the stakeholders for full scale CSS technology deployment in the iron and steel making processes.

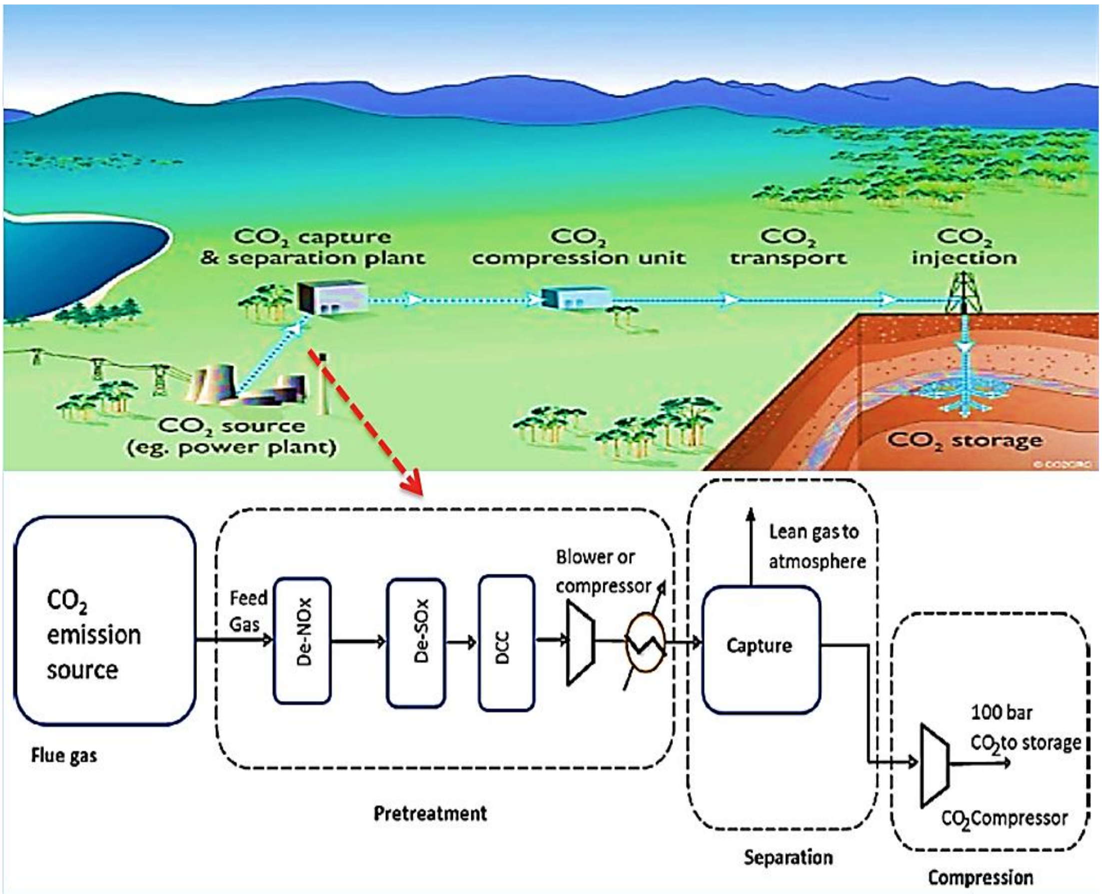


Figure 1.3: Typical layout of CCS systems (Chalmers et al., 2013b)

In addition, during the joint selection and deployment of CCS technologies with iron-making emerging technologies, decision makers (DMs) face different uncertainties and barriers (Watson et al., 2014b) in fuzzy environment. They have to take into account a large number of important factors such as thermal energy consumption, CO_2 removal efficiency, eutrophication potential, CO_2 concentration etc. simultaneously for successful outcomes and optimal decision making (Chalmers et al., 2013b). These factors and sub-factors often conflict each other (Prabhu & Vizayakumar, 2001). CO_2 capture technologies in alternative iron-making process have different performance for each evaluation characteristic. So, there is no CO_2 capture technology in iron-making process that could satisfy all criteria. Therefore, the evaluation of CO_2 captures technology with alternative iron-making technology; need to consider the engineering, environmental, economic and social trade-offs conditions with involvement of a group of experts. Also, it is essential that a systematic process of evaluation to find out the cause and effect relationship among factors in order to investigate the feasibility, to address and understand the various issues and barriers for the implementation of CCS technologies in an integrated steel mill. Due to the complexity of the problem an appropriate systematic method is necessary to ease the human decision maker. Mathematical programming and multi-criteria decision making (MCDM) models are widely used by researchers to solve multi-criteria problems which are suitable in the kind of problems.

1.3 Research gap analysis and highlights

A review of the present literature reveals that no earlier research work that used multi-criteria decision making model to evaluate the internal barriers and influential factors considering four dimensions (engineering, economic, environmental and social) for the selection of CO_2 capture technologies with alternative iron-making technologies. To the best of our knowledge, there is only one published work (Prabhu & Vizayakumar, 2001) in 2001 that proposed fuzzy hierarchical decision making (FHDM) model only for the selection of alternative iron-making technology without CCS systems. Another limitation of the current literature is the lack of studies that quantitatively prioritize and analyze the interactions among the several complex factors and dimensions. In addition the review of the literature indicates that although the existing methods provide many useful tools for the evaluation of CCS technologies, most of them still lack of capability to explore the relationships among evaluation criteria for more in depth analysis. To fill up this gap this study proposes a hybrid multi-criteria decision making (MCDM) model, combining three quantitative methods: the Decision Making Trial and Evaluation Laboratory (DEMATEL), Analytic Hierarchy Process (AHP) and Extent Analysis method on Fuzzy AHP (EFAHP). AHP is applied to prioritize and rank complex factors in terms of their contribution to complexity of CCS development and implementation.

DEMATEL is used to define and describe the interactive relations and dependences between the different factors via a causal-effect relationship map. Finally, alternative CO_2 breakthrough iron making technologies selection with CCS are selected and ranked by using EFAHP method.

1.4 Research objectives

Based on the aforementioned problems, this research is intended to achieve the following objectives:

1. to evaluate the internal barriers and critical criteria of development and implementation of carbon capture and storage (CCS) in iron and steel industry.
2. to select the alternatives CO_2 breakthrough ironmaking technologies with CCS technologies using integrated DEMATEL and AHP approach.
3. to identify the best alternative technology using the extent analysis method on fuzzy AHP (EFAHP) method.
4. to develop a selection model for sustainable green CCS technology in an integrated iron and steel industry.

1.5 Structure of the thesis

Chapter one begins with the background and motivation of the work by highlighting the alarming situation of CO_2 emission from iron and steel industry that has contributed to the global warming and climate changes. Then it focuses on the existing and relevant problems and draws the objectives of the research. In Chapter two, a brief description of CO_2 breakthrough ironmaking and steelmaking technologies that are still at different stages of demonstration in the laboratory or small pilot plant has been presented. Moreover, a comprehensive overview of previous CCS studies including working mechanisms, current research status, challenges and future prospects in steel manufacturing sector has been presented. Chapter three describes the methodology for achieving the four objectives. There are a short description on DEMATEL method, Analytic Hierarchy Process (AHP) method, Fuzzy AHP (FAHP), and Extent analysis method on Fuzzy AHP (EFAHP). It also focuses on the relevant application of those methods in different fields. Thereafter, complete methodology of four objectives has been described by a few flowcharts. At the beginning of the Chapter four, the results of dimensions and criteria selection and evaluation by using Delphi and 2-tuple DEMATEL have been deliberated in subsection 4.2. In addition, cause and effect group of criteria with their influential relation map and diagram has been illustrated. Than selective criteria evaluation and alternatives selection procedure are calculated using AHP and Extent analysis on fuzzy AHP method in subsection 4.3 and 4.4. Chapter five illustrates the critical analysis and comparative discussions of findings of this research. In chapter six, a brief summary of this research has been given with limitations of this work and future research directions.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter explores important literature for systematic research. The literature review is divided into twelve subsections to provide a better understanding of the concepts behind CO_2 capture and storage practices in the iron and steel sector are discussed. In addition, relevant barriers/criteria for its development and implementation are discussed as well. The second subsection describes iron and steel production routes. Third represents energy consumption in iron and steel production. Fourth subsection illustrates CO_2 emission sources from whole iron and steel production with the flue gas composition of different manufacturing routes. Fifth, the current CCS research in the iron and steel industry and sixth presents the key challenges for CCS implementation in steel industry energy consumption. The seventh subsection presents a broad overview of the current status and performance of CO_2 breakthrough ironmaking technologies. Eighth and ninth subsection shows CCS technologies in the worldwide iron and steel industry. Finally, the internal criteria/barriers for CO_2 capture technology deployment are explained, along with supporting literature, in the last three subsections.

2.2 Iron and steel production routes

Steel is produced after several processing steps, including iron making, primary and secondary steelmaking, casting and hot rolling. These processes are followed by various fabrication processes: cold rolling, forming, forging, joining, machining, coating and/or heat treatment. Steel industry produces steel from raw materials (e.g. iron ore, coal and limestone) or recycling steel scrap (W. S. Association, 2014).

An overview of iron and steel production routes is shown in Figure 2.1. There are two main routes for steel production: (1) primary steel production, where raw materials (iron ore and coal) are used for steel production and, (2) secondary steel production from recycled steel scrap (Napp et al., 2014).

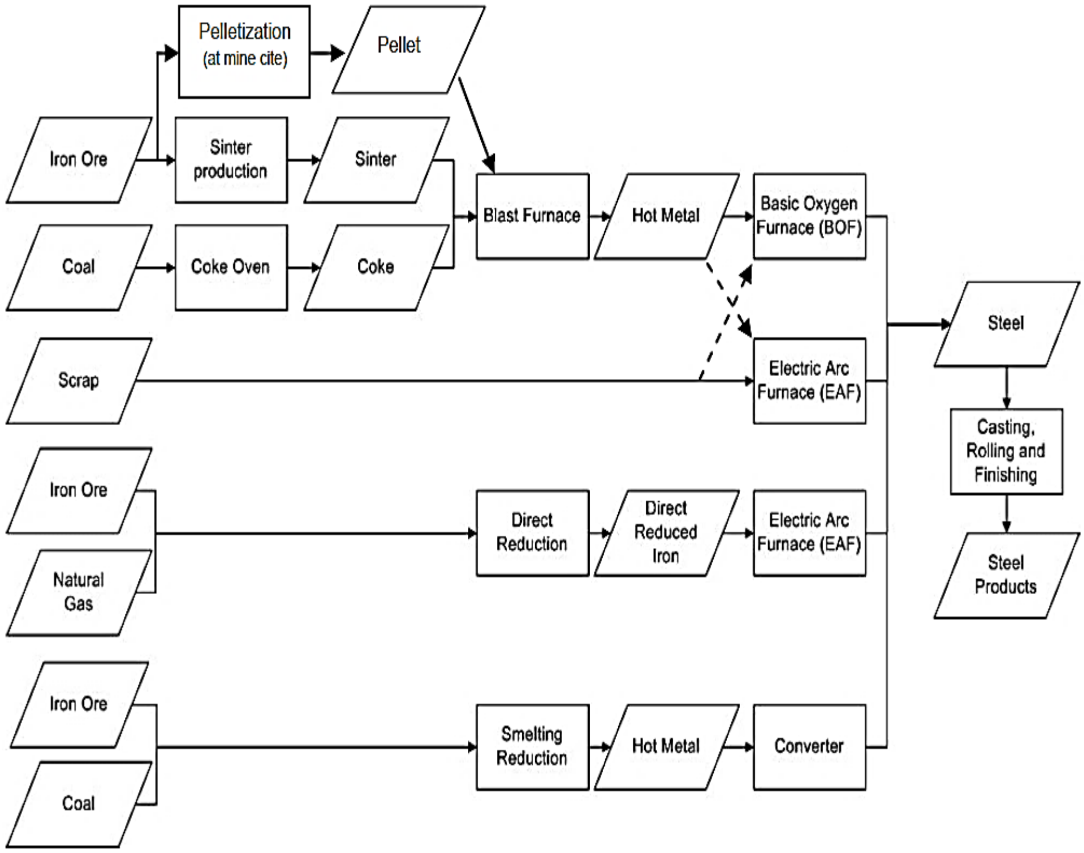


Figure 2.1: Flow diagram on various routes of Steel production (Hasanbeigi, 2014)

The most common primary steel production route is the basic oxygen process (BOF). In BOF, blast furnace (BF) process involves two stages and steel production route is known as BF-BOF route (Napp et al., 2014). Approximately, 70% of steel is being produced using the BF-BOF route (W. S. association). In secondary steelmaking route, steel is produced from recycled steel scrap that is molted by using high power electric arcs in an electric arc furnace (EAF). Steel scrap is used as a supplement of pig iron called direct reduced iron (DRI), also known as 'sponge iron'. Different additives, such as alloys, are used to bring about the desired chemical composition (W. Association, 2012). The resulting iron is more pure than pig iron produced using blast furnace and suitable raw materials for electric arc furnaces. The DRI-EAF process is an alternative primary steelmaking route of the BF-BOF process. Around 29% of steel is produced through the EAF route (W. S. Association, 2008). However, steel making by EAF is the world dominant route in some countries such as, the USA which produces almost 61% of the total country steel production and all steel production in Saudi Arabia and Venezuela in 2010 (W. S. Association, 2011). Another steelmaking technology called open hearth furnace (OHF), is very energy intensive process and has huge environmental and economic disadvantages. It is being phased out over the past decade. Today about 1% of global steel is produced from this route (Napp et al., 2014).

2.3 Energy consumption in iron and steel production

Manufacturing of steel is an energy- and CO_2 intensive process which requires a large amount of natural resources. In 2010, iron and steel mill consumed around 15% of global industrial final energy consumption while chemicals and petrochemicals consumed about 13% and non-metallic 12% (IEA, 2012). And total industrial final energy consumption was 114EJ excluding petroleum feed stocks (Carpenter, 2012a).

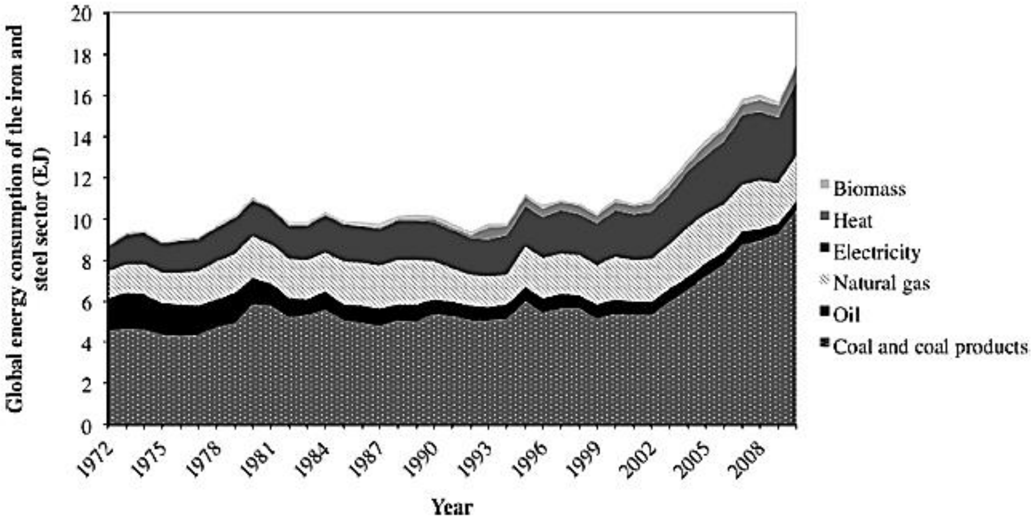


Figure 2.2: Share of fuels consumed by the iron and steel sector from 1972 to 2010 (IEA, 2012)

In 2005, the iron and steel industry consumed 560 Mtoe (23.4 EJ) and emitted 1.99 Gt of CO_2 (Tanaka, 2008) whilst producing 1144 Mt of crude steel (W. S. Association, 2011). Only after two years, energy consumption had increased to 616 M tone (25.8 EJ), and released CO_2 emissions 2.3 Gt (Taylor, 2010), when steel production was 1347 Mt. The high CO_2 emission is due to the energy intensity of steel production, its reliance on coal as the main energy source and the large volume of steel produced.

Figure 2.2 shows the total global energy consumption of the iron and steel sector by fuel types from the year of 1972 to 2010. In 2010, the total energy consumption was 17.6 EJ while it was around 10 EJ in the 1990, which is almost double the energy demand. Approximately 60% of the energy is consumed in the iron and steel sector from coal and coal products supply that is responsible for large amount of emissions.

2.4 CO_2 emissions sources in iron and steel industry

An Integrated Iron and Steel Mill (ISM) consist of a number of complex series of interconnected plants, where emissions comes out from many sources (10 or more) (J. Birat et al., 2010). Huge amount of CO_2 is produced by the reduction reaction in the blast furnace and the combustion reaction of carbonaceous materials (coke breeze, etc.) and carbon-containing gases, such as blast furnace gas (B gas) and coke oven gas (C gas) in the sintering machine, coke ovens, and hot stoves (Sato et al., 2013). Thus, Iron oxides are chemically converted into molten iron (Fe) producing huge amount of CO_2 and carbon monoxide (CO) as a by-product gas or blast furnace gas (BFG). The basic chemistry of iron-making processes is listed as following equations (Germeshuizen & Blom, 2013):

$$C + \frac{1}{2} O_2 \rightarrow CO$$

$$C + O_2 \rightarrow CO_2$$

$$Fe_2O_3 + 3CO \rightarrow 2Fe + 3CO_2$$

$$2CO + O_2 \rightarrow 2CO_2$$

$$2Fe + O_2 \rightarrow 2FeO$$

$$Si + O_2 \rightarrow SiO_2$$

$$2Mn + O_2 \rightarrow 2MnO$$

$$2P + 5FeO \rightarrow P_2O_5 + 5Fe$$

$$C_nH_m + (n+m/4)\ O_2 \rightarrow nCO_2 + (m/2)\ H_2O$$

A CO_2 emission profile of a typical BF/BOF integrated steel plant has been presented in Figure 2.3. It gives a simplified carbon balance with major entry sources (coal and limestone) and the stack emissions in volume (kg/t of hot rolled coil) and intensity of CO_2 (volume %). It shows that the total CO_2 emission is 1.8 t CO_2/t rolled coil, of which 1.7 t CO_2/t rolled coil is contributed by using coal and the other 0.1 t CO_2/t rolled coil is emitted by lime use (Hasanbeigi et al., 2014).

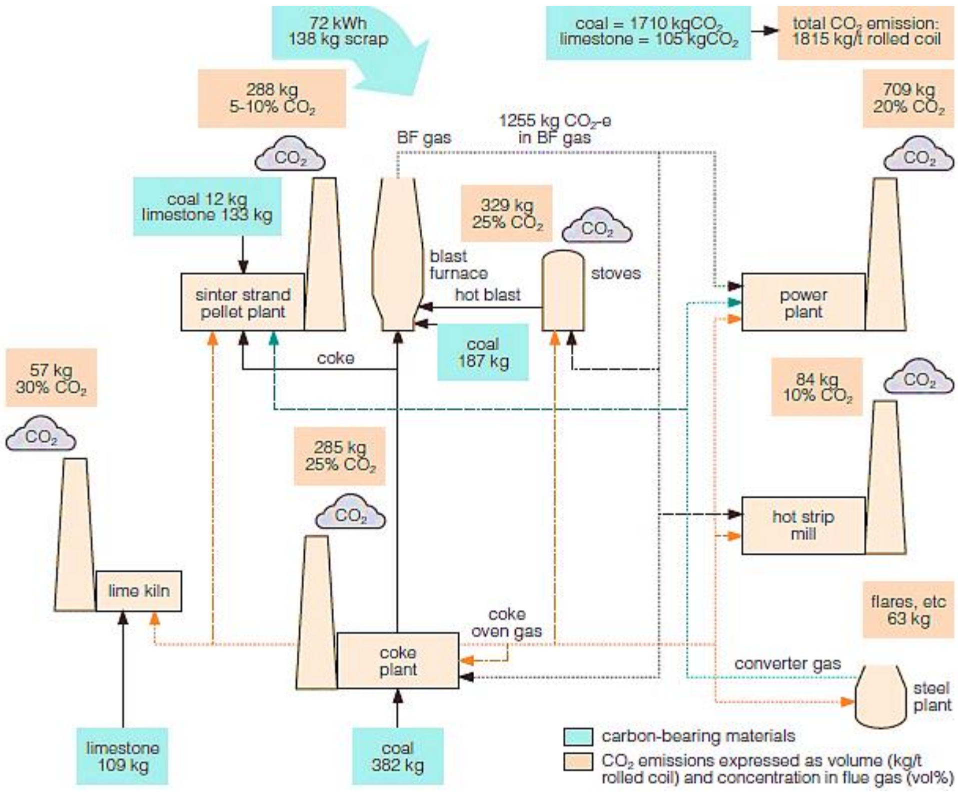


Figure 2.3: CO_2 emissions from a typical iron and steel industry (J. P. Birat et al., 2010)

The main process units at iron and steel production where raw materials combination with fuel combustion, contribute to CO_2 emissions including pellet/sinter plant, non-recovery coke oven battery combustion stack, coke pushing, BF exhaust, BOF exhaust, and EAF exhaust (Hasanbeigi et al., 2014).

The primary combustion sources of CO_2 are product recovery coke oven battery combustion stack, BF stove, boiler, process heater, reheat furnace, flame-suppression system, annealing furnace, flare; ladle reheater, and other miscellaneous (Xu & Cang, 2010). The major CO_2 stream comes out from blast furnace that accounts for 69% of the

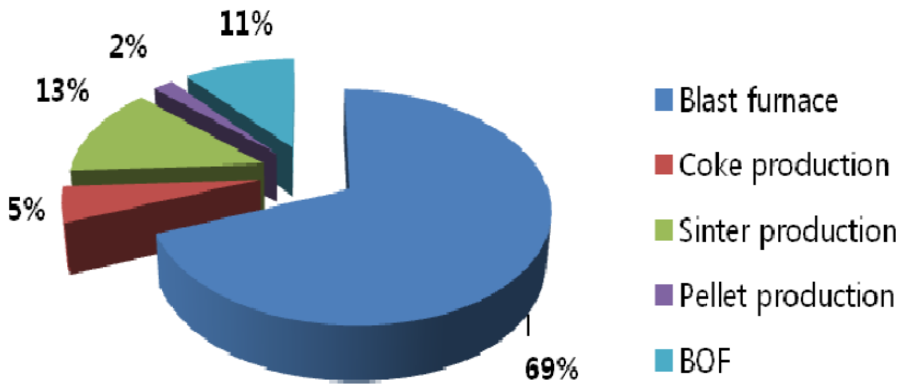


Figure 2.4: Breakdown of the CO_2 emissions from the iron and steel production process at a conventional integrated steel mill (Ho et al., 2013)

total steel mill emissions to the atmosphere, because in BF most of the reduction reactions take place by consuming maximum energy. The top gas of the blast furnace is composed of approximately 25% of CO_2, the rest being CO with a complement of nitrogen at a similar concentration. The other stacks all together account for 31% of the emissions showing rather low CO_2 concentration shown in Figure 2.4 (Carpenter, 2012a).

There are mainly eight direct emission points of sources grouped into two sections: (1) iron production (i.e. power plant stack, COG, blast furnace stoves, sinter plant stack, and lime kiln stack) and (2) steel production (i.e. BOF stack, hot strip mill stack, plate mill stack). The composition and volume of the exhaust gases for each emission point of sources are different exhaust (Hasanbeigi et al., 2014; Ho et al., 2013). Figure 2.5 shows the direct emission point of sources in a conventional integrated steel mill.

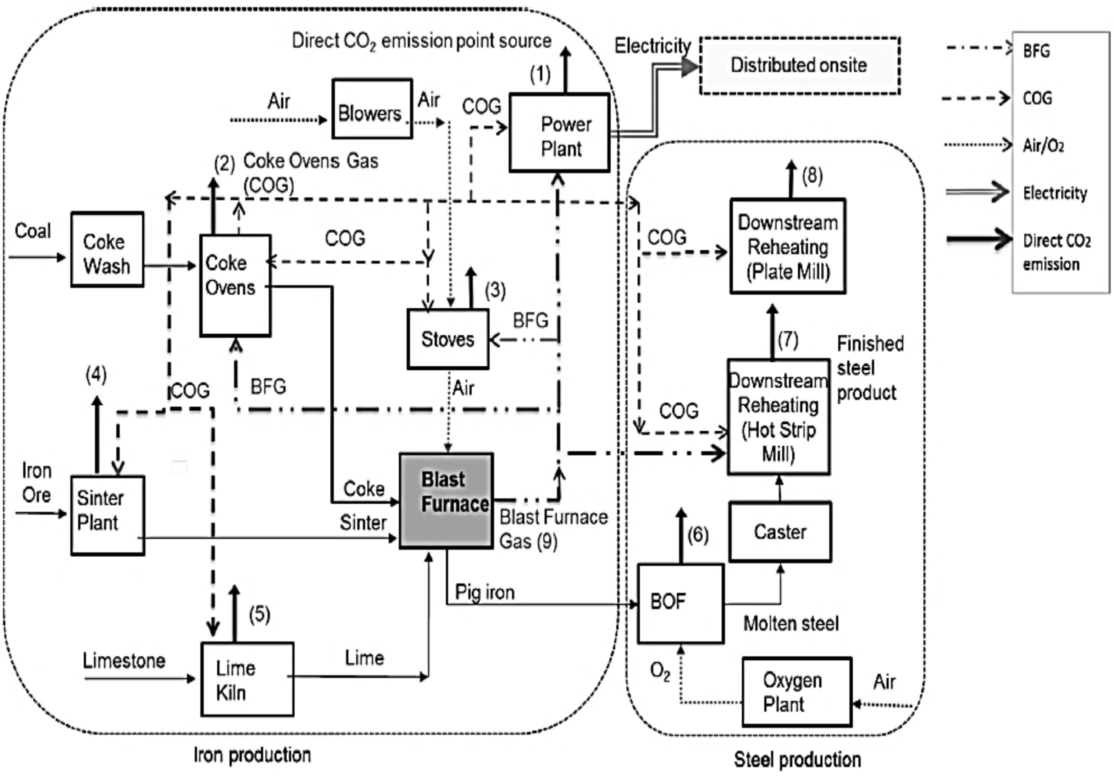


Figure 2.5: Schematic for a conventional integrated steel mill (Ho et al., 2013)

Table 2.1: Flue gas composition of different routes in iron and production

% volume of fraction	BF[a]	TGRBF[b]	COREX[c]	Hismelt[d]
CO_2	16-23	25-37	24-33	23
N_2 + Ar	50-56	5.5-10	2-12	52
O_2	0	0	0-0.5	0
H_2O	0	0	1-2	6
H_2	3-3.5	8-9	17-20	5
CO	21-27	44-48	35-44	23
CH_4	0-0.5	NA	1-2	NB
SO_x (ppm)	200-220	NA	20	~20
NO_x (ppm)	33	NA	NA	~20

Source:

a) (Gielen, 2003; Lampert et al., 2010; Remus, et al., 2013)
b) (K. Afanga et al., 2012; J.P. Birat 2005; Gérard Danloy et al., 2008)
c) (Ho et al., 2008; C. Hu et al., 2009; Lampert & Ziebik, 2007)
d) (Wingrove et al., 1999)

Table 2.1 shows compositions of flue gases emitted from different production technologies of iron and steel manufacturing based on several previous studies. The proportion of CO_2 in flue gases is different, based on applied emerging technologies. Furthermore, other impurities that affect into the capture process are also different in terms of CO_2 capture performance. Therefore, during the reducing process of pig iron production CO_2 technologies have to be implemented by the properties of the flue gases (Choi, 2013).

2.5 CCS research in iron and steel industry

Nowadays, due to the increasing importance of development and deployment of CCS technology into the iron and steel industry, a large number of studies have been focused on various issues. For example, diverse researches like technology strategy for reducing CO_2 emission (Anderson & Newell, 2004; Bennaceur et al., 2008; Lee, 2013; Rubin & De Coninck, 2005), socio-technical analysis (Berkhout et al., 2009), techno-economic and scenario assessment (Bellqvist et al., 2014; Germeshuizen & Blom, 2013; IEA, 2013 ; Kuramochi et al., 2011; Tsupari et al., 2013; Wortler, 2013 ; Zhang et al., 2013) hydrogen based steelmaking (Fischedick et al., 2014; Germeshuizen & Blom, 2013; Morfeldt et al., 2014), biomass based steel making (Fick et al., 2014; Goldemberg, 1996; Suopajärvi et al., 2014), technology selection (Li et al., 2013), chemical absorption process modeling (Arasto et al., 2013; Kuramochi et al., 2012; Lampert & Ziebik, 2007; Tobiesen et al., 2007), physical adsorption process modeling and simulation with environmental impact assessment (Ho et al., 2011; C. Hu et al., 2009; Lampert & Ziebik, 2007) have been done with respect to the implementation of different emerging iron-making technologies with CCS. Table 2.2 shows key parameters of numerous CO_2 capture options for different steelmaking processes reported in the literature and Table 2.3 presents performance and energy requirements of different CCS technologies in iron and steel industry.

Table 2.2: Different parameters of numerous CO_2 capture options for different steelmaking processes described in the literature

Source of capture	CO_2 Capture technology	CO_2 Capture efficiency (%)	CO_2 Captured ($MtCO_2$/yr)	Energy consumption (GJ/t-CO_2)	Capture cost (€/tCO_2)	References
BFG (~23% CO_2)	Aqueous ammonia	90		2.5	-	(Han et al., 2014)
Oxygen blast furnace (OBF)	VPSA	2.713Mt/a 84	-	78.2MW/a	-	(Arasto et al., 2014)
Blast furnace	NH_3	90	-	-	-	(Rhee et al., 2011)
Blast furnace	MEA solvent	90	2.8	-	74	(Ho et al., 2011)
BF	MDEA/MEA solvent	90	2.8	-	35	(Farla, 1996)
Advanced smelting reduction	VPSA	90	-	-	40 – 50	(Kuramochi et al., 2011)
Air-blown BF	MEA MDEA Selexol Shift + selexol Advanced solvents	90	-	3.71-4.95 0.77 1.13-1.53 2.75	70-90 180 20-190 70	(Ho et al., 2011) (J.C.M. Farla, 1995) (Vlek, 2007) (Ho et al., 2011; Vlek, 2007) (Tobiesen et al., 2007)
TGRBF	MEA,VPSA, Selexol Membrane Membranes, VPSA, MEA	90 80-97 90	3.35 Variable Variable	3.92	23-37 15-17 26-64	(Torp, 2005) (Lie et al., 2007) (Duc et al., 2007) (Kuramochi et al., 2011)
COREX	MEA solvent Selexol Shift + selexol Membrane	90 90	2.0 Not stated	4.85 Not stated 1.23	56 40 20-110	(Ho et al., 2011) (K. Lampert, 2010; Torp, 2007) (Gielen, 2003)
Advanced smelting reduction	Purification only	Not stated	Not stated	Not stated	Not stated	(J.-P. Birat, 2006)
Onsite power plant & blast stoves	MEA, new solvents	90	1.9-2.4	-	55-85	(Tsupari et al., 2013)

Table 2.3: Performance and energy requirements for a range of mature CO_2 capture technologies for the iron and steel industry (Hooey et al., 2013; Romano et al., 2013; Rootzén & Johnsson, 2013; Saima et al., 2013)

	Units	PSA	VPSA	VPSA+ compression and cryogenic flash	Amines + compression	PSA + cryogenic distillation compression
Recycled gas (process gas)						
CO yield	%	88,0	904	973	999	100
CO	% vol	71,4	682	689	678	695
CO_2	% vol	27	30	30	29	27
N_2	% vol	135	157	156	151	154
H_2	% vol	124	130	126	121	124
H_2O	% vol	0	0	0	21	0
CO_2 rich gas captured						
CO	%vol (dry)	121	107	33	0	0
CO_2	%vol (dry)	797	872	963	100	100
N_2	%vol (dry)	56	16	3	0	0
H_2	%vol (dry)	25	6	1	0	0
Suitable for transport and storage?		NO	NO	Yes	Yes	Yes
Energy requirements for CCS process						
Capture process	KWh/tCO_2	100	105	160	55	195
Compression for storage (110bar)	KWh/tCO_2	-	-	132	115	115
Electricity consumption (CP+CS)	KWh/tCO_2	**100**	**105**	**292**	**170**	**310**
LP steam consumption	GJ/t CO_2	0	0	0	32	0
Total energy consumption	**GJ/t CO_2**	**0.36**	**0.38**	**1.05**	**3.81**	**1.12**

However, a number of studies (Corsten et al., 2013; Petrakopoulou & Tsatsaronis, 2014; B. Singh et al., 2011; Zapp et al., 2012) discussed the overall environmental impact assessment of CCS technology implementation including eutrophication potential (EP), acidification, climate change, global warming potential (GWP) and human toxicity potential (HTP). The following subsection descries the key challenges of CCS implementation in the iron and steel making industry.

2.6 Key challenges for CCS implementation

From these researches, IEA Greenhouse Gas R&D Program ("IEA Greenhouse Gas R&D Programme") and CO_2 breakthrough programs (i.e. ULCOS, AISI, POSCO, COURSE50, etc.), we can summarize some of the key challenges to the development of the CO_2 capture technologies for the iron and steel industry:

- to handle impurities, other than CO_2 in the flue gas stream.
- unlike power plants, where CO_2 is emitted from a single source, an integrated steel mill has multiple sources of CO_2 emissions emitted from several stacks and happen from start to end of iron and steel production.
- cost competitive and energy efficient CO_2 capture methods and processes,
- efficient, permanent and cost-effective storage,
- effective design and operation of CO_2 transport systems, and
- implementation of CCS in the steel production that required a worldwide solution that would offer a level playing field- which is critical to make CCS in the iron and steel industry workable.

2.7 CO_2 breakthrough iron-making technologies

A set of new CO_2 breakthrough technologies is necessary to make a paradigm shift in industrial production that can change the way of steel making processes around the world. Hence, to tackle CO_2 emissions government and international bodies need the invention and implementation of radical new production technologies. In 2003, the World Steel Association launched the 'CO_2 Breakthrough Programs', an initiative to exchange knowledge and information on regional activities around the world (Asssociation, 2009). Research and investment is taking place in the following countries (W. Association, 2012):

- the EU (ultra-low CO_2 steelmaking, or ULCOS I and ULCOS II)
- the US (American Iron and Steel Institute)
- Canada (Canadian Steel Producers Association)
- South America (ArcelorMittal Brazil)

- Japan (Japanese Iron and Steel Federation)
- Korea (POSCO)
- China (Baosteel) and Taiwan (China Steel) and
- Australia (BlueScope Steel/One Steel CSIRO coordination)

Under those programs, a range of industrial expertise, scientific expertise from labs and academic institutions around the world has been called on to identify steelmaking technologies to reduce a large portion of CO_2 emissions. They explore feasibility of technologies at various scales, from lab works to pilot plant development and ultimately commercial implementation. Each regional initiative explores the best solutions according to the local constraints and cultures (Asssociation, 2009).

2.7.1 Top gas recycling blast furnace (TGR-BF)

Blast Furnace (BF) is the most energy consuming process in integrated steel plants. So it is essential to reduce fossil CO_2 emissions from this process (Siitonen et al., 2010). ULCOS has invented top gas recycling blast furnace (TGR-BF) which is a blast furnace gas separation technology for clean steel production. Top gas used to absorb CO_2 inside blast furnace acts as a reducing agent. It effectively reduces carbon emission around 50%. The integrated use of TGR-BF and CO_2 capture and storage (CCS) technologies is helpful to remove nitrogen from the TGR-BF and oxygen injection into BF can also effectively recover CO_2 shown in Figure 2.6. After extraction of CO_2 from recycled gas by using VPSA CCS technology, the cryogenic techniques is applied to store (K. Afanga et al., 2012).The following three different versions were tested (Hattink et al., 2014):

- version 4, the treated is a recycled gas in the main tuyeres and additional tuyeres located in lower stack at 1250^0C and 900^0C respectively. The expected carbon saving is 26%.

- version 3, the treated gas is recycled through the main tuyeres only and expected carbon saving is 24%.
- version 1 has the same flow sheet like version 4 but the recycled gas is cold and expected carbon saving is 22%.

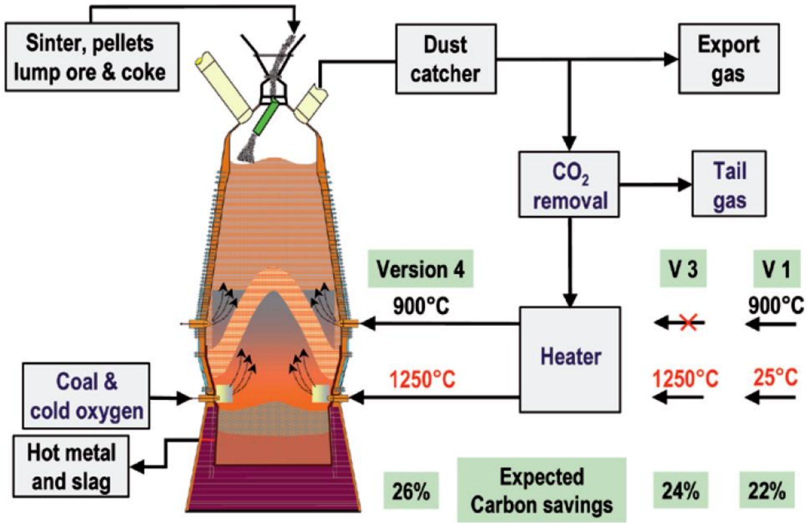


Figure 2.6: Different types of the ULCOS Blast Furnace with process flow (Danloy et al., 2009; Hattink et al.)

In 2007, the first experiment was successfully done at LKAB's Experimental Blas Furnace (EBF) in Lulea, Sweden and it ran efficiently with high thermal stability, including up to 24% CO_2 reduction. After this, for the second phase ULCOS 2, EU invested hundreds of million euros for the promotion and planning of TRG-BF. It was successful, this technology will hopefully, mitigate CO_2 emission of almost 1.5 Mt per year, i.e. about 1/3 for a BF ("Top Gas Recycling," 2014).

Status (Guangqing, 2009; van der Stel, 2011; Wyns, 2012):

- demonstration project in Florange as a part of EU ETS (NER 300),
- top gas recycling has been experimentally tested at the LKAB s' Experimental Blast Furnace (EBF) in Luleå, Sweden, two RFCS projects: ULCOS-NBF (2004 to 2009) and ULCOS TGR-BF RFCS (started in 2009).

- ULCOS BF, version 1, 3, 4 were tested, finally V 4 was preferred for the follow-up ULCOS BF demonstration project on industrial scale under ULCOS II at ArcelorMittal, Florange (France) and ArcelorMittal Eisenhüttenstadt (Germany).
- ULCOS BF mode without CO_2 storage is expected at Eisenhüttenstadt plant in 2014
- ULCOS BF mode with CO_2 storage is expected at Florange plant in 2016
- first full scale (industrial) CCS project and operational within 2014-2015
- test phase of +/- 10 years
- industrial implementation after 2020

2.7.2 HIsarna smelter

The HIsarna process is based on a modified version of the HIsmelt smelter technology. It is a concept using a combination of three new ironmaking technologies: (a) coal preheating and partial pyrolysis in a reactor, (b) melting cyclone for ore melting and, (c) melter vessel for final ore reduction and iron production.

HIsarna is a bath-smelting technology that combines coal preheating and partial pyrolysis in a reactor. It uses a smelter vessel for final ore reduction and a melting

Figure 2.7: Schematic diagram of HIsmelt smelter technology (ULCOS, 2014a)

cyclone for ore smelting. By removing sintering and coking processes it reduces CO_2 emission shown in Figure 2.7. Moreover, by using biomass or natural gas instead of coal, processing combustion gases, storing CO_2 and recycling heat energy HIsarna technology reduces almost 70% CO_2 emission (ULCOS, 2014a).

Benefits of the HIsarna process are:

- reduction of the CO_2 emissions per ton with 20 %
- reduction of the CO_2 emissions per ton with 80 % if the process is combined with CCS
- elimination of coke and sinter/pellet plant emissions
- use of non-coking coal qualities
- use of low cost iron ores, outside the blast furnace quality range
- economically attractive even at small unit size (0.8–1.2 M thm/y)

Figure 2.8: Tata pilot plant during charging (Meijer et al., 2013)

A pilot plant of this technology was set up by TATA Iron and Steel Group of European Companies in Holland IJmuiden in September 2010 with 65 kt annual outputs under ULCOS II project Design output of TATA Steel HIsarna pilot plant is 8 t/h of hot metal. Ore and coal injection capacity are 8 t/h and 15 t/h respectively. The basic set-up pilot plant is shown in Figure 2.8. However, if it is going to be successful, the technology will be used at a commercial level before 10-20 years (Assefa et al., 2005)

Status (Wyns, 2012):

- demonstration plant built in Ijmuiden, Germany (TATA Steel) in 2011 without CCS
- piloting continued until 2012
- industrial scale demonstration would be launched within 2014-2018
- industrial implementation would be done in 2020 and beyond

2.7.3 Direct-reduced iron with natural gas (ULCORED)

The project ULCORED is built up for iron ore pretreatment especially for sintering and preheating. To produce direct-reduced iron (DRI) for sending to electric arc furnace (EAF) the reducing agent such as natural gas or biomass gas is used in a reactive level for the iron ore sintering process. In gas purification process traditional reducing agent is replaced by natural gas. Top gas recycling and preheating processes; reduce natural gas consumption seen Figure 2.9 (ULCOS, 2014b).

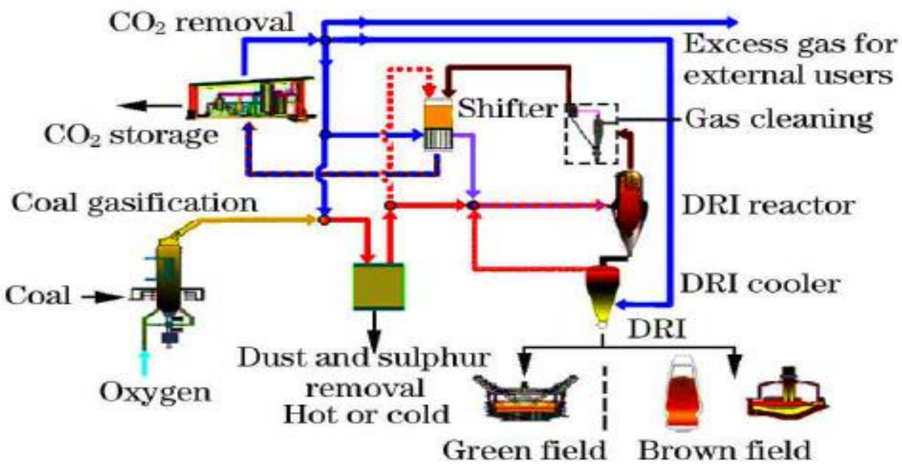


Figure 2.9: ULCORED direct reduction process (Fu et al., 2014)

By this technology, we can reduce 60% CO_2 emission and also it is an economical and efficient process since natural gas is expensive.

Status (Wyns, 2012):

- reduction likely up to 70% CO_2 including CCS compared to average EU BF
- direct Reduction with natural gas mainly through Midrex technologies
- still need to move to pilot phase

2.7.4 Direct electrolysis of iron ore (ULCOwin & ULCOlysis)

The principle of the direct electrolysis of iron ore has been applied in ULCOWIN project, in which the products are iron and oxygen with zero carbon emission. The ULCOWIN technology is different from others conventional smelting process which employs a new method for steel production. Its reaction temperature is around 110 ^{0}C where iron ore and iron are used as an anode and cathode precipitation respectively. Electrolysis of iron ore does not emit CO_2 shown in Figure 2.10.

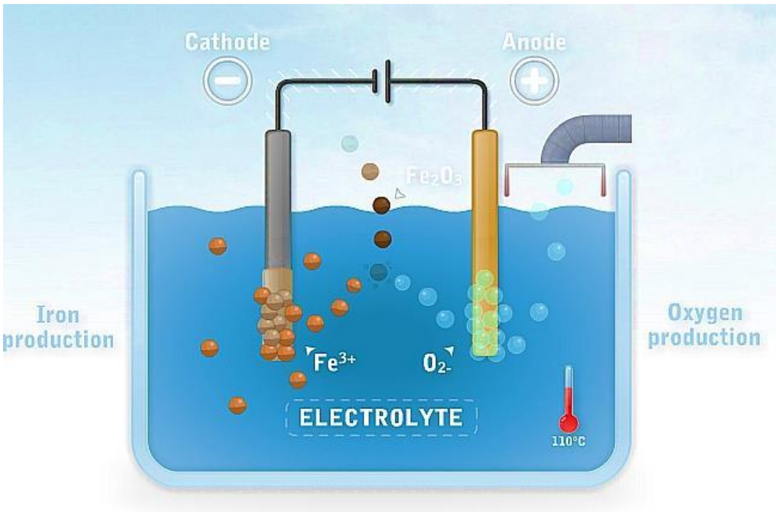


Figure 2.10: Electrolysis of iron ore (Staal, 2004)

Although, its initial production rate is very low production with efficiency of only 5 kg iron per day, but its cost is reasonable. Hence, the ULCOS team developed a process named ULCOLYSIS for melting iron ore at 1600^{0}C by using electric direct reduction (Abbasi, Farniaei, Rahimpour, & Shariati). This is the least developed technology in contrast with other three alternatives (Staal, 2004).

Status (Wyns, 2012):

- still in Laboratory phase but proof of concept is achieved
- shows diverge when market-ready post 2030 (EU) or post 2050 (US)
- MOE is becoming a “hot” field in metallurgic research, especially as potential (cheap) storage technology for intermittent renewable energy

2.7.5 COREX process

COREXs are an industrially and commercially proven SR process that allows for production of hot metal directly from iron ore and non-coking coal. The process was developed to industrial scale by Siemens VAI. COREX differs from BF production in using non-coking coal as reducing agent and energy source. In addition, iron ore can be directly charged to the process in the form of lump ore, pellets and sinter as seen Figure 2.11 (Hasanbeigi et al., 2014).

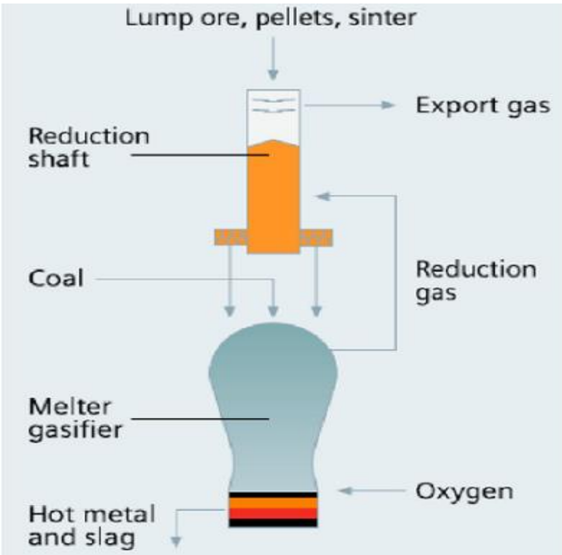


Figure 2.11: Simplified flow diagram of the COREX process (Hasanbeigi et al., 2014)

Status (US DOE, 2003):

- dry fuel consumption with and without off-gas recycling is reported to be 770 kg/t-HM and 940 kg/t-HM
- CO_2 emissions per ton of combined product (hot metal + DRI) are lower by ~20% compared to blast furnace route

- total CO_2 emissions for steel produced with 60% hot metal from Corex and 40% DRI is reported to be around 3.78 t/t-steel
- Capital and operational costs for producing steel with 60% Corex hot metal and 40% DRI is reported to be \$373.5 and \$218.3 per ton of steel, respectively.

2.7.6 FINEX process

The FINEXs smelting-reduction process, developed by Siemens VAI and the Korean steel producer POSCO, is based on the direct use of non-coking coal and fine ore. The major difference between the COREX and FINEX processes is that the FINEX process can directly use sinter feed iron ore (up to 0.012m) , without agglomeration (Hasanbeigi et al., 2014). Hot metal is produced on the basis of low-cost iron-ore fines and non-coking coal. Production costs can be reduced by approximately 15 percent in comparison to the blast-furnace route. Environmental emissions are also far lower than in the conventional blast-furnace route because coking and sintering plants are not required.

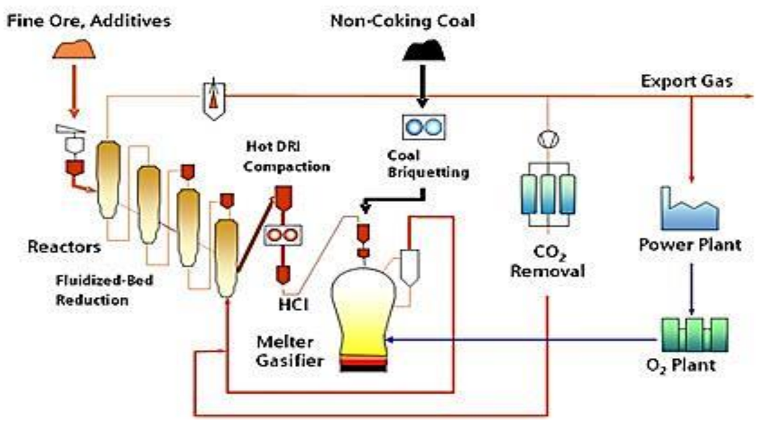


Figure 2.12: The SIMETAL cost-effective and environmentally FINEX process (Hasanbeigi et al., 2014)

Status:

- coal consumption of the process is less than 700 kg-coal/t-HM
- an additional energy reduction of 1.3 GJ/t-HM is reported by utilizing off-gases after CO2 removal

- the process is reported to have 4% less CO2 reductions, as compared to blast furnace route.

2.7.7 MIDREX process

The MIDREXs direct reduction process uses a natural-gas- based shaft furnace process that converts iron oxides (pellets or lump ore) into DRI. The MIDREX direct reduction technology has evolved during the past four decades from plant capacities of just 150,000t/year to capacities now approaching 2 million t / year. This process currently produces 60 percent of the world's DRI annually as seen in Figure 2.12 (Hasanbeigi et al., 2014).

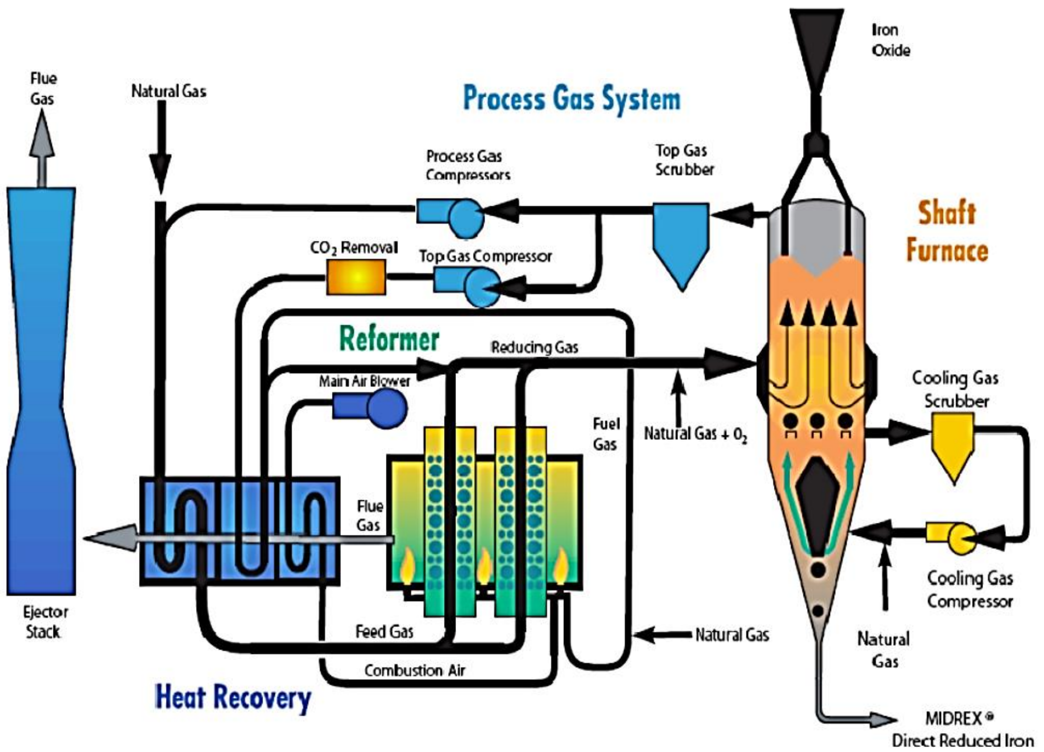


Figure 2.13: Schematic diagram of Midrex with low CO_2 emissions (Hasanbeigi et al., 2014)

Status (IEA, 2009)**:**

- commercially available
- total primary energy demand of the process is around 10.4 GJ/t. The natural gas consumption of eficiency Midrex plants are aruond 9.62GJ/t-DRI

- Some MIDREX plant/EAF facilities emit only one-third of the CO2 per tonne of steel of a BF/BOF complex

2.8 CO_2 Capture technologies

Carbon capture and storage (CCS) is generally recognized as one of the key global warming and climate change mitigation option and the technology could be utilized in the iron and steel industry as well. CO_2 capture opportunities may economically be feasible in steel production considering the probable future costs for CO_2, for example in the EU Emission Trading Scheme (EU ETS) (Demailly & Quirion, 2008). In addition, steel production is a large production process with relatively high CO_2 concentrations, utilization of pure oxygen and recoverable heat (Arasto et al., 2013). Figure 2.13 illustrates the several CCS concepts applied to the steelmaking industry and combustion process (J. P. Birat et al., 2010).

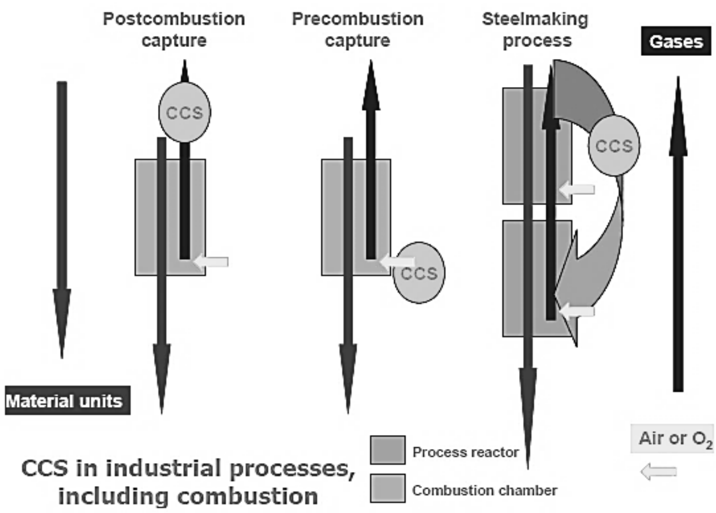


Figure 2.14: Implementation of CCS in Steelmaking industry (JP. Birat et al., 2010)

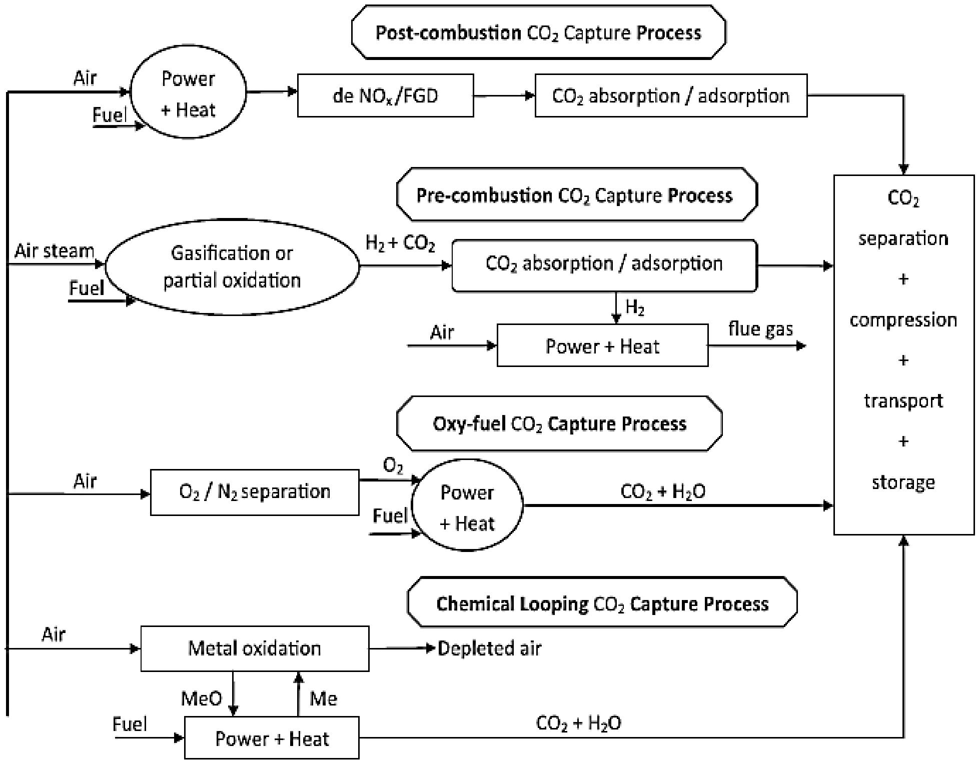


Figure 2.15: Flow diagram of CO_2 captures technologies (Leung et al., 2014).

However, the choice of an appropriate CO_2 removal process depends on the type of combustion process (Blomen et al., 2009). Based on the combustion systems there are three main CO_2 capture systems such as post-combustion, pre-combustion and oxyfuel combustion (Leung et al., 2014). These three major technologies are described in Figure 2.15.

It is estimated that the capture stage could account for 70–90% of the total operating costs of a CCS system (M. Patel & Mutha, 2004). Due to this high cost percentage much research has been conducted in the area of CO_2 capture. Currently, CO_2 capture technology can be divided into four categories, each of which requires a distinctly different approach to CO_2 capture (Spigarelli & Kawatra, 2013). The four categories are: (1) Post-combustion, (2) Pre-combustion, (3) Oxy-combustion and (4) Chemical looping combustion. Table 2.4 discusses about advantages and disadvantages of capture technologies. Figure 2.16 shows the various CO_2 capture technologies applied in industrial sectors.

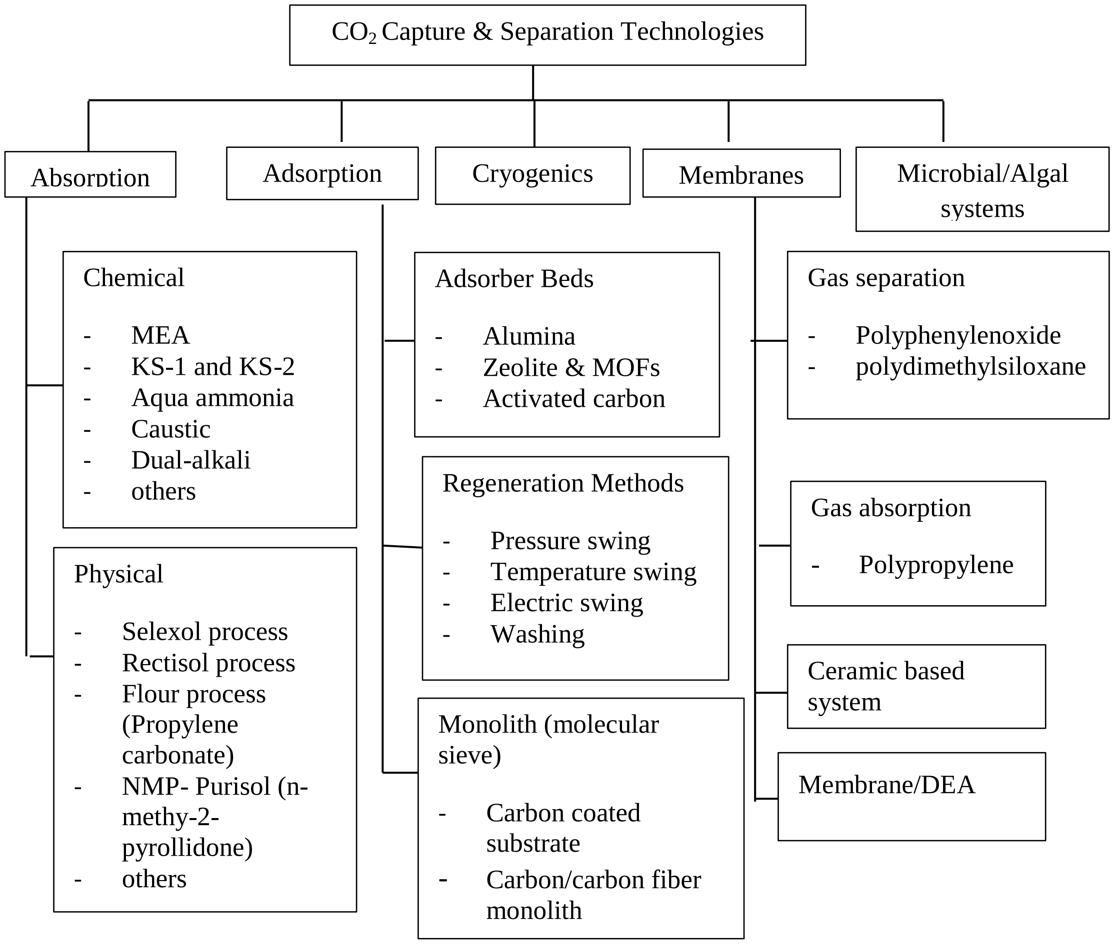


Figure 2.16: Various CO_2 capture technologies

Table 2.4: Advantages and disadvantages of CO_2 capture technologies

Capture option	Advantages	Disadvantages
Pre-combustion	Lower energy requirements for CO_2 capture and compression	Temperature and efficiency issues associated with hydrogen rich gas turbine fuel
Post-combustion	Fully developed technology, commercially deployed at the required scale in other industrial sectors Opportunities for retrofit to existing plants	High parasitic power requirement for solvent regeneration High capital and operating costs for current absorption systems
Oxy-fuel combustion	Mature air separation technologies available	Significant plant impact makes retrofit less attractive

Carbon capture technologies produce concentrated form of CO_2 for potential compression, transport and separation or storage. The technologies for capturing CO_2 from the various gaseous stream can be divided into (Carpenter, 2012a):

- chemical or physical absorption, or combined chemical and physical absorption (hybrid system);
- adsorption using solid adsorbents;
- physical separation via membranes or molecular sieves;
- phase separation by cryogenics and gas hydrates;
- chemical bonding via mineral carbonation.

2.8.1 Absorption processes

In absorption process CO_2 from gas streams can be separated by chemical or physical absorption or by using hybrid method (Physical and chemical). By using chemical or physical solvent CO_2 is removed in one reactor (absorption column) and a second reactor (stripping column) generates the solvent (Carpenter, 2012a). Absorption processes are widely used in the chemical, refinery and gas processing industry and could potentially be applied in the iron and steel industry (IEA, 2010).

2.8.1.1 Development of chemical absorption technology

Chemical solvents are most suitable process for removing CO_2 deeply. Nowadays, chemical absorption is being examined for BFG, BOF gas, natural gas DRI process gases, fluidized bed DRI production gases, smelting off gases and others (Gielen, 2003). However, chemical absorption processes are expensive due to the large amount of thermal energy required to break the strong bonds created between the solvent and CO_2. Amines are the most common chemical solvents for CO_2 capture which have high capture efficiency and selectivity. Russia used monoethanolamine (MEA) solvent to remove CO_2 from the BFG (Tseitlin et al., 1994). But it has some disadvantages such as equipment corrosion, solvent degradation, low CO_2 loading capacity, high thermal energy consumption during solvent regeneration, large footprint, and removal and disposal of solvent degradation products (Davidson, 2007). Tobiesen et al., (2007) modeled the performance of different amines for capturing CO_2 from BFG before recycling to the BF and found that 2-amino-2-methyl-1-propanol was more energy efficient (based on steam consumption) than the methyldie thanolam ine /pipe razine mixture. To remove CO_2 from the hot stove flue gas containing 30 vol% CO_2, Cheng et al., (2010) investigated the use of aqueous solutions of MEA, 2-(2-aminoethylamino) ethanol (AEEA) and piperazine solvents, and their mixtures. Inorganic solvents such as, sodium and potassium carbonates are commercially available but have a low corrosion and reaction rate and higher energy consumption for regeneration compared to alkanolamines (Q. Z. 2011). A potassium carbonate/hindered cyclic diamine solvent was developed by Yoon et al., (2011) that could be used in the steel industry for gases containing 15–20% CO_2.

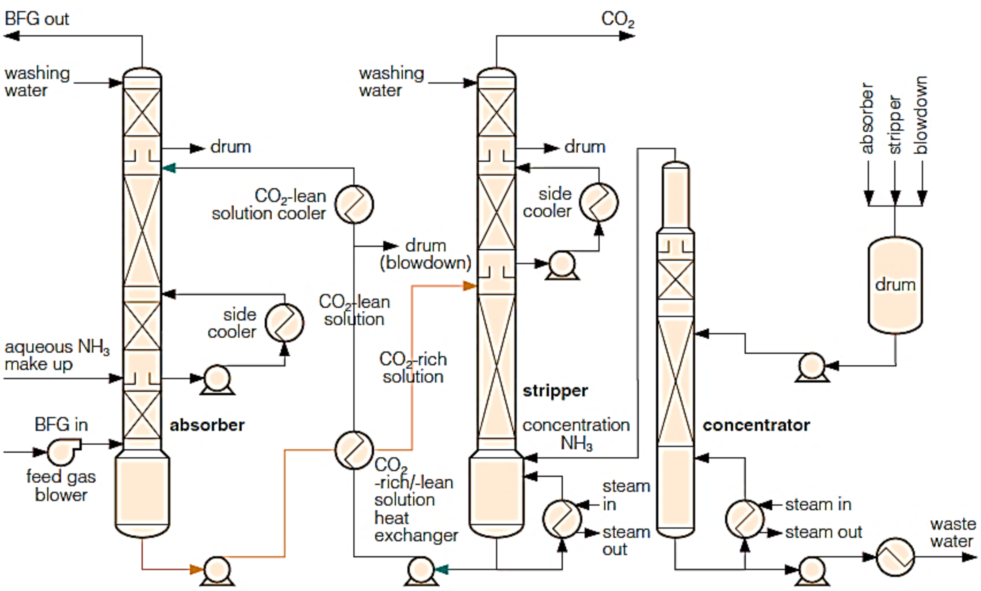


Figure 2.17: Process schematic of CO_2 capture using aqueous ammonia (Rhee et al., 2011)

Korea has investigated the use of aqueous ammonia solvent for capturing CO_2 from BFG due to higher removal efficiency, higher CO_2 loading capacity (three times of MEA), lower cost, and lower regeneration energy (Rhee et al., 2011). However, ammonia can easily be lost from the process due to its volatility and the formation of precipitates. Now, steel mill is using ammonia to remove H_2S and other sulphur compounds from COG for a long time (Kim et al., 2009). POSCO started the first pilot plant that uses ammonia to absorb and separate CO_2 from the blast furnace gas (BFG) with a processing capacity of 50 Nm^3/h in December 2008 (Kim et al., 2009). To reduce ammonia loss from outlet gases, washing water is supplied to the upper part of the absorber and stripper columns. Then, from a concentrator column ammonia is recovered and recycled in lower part of stripper shown in Figure 2.17. It has achieved a CO_2 capture efficiency of over 90% and CO_2 purity around 95% (Rhee et al., 2011).

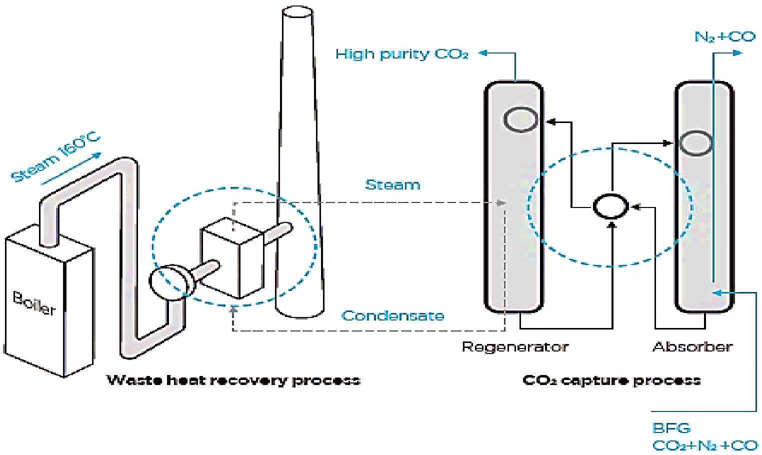


Figure 2.18: Capture of CO_2 from Steelmaking byproduct gas using ammonia (POSCO, 2013a)

A second stage pilot plant with capacity of 1,000 Nm^3/h of BFG was installed in 2010 at Pohang steelworks. Here, CO_2 is captured from steelmaking byproduct gases as seen in Figure 2.17 (POSCO, 2013a). The Japan Iron and Steel Federation (JISF) under the project of COURSE50 developed a chemical absorption technology to capture CO_2 from blast furnace gas (BFG). According to this process, an alkaline aqueous solution, or absorbent, for example amine contacts with blast furnace gas (BFG) and absorbs CO_2, which contains in an absorption tower. After heating in a regeneration tower, the CO_2-laden absorbent releases CO_2 shown in Figure 2.18 (Federation, 2011). The aim of this project is to enhance the absorption capacity approximately 30t-CO_2/day from a real steelmaking plant. This scheme will discourse the following technical issues: energy consumption reduction, new absorbent solutions development and effective utilization of waste heat energy and finally quantification of effects of CO_2 capturing technologies on steelmaking processes.

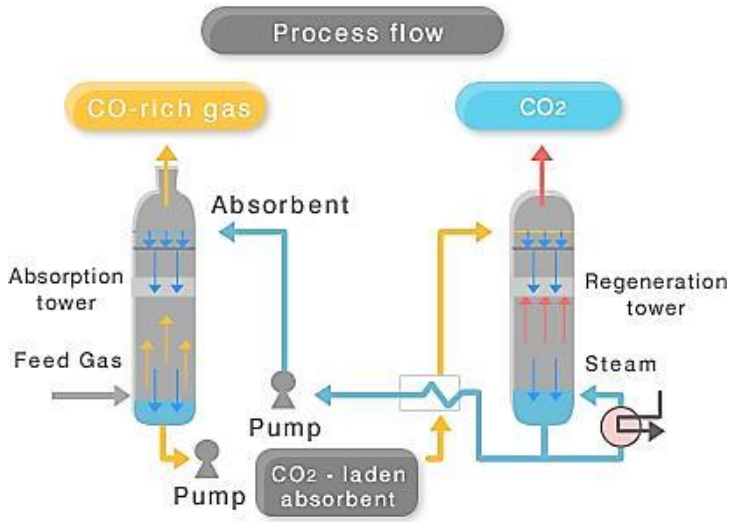


Figure 2.19: Process flow of chemical absorption (Federation, 2011)

Innovative Technology for Cool Earth 50 (COURSE50) project developed new chemical absorbents where CO_2 capture system can be operated with lower CO_2 capture energy. They used computational method to predict chemical reactions and experimental methods to evaluate CO_2 capture performance shown in Figure 2.19 and Figure 2.20 (Federation, 2011).

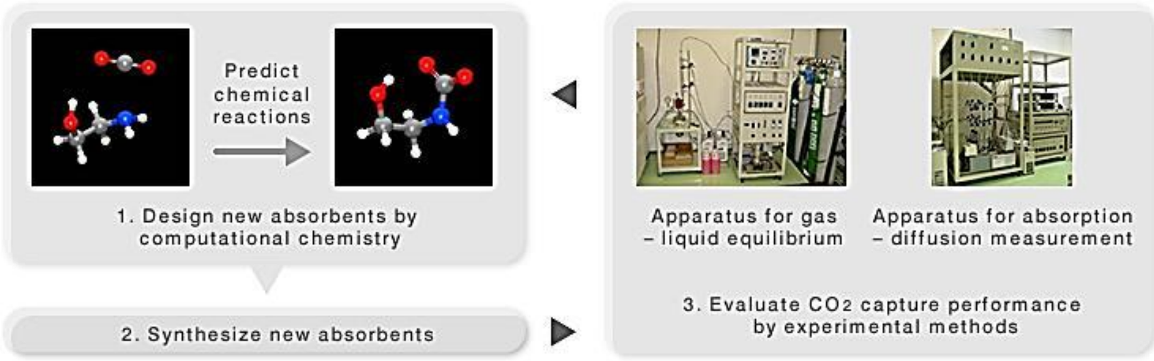


Figure 2.20: Development of novel chemical absorbents ("CRC for Greenhouse Gas Technologies (CO2CRC)," 2014)

2.8.2 Adsorption processes

Adsorption is a surface-based process passing the CO_2 containing gas through a bed of solid absorbent (such as zeolites or activated carbon) which adsorb the CO_2. The bed is loaded by reducing the pressure (pressure swing adsorption PSA or vacuum pressure swing adsorption, VPSA), increasing the temperature (temperature swing adsorption, TSA) or applying a low voltage electric current (electric swing adsorption, ESA). But, only PSA and VPSA processes are used commercially in the iron and steel industry, and other industrial facilities (Kuramochi et al., 2011).

Under the project of Cool Earth 50 (COURSE50), Japan Iron and Steel Federation has developed a physical adsorption technology that can separate and recover CO_2 with low energy consumption, though requiring a simple system configuration. In this method, CO_2 is adsorbed in the surface of the adsorbents with the help of the van der Waals force. Then applying reduced pressure adsorbed CO_2 is released, consequently allowing CO_2 capture separation and recovery with high purity at high recovery rates shown in Figure 2.21. In this project, 3t-CO_2/day capacity assessment plant will be built at a steel plant (Federation, 2011).

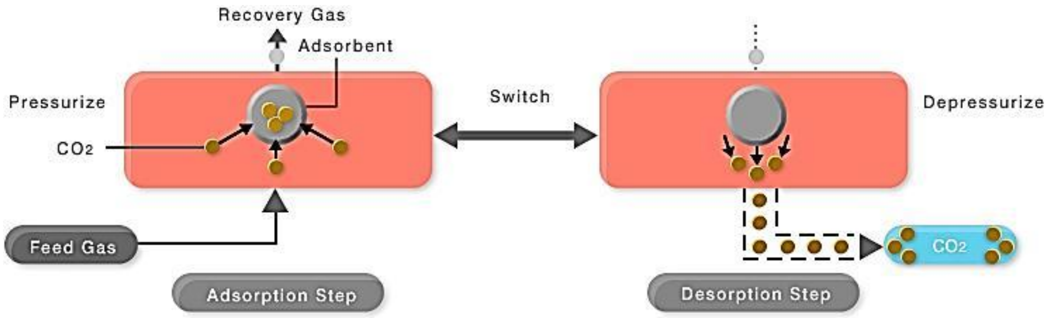


Figure 2.21: Process flow of physical adsorption (Federation, 2011)

In 2011, POSCO (Korea) started developing a technology for CO and CO_2 separation using Pressure swing adsorption (PSA) method. Here, they optimized the gas sequestration PSA process for byproduct gases from steelmaking. It already gained over 99% capture purity of CO from a small pilot plant with 1 Nm^3/h capacity shown in Figure 2.22 (POSCO, 2013b).

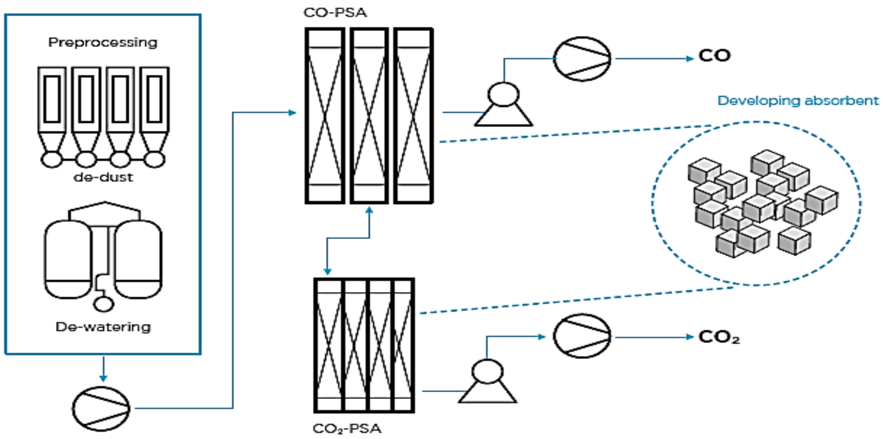


Figure 2.22: Technology for separation of CO and CO_2 using the PSA method (POSCO, 2013b)

2.8.3 Membranes

Gas separation membranes, for example, polymers, ceramics, metals and zeolites, depend on differences in physical and chemical interactions between gases and membrane material. It can achieve over 80% CO_2 separation efficiency (Carpenter, 2012a). In 2007, Lie et al., (2007) studied a simulation study of performance of three types of membranes to capture CO_2 from BFG. Result showed that 97% CO_2 recovery was achieved from O_2-blown BFs. In Australia under the project of CO2CRC, a new technology of gas separation membrane has been developing to remove industrial CO_2 emissions from feed gas. It aims to test a number of gas separation strategies, investigate the influence of syngas and minor gas components shown in Figure 2.23 (CO2CRC).

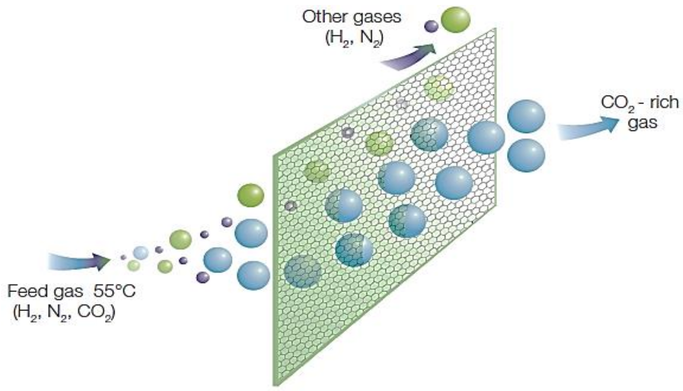


Figure 2.23: Gas separation membrane flat sheet module (CO2CRC)

2.8.4 Cryogenics

By using cooling and condensation methods CO_2 can be separated from gases. To separate CO_2 from high pressure gas or offgas or O_2-blown BFs is the most auspicious applications for cryogenics separation. In a project of TGR-BF (O_2-blown) under the ULCOS program, captured CO_2 by PSA unit will be further purified by cryogenics to produce liquid CO_2 for underground storage. Besides, cryogenic unit produces reducing extra gas stream for recycling to the BF. As it generates large amount of CO_2 gas stream, cryogenic unit can be used on its own in the HIsarna process (P, 2010).

2.8.5 Gas hydrates

CO_2 separation by gas hydrates is still under research and development phase. In this technology CO_2 formed by H_2O and trapped in cages, or clathrate hydrates at high pressure and low temperature. Then, either by heating or depressurization CO_2 is removed from hydrates (Carpenter, 2012b). A continuous hydrate process has been investigated by Duc et al., (2007) for capturing CO_2 from BF gases using tetra-n-butyl ammonium bromide ($C_{16}H_{36}NBr$, TBAB) as the hydrate promoter. For pipeline transport and storage, six stages of crystallisation are required to meet the CO_2 specification (<4 vol% CO_2, 0°C, 11 MPa). Pressures in the six stages fluctuated from 0.75 to 5 MPa, and the temperature in each crystallizer is kept constant at 10°C. The electric power consumption was investigated for the four kinds of BF which varied from 362 to 1302 kWh/tCO_2 captured, at a cost of 14.5 to 29.6 A/tCO_2 captured see in Table 2.5.

Table 2.5: Power consumption and cost of hydrate CO_2 capture (Duc et al., 2007)

	N_2-free BF with shaft injection (TGR-BF)	Conventional BF top gas	N_2-free BF plasma	Conventional BF flue gas
CO_2 concentration of inlet gas, %	36	23	35	24
Electric power consumption, kWh (GJ)/tCO_2 captured	420 (1.51)	1302(4.69)	362(1.3)	730 (2.63)
Cost, e/tCO_2 captured	16.8	22.4	14.5	29.6

2.8.6 Mineral carbonation

Slag generation processes from iron and steel making has huge amount of alkaline earth metal oxide (such as silicates, free lime and others minerals). It can be utilized to capture and store CO_2 by mineral carbonation. Stable calcium carbonate (calcite) can be produced by the reaction of calcium oxide and magnesium oxide with CO_2 (Carpenter, 2012b). Developing carbonation processes can be classified (Baciocchi R, 2010) as:

(1) direct process , where the reactions with CO_2 occur either in the aqueous phase (such as the two-stage slurry reactor developed at the Missouri University of Science and Technology in the USA (Richards et al., 2008) or at the gas-solid interface;

(2) Indirect process, in which the alkaline metal is first extracted from the slag matrix and is then precipitated as carbonate. Extraction agents investigated include acetic acid

Table 2.6: Advantages and disadvantages of CO_2 separation technologies

Technology	**Examples**	**Advantages**	**Disadvantages**
Physical absorption	• Selexol process	• Low toxicity	• Low capacity
	• Rectisol process	• Low corrosion	• High capital and operational costs
	• Purisol process	• Low energy consumption	
Chemical absorption	• MEA, DEA, MDEA	• Well-understood technology, already implemented in large scale in different industries	• Significant energy requirement due to solvent regeneration
	• Sterically hindered amine (AMP)	• Suitable for retrofit	• Solvent loss
		• Applicable to separation of CO_2 at low concentrations	• Degradation and equipment corrosion
		• Recovery rates of up to 95%	• Environmental impacts due to solvent emissions
		• Product purity >99 vol%	• Large absorber volume
	• Ionic liquid	• Low vapor pressure	• High viscosity
		• Non-toxicity	• High regeneration energy requirement
Physical adsorption	• Activated carbon	• Regeneration and CO_2 recovery is less energy extensive	• Difficulty in handling solid
	• Zeolite	• CO_2 and H_2S capture can be combined	• Slow adsorption kinetics
	• Mesoporous silica	• High pore size and tunable pore structure (Mesoporous silica and MOFs)	• Low CO_2 selectivity
	• MOFs	-	• Thermal, chemical, and mechanical instability in cycling
Chemical adsorption	• Amin-based adsorbent	• High adsorption capacity	• Loss of sorption capacity over multiple cycles
	• Alkali-earth metal adsorbent	• Low cost in natural minerals	• Low CO_2 selectivity
		• Exothermal reaction	• Diffusion resistance issue
Membrane technology	-	• No regeneration process	• Plug of membranes by impurities in the gas stream
		• Simple modular system	• Not proven industrially
		• No waste streams	
Oxy-fuel	-	• Relatively simple technology	• Significant energy requirement for separation of O_2 from air
		• Suitable for retrofit	
		• Significantly less NO_x	
CLC	-	• Well-known technology	• No large-scale demonstration
		• Suitable for retrofit	• Decay in sorbent's capture capacity
		• Cheap and abundant sorbent (limestone)	-
		• Harmless exhaust gas stream	-
		• No thermal formation of Nox	-

(Eloneva et al., 2008; Teir et al., 2007), nitric acid (Doucet, 2010), hydrochloric acid (Kunzler et al., 2011), hydroxides and ammonium salts (Fogelholm C. J., 2009).

But selecting proper methods for capturing CO_2 depends on the flue gas conditions, the concentration and pressure. Generally, the higher CO_2 concentration leads high CO_2 recovery ratio. It is usual to employ the chemical absorption method if the CO_2 concentration in feed stream is comparatively low and the feed gas stream is at

Table 2.7: Summary of current status of CO_2 separation techniques

Separation techniques	**Type**	**Status**
Chemical absorption	MEA	Commercially available
	KS-1	
Physical adsorption	PSA method	Under research
	PTSA method	
Membranes	Polymeric	Commercially available
	Inorganic	
	Zeolite	
	Silica	
Amine and membranes	Amine solvent + membrane	Under research
CLC	MeO (Me = Ni, Cu, Mn or Fe)	Commercially available
Cryogenic	Cryogenic	Commercially available

2.9 CO_2 utilization, transportation and storage

CO_2 utilization is attractive because it can offset a part of the cost of CCS development and deployment. The CO_2 can be used either directly as a working fluid or as a feedstock of chemical synthesis processes. The latter usage can be a challenge because the CO_2 is thermodynamically stable. Current examples for CO_2 utilization are urea, refrigeration systems, inert agent for food packaging, welding systems, fire extinguishers, water treatment processes, horticulture, and many other smaller-scale applications. The CO_2 can also be used for the production of organic chemicals, polymers and fuels. The industrial utilization of CO_2 can prevent the CO_2 from emitting into the atmosphere. However, the scale of CO_2 utilization is small compared to manmade CO_2 emissions, and the utilization is usually in a short term. Therefore, the industrial utilization of CO_2 is not expected to mitigate the man-made CO_2 emissions significantly.

CO_2 is commercially transported by using pipelines and ships in liquid phase where less volume is required. Generally for a short distance, pipelines are preferred and for long distances, ships are better choices for example, it can be huge expensive to construct long pipelines. For comparatively small quantities on the order of hundreds of tons of CO_2 per year, trucks might be the least expensive option (IPCC, 2005 and IPCC, 2006). For distances that are up to 1,000 kilometers and those that involve larger quantities of CO_2, pipelines are the preferred option. For overseas transportation, ships can be the most economically attractive option see in Figure 2.24 (Metz et al., 2005). As CO_2 transport via pipeline is currently the most widely used transportation method.

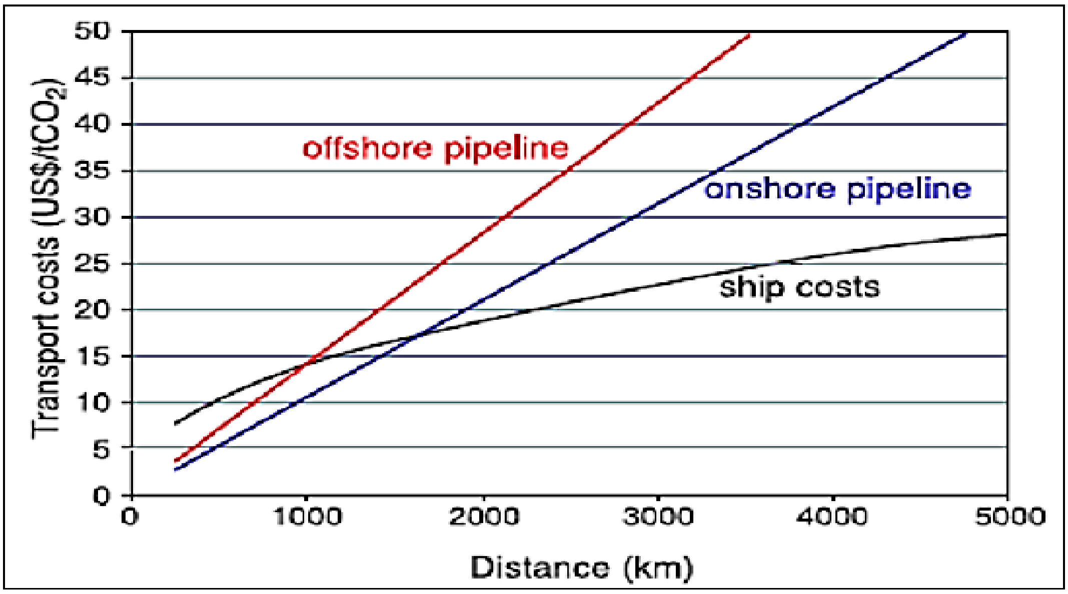


Figure 2.24: Costs of transporting CO_2 by method and distance (IPCC, 2005)

Cost of transportation processes can be much lower compared to CO_2 capture processes although investment on the construction of pipelines and ships plays an important part in the total cost. The CO_2 storage sites are regarded as carbon sinks. Two main ways exist for CO_2 storage-underground geological storage and ocean storage. The CO_2 can also be stored by mineral carbonation and industrial utilization, but the capacity is much smaller compared with the two main ways. The geological storage sites can be divided into two categories: non-value added sites and value added sites. Non-value added sites refer to those developed only for CO_2 storage, like depleted oil and gas reservoirs, deep aquifers and salt caverns. Value added sites refer to those developed primarily for enhanced recovery of fossil fuel fluids and storage of CO_2 as a secondary benefit, such as the sites for enhanced oil recovery (EOR), enhanced gas recovery (EGR) and enhanced coal bed methane recovery (ECBM). Figure 2.25 shows that Geological storage options for CO_2. These storage options can be very attractive since the cost of CCS can be offset in this case.

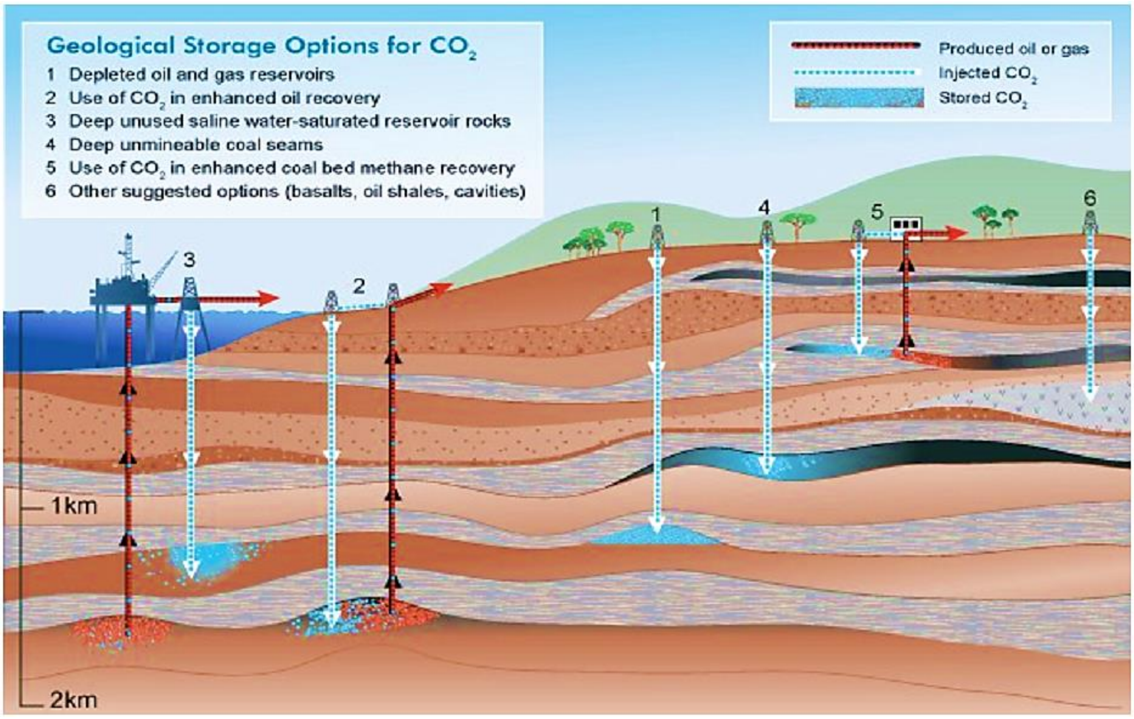


Figure 2.25: Geological storage options for CO_2 (CO2CRC, 2008a)

2.10 Appropriateness of DEMATEL, AHP, Fuzzy AHP and EFAHP in CCS systems analysis

Mathematical programming provides a powerful framework for designing sustainable systems (Srivastava & Nema, 2012). In addition, the implementation of mathematical programming models for technology selection decision making planning can significantly improve economic and ecological performances of the entire system (Kara & Onut, 2010), and waste electrical and electronic products (Dat et al., 2012). DEMATEL, AHP, Fuzzy AHP, and Extent analysis method on Fuzzy AHP methods are being applied worldwide for evaluation of criteria and alternatives due to their relevance. Chou, et al., (2012) evaluated the criteria for human resource for science and technology (HRST) based on an integrated fuzzy AHP and fuzzy DEMATEL approach. Wu and Tsai (2011) used DEMATEL and AHP method for evaluating the causal relations among the criteria in auto spare parts industries in Taiwan. Chao and Chen (2009) evaluated the criteria and effectiveness of distance e-learning with consistent fuzzy AHP method. B. Chang, et al., (2011) used Fuzzy DEMATEL method for developing supplier selection criteria. Hsu (2012) evaluated criteria by using factor analysis and DEMATEL for blog design and analysis of causal relationships. Wu, et al., (2010) used DEMATEL method to evaluate performance criteria of Employment Service Outreach Program.

Ren, et al., (2013) identified the critical criteria and cause-effect analysis for enhancing the sustainability by using DEMATEL method. Similarly Irajpour, et al., (2012) also used fuzzy DEMATEL Method to evaluate the most effective criteria in green supply chain management in automotive industries. Wang and Chan (2013) used Fuzzy extent analysis and TOPSIS approach for evaluating remanufacturing alternatives of a product design. H. Hu and Wu (2009) applied FMEA and FAHP approach for Risk evaluation of green components to hazardous substance. Seçme, et al., (2009) used fuzzy extent analysis and TOPSIS approach for performance evaluation in Turkish banking sector. Vahidnia, et al., (2009) used fuzzy AHP and fuzzy extent analysis for Hospital site selection.

Güngör, et al., (2009) applied fuzzy AHP approach to personnel selection problem. Torfi, et al., (2010) used fuzzy AHP to determine the relative weights of evaluation criteria and Fuzzy TOPSIS to rank the alternatives. A. H. Lee (2009) applied fuzzy extent analysis for supplier selection model with the consideration of benefits, opportunities, costs and risks. Shaw, et al., (2012) applied extent fuzzy AHP and fuzzy multi-objective linear programming for supplier selection in low carbon supply chain. Tseng and Chiu (2009) shown fuzzy AHP based study of cleaner production implementation in Taiwan PWB manufacturer. So, multi-criteria analysis is the useful method for complex technology assessment. In addition, the review of the current literature related to CCS in steel industry indicates that most of them still lack of capability to explore the relationships among CCS evaluation criteria for more in depth analysis. Therefore, the selected methods Delphi, 2-tuple DEMATEL, AHP and EFAHP are the appropriate methods for CCS technology selecting and robust ranking.

2.11 Criteria of CCS implementation iron and steel industry

In order to afford appropriate understanding of the relationships among proposed CO_2 capture and storage criteria in iron and steel industry, this subsection clearly presents the several useful critical success criteria. The method of criteria selection is explained below.

There are various criteria for the performance of CCS systems, where it is not absolute that more and more criteria are supportive to the CCS technology decision-making. Based on the five principles: (1) systemic principle, (2) consistency principle, (3) independency principle, (4) measurability principle and (5) comparability principle instruction was given to the decision makers to select “major” criteria (Rowe & Wright, 2001). However, to escape from the possibility to be chosen “minor” criteria, the Delphi method was used. It is a systematic interactive method relies on a panel of independent experts (Clayton, 1997; Rowe & Wright, 2001). Experts answer questionnaires were carefully selected for criteria selection to evaluate CCS systems in iron and steel industry in three rounds. After each round, the summaries of the experts from the

Table 2.8: Typical evaluation criteria of CCS technology in iron and steel industry

Dimensions	Criteria /barriers	Units	Descriptions	References
Engineering (D_1)	Safe storage (C_1)	Point	Protect underground sources of drinking water and other natural resources (ecosystems).	(Chalmers et al., 2013a)
	Maturity/consolidation/feasibility(C_2)	Point	Technology readiness.	(Rhee et al., 2011)
	Compatibility with process (C_3)	Point	Suitability with each production process	(Sano et al., 2013)
	Ease of technology adoption / flexibility (C_4)	Point	Technology transfer is the process of transferring skills, knowledge, technologies, and methods of manufacturing.	(Yincheng et al., 2011)
	CO_2 removal efficiency (C_5)	% GJ/t CO_2	CO_2 capture efficiency refers to the percentage of CO_2 gas that is captured from the flue gas of an iron & steelmaking industry.	(Sano et al., 2013)
	CO_2 concentration (C_7)	% (w/w)	Proper technology for capturing CO_2 depending on the flue gas conditions, concentration and pressure. Higher CO_2 concentration leads high CO_2 recovery ratio. Basically, thermal energy requirement during the regeneration of absorbent solution.	(Han et al., 2014; Saima et al., 2013)
Economic (D2)	Investment/capital cost (C_8)	$	The total cost of funds used for CCS development &deployment.	(Eide, Herzog, & Webster, 2013)
	Operation and maintenance cost (C_9)	$/year	The O&M cost of the CO_2 capture facility, for example, steam requirement, electricity consumption for pumps and cooling tower operation, process water consumption, and chemical loss, etc.	(Koelbl et al., 2014)
	Capture & storage cost (C_{10})	$/t$CO_2$	Storage cost includes all aspects of injecting and monitoring CO_2 into a geological reservoir	(Sano et al., 2013)
	Fuel & electric cost (C_{11})	$	Total fuel and electric cost during capture separation, transportation and storage.	(Han et al., 2014)
	Payback period /return on investment (C_{12})	$	The period of time required to regain the funds expended in an investment.	(Sano et al., 2013)
	Service life/plant life time (C_{13})	Year	The service life of an asset is the total period during which it remains in use, or ready to be used, in a productive process.	(Koelbl et al., 2014; Arasto et al., 2013)
Environmental (D_3)	CO_2 emission (C_{14})	tCO_2	CO_2 emission during pelleting, sintering, furnace combustion.	(Zapp et al., 2012)
	CO/SO_2/Nx emission (C_{15})	t	Different gases with CO_2 emission.	(Corsten et al., 2013)
	Particles emission /Non-methane volatile organic compounds (C_{16})	Km^2/tCO_2	Most of the air pollutants, that is, SO_2, NOx, and particulate matter (PM), share the common source with CO_2 emissions by fossil fuel combustion.	(Mao et al., 2013)
	Land use (C_{17})	PO_4^{3-}/t steel	Land used over the entire lifecycle of the plant (e.g. fuel extraction, construction, processing and delivery, operation and decommissioning)	(Petrakopoulou & Tsatsaronis, 2014)
	Eutrophication Potential (EP) (C_{18})	t CO_2/t steel	A series of chemicals such as NOx, SO_2, NH_3 and PO_4^{3-} and refers to the excessive supply of nutrients to soil and water. NH3 is the main eutrophication contributor caused by the degradation of the MEA medium used in the CO_2 capture process.	(Zapp et al., 2012)
	Global Warming Potential (GWP) (C_{19})	Point	The measure of an activity's impact on climate change, relation to carbon dioxide, which has a default rating of 1.	(Burchart-Korol, 2013)
Social (D_4)	Public acceptance (C_{20})	Point	Public preference for the deployment or deployment of a certain CCS technology. It may be crucial to CCS development, but is uncertain. Attitudes to CCS are shaped in social interaction.	(Chalmers et al., 2013a)
	Job creation (C_{21})	Person-yr/tCO_2	"Job-years" of full time employment created over the entire life cycle of the plant.	(Karayannis et al., 2014; Steeper, 2013)
	Human Toxicity Potential (HTP) (C_{22})	Years of life lost	Human toxicity is mostly a function of flue gas emissions from.. (HF, NOx, SO_2, HCl and particulate matter all of which have a negative impact on human health.	(Burchart-Korol, 2013)
	Climate change (C_{23})	Point	Perceived impact of CCS on climate change relative to other climate change mitigation options.	(Eide et al., 2013)
	Knowledge of CCS (C_{24})	Point	Awareness and understanding of CCS by the public.	(Chalmers et al., 2013a)
	Policy, Politics &, Regulation (C_{25})	Point	CCS development is intensely influenced by, political support, uncertainties, the choice and design of policies and regulations.	(Watson et al., 2014a)

previous round were fed back to the experts to revise their earlier answers in light of the replies of other members of the group. Finally, twenty five “correct” criteria were selected that influence the choice of appropriate CO_2 captures technologies with iron-making technologies. Based on previous literature studies and experts opinions, twenty five are divided into four main dimensions such as engineering, economic, environmental and social (Zopounidis & Pardalos, 2010). A brief description of each dimension and their criteria is given to indicate their influence on the choice, as shown in Table 2.8.

2.12 Alternative ironmaking technologies with CO_2 capture technologies

By using same procedure used for criteria selection, alternatives have been selected from different iron making and CO_2 capture technologies. The Delphi method, a systematic interactive method relies on a panel of independent experts was used to select alternatives. Finally, based on the group of expert’s discussions, eight alternatives iron making technologies with CCS technologies have been selected. A brief description of each alternative is given to indicate their influence on the choice, as shown in Table 2.9.

Table 2.9: Alternative ironmaking technologies with CO_2 capture technologies

Symbol	Emerging ironmaking technologies	CO_2 capture technologies	Abbreviate name
A1	Conventional Blast Furnace	MEA solvent	CBF +MEA
A2	Top gas recycling blast furnace	VPSA/chemical adsorption	TGRBF + VPSA
A3	Corex	Physical absorbent selexol	Corex + selexol
A4	Hismelt	MEA solvent	Hismelt + MEA
A5	Oxy-blast furance	PSA	OBF + PSA
A6	ULCORED	Cryogenic/PSA	ULCORED + Cryogenic/PSA
A7	Finex	MEA solvent	Finex + MEA
A8	Midrex	MEA solvent	Midrex +MEA

2.13 Conclusions

Literature shows that the development and implementation of CCS with energy efficient CO_2 breakthrough technologies in coal-based integrated steel plant would be an effective way for sustainable green iron and steel manufacturing. Because, the ironmaking process is accounted for 70-80% of the carbon input that caused the CO_2 emissions during the crude steel production from virgin ore. This study investigates the critical criteria and evaluates its effects on CCS implementation in iron and steel industry for radical reduction of CO_2 emission. Finally, it is clear that CCS and CO_2 breakthrough technology has not fairly reached the level of being technology for the deployment in the steel industry as it is still a concept that needs to be come out and authenticated at a credible scale. More importantly, shifting away from traditional processes will require extensive research and development to address the issues and barriers confronting CO_2 breakthrough technologies, both government and private support and funding for development and deployment of alternative low-carbon technologies. It predicts that in the steel sector, CCS technology could be implemented from 2020 to 2050 since all technical, financial and cost berries would be overcome.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This Chapter presents how this research has been carried out. The methodology adopted to achieve each objective laid down in Chapter 1 is narrated. The flowcharts demonstrate the sequence of the tasks, specific steps taken for each objective and a combination of procedures to reach on the outcome of all objectives. The mathematical modeling techniques used for data analysis for this research is also presented.

3.2 Mathematical modeling by 2-tuple DEMATEL, AHP, and EFAHP

According to the research objectives four methods are selected for achieving goals. For the efficient calculation and result of research objectives, selected methods are appropriate, already discussed in previous chapter. Figure 3.1 shows the CCS technology selection model based on MCDM analysis. Then, to illustrate the framework, surveys were conducted in five iron and steel manufacturing industries (ISO certified) in Bangladesh and Malaysia, where industrial experts and managers expressed their interest in and concern for our study. MCDM model would be evaluated by following objectives one, two and three with methodologies described in Figure 3.2, Figure 3.3, and Figure 3.4 respectively. The proposed model could handle the complex interactions and interdependences among dimensions and criteria, and produce results that allow us to build a visible causal relationship diagram for evaluating the CCS alternatives. The model would be validated based on existing relevant literatures and experts' decisions and assessment and surveys in iron and steel industry. Surveys have been conducted with interview from a total of four categories of expert using questionnaires. The four categories of experts are one academic experts, one scientist in R and D, one engineer from industry and one from government. Questionnaires were sent to total 30 experts in which 7 experts from R and D scientist, 7 engineers from industries, 7 experts from government and 9 experts from academic profession. Moreover, criteria data were collected by sending email to different industrial experts and managers in different countries such Japan, India, France etc. around the globe. Total 20 questionnaires were sent by email and 10 questionnaires were conducted face

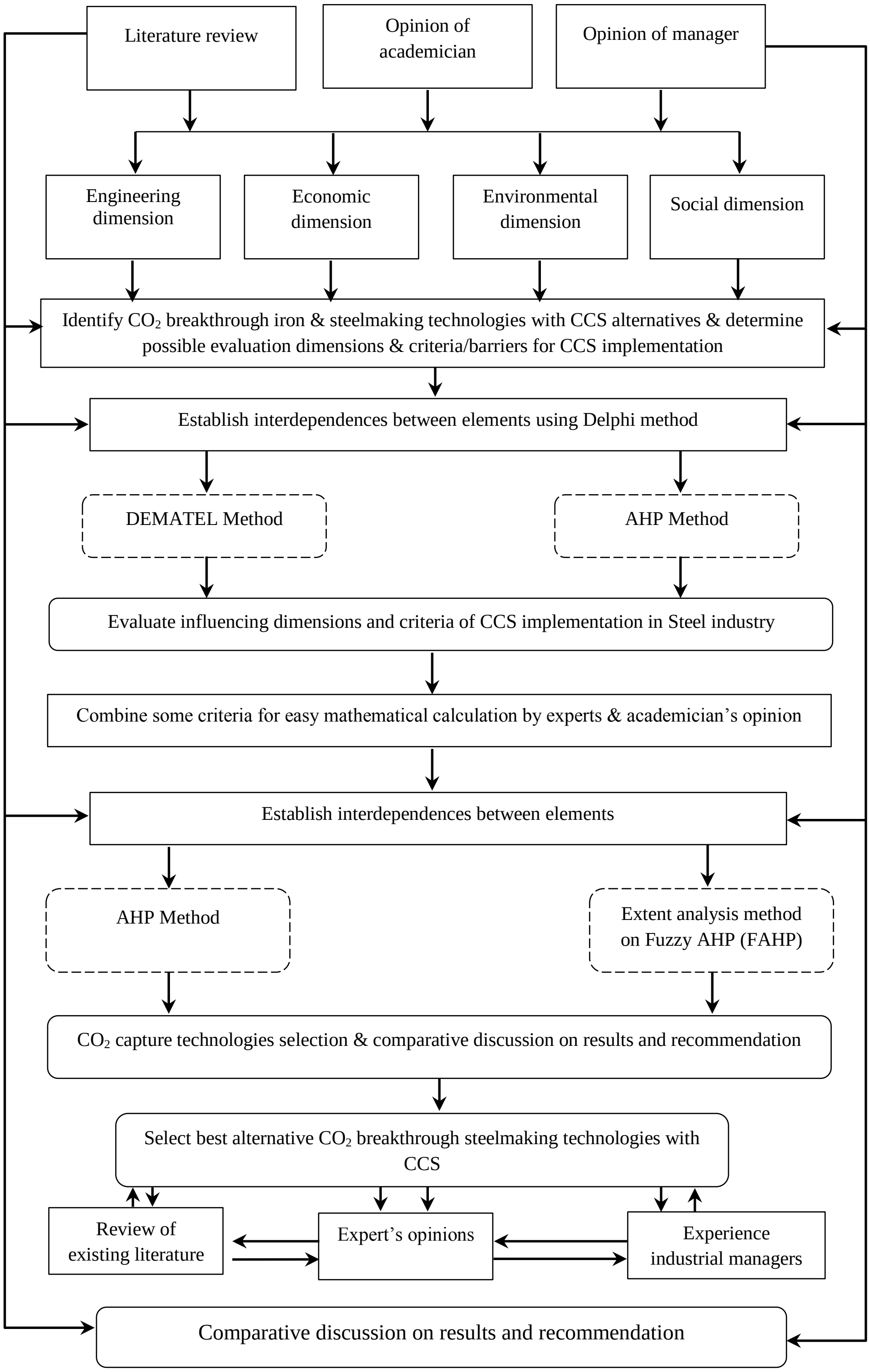


Figure 3.1: Proposed MCDM model for CCS implementation in an integrated steel industry

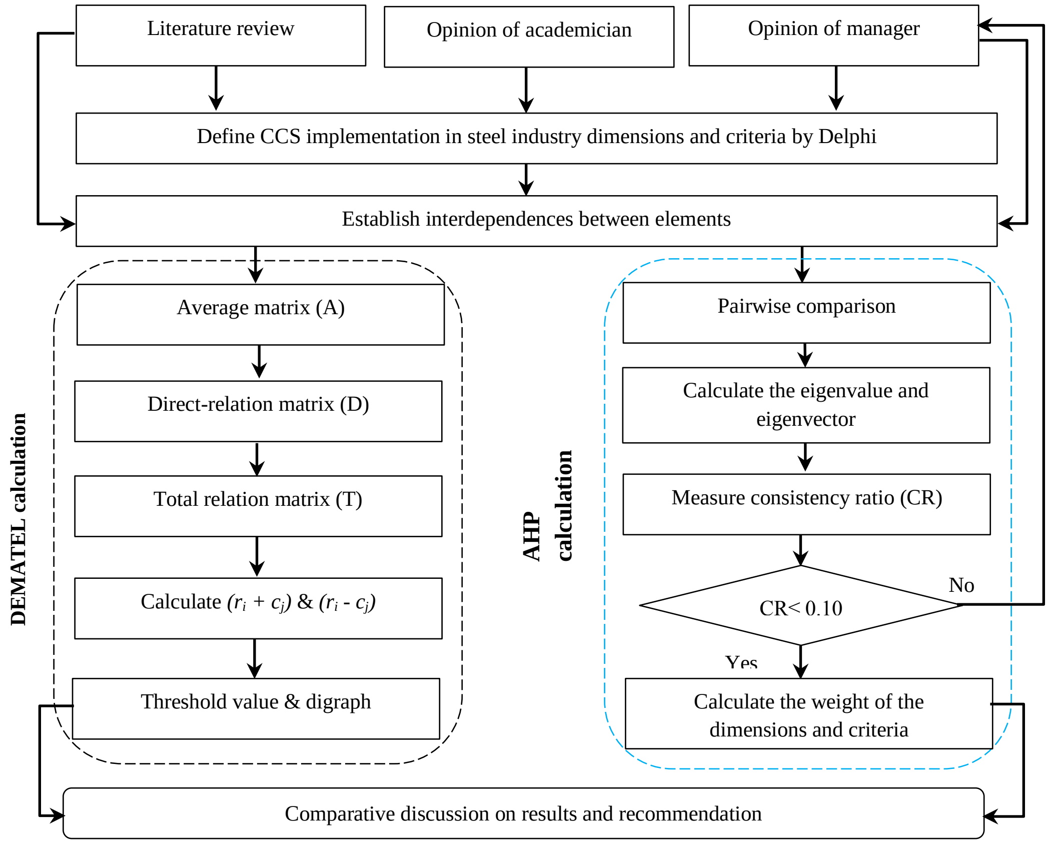


Figure 3.2: CO_2 breakthrough steelmaking technologies with CCS dimensions and criteria selection

to face interviews. From email feedback total 10 email responses were received.

After achieving the objective-1, top most influential 14 criteria will be selected from DEMATEL result. This is, because the mathematical modeling allows the decision makers to consider criteria according to their interest by adding or subtracting criteria for their decision making calculation. The following subsections described the calculation of Delphi, DEMATEL, AHP and extent analysis on fuzzy AHP approaches.

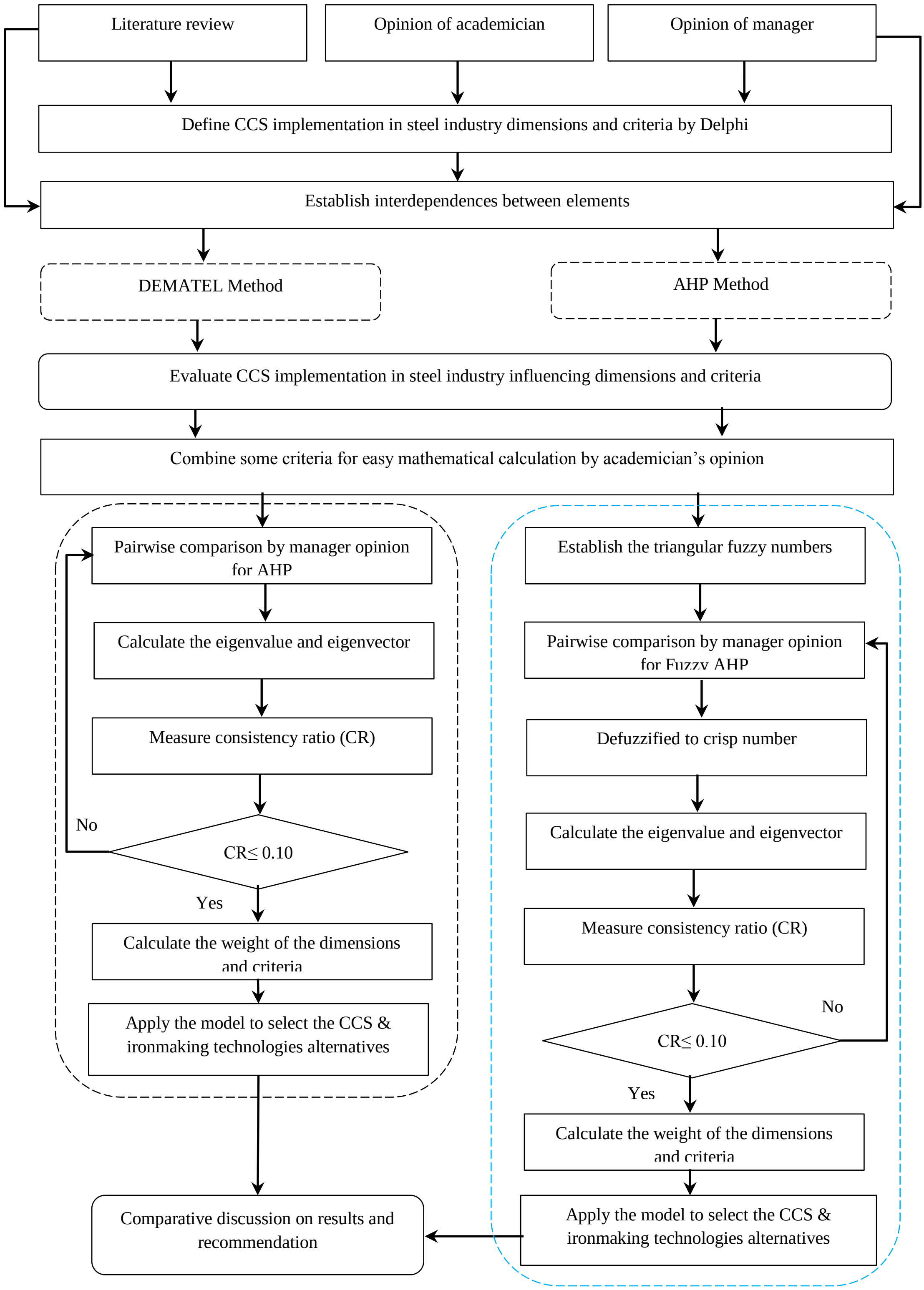


Figure 3.3: CO_2 breakthrough steelmaking technologies with CCS alternative(s) selection by 2-tuple DEMATEL and AHP

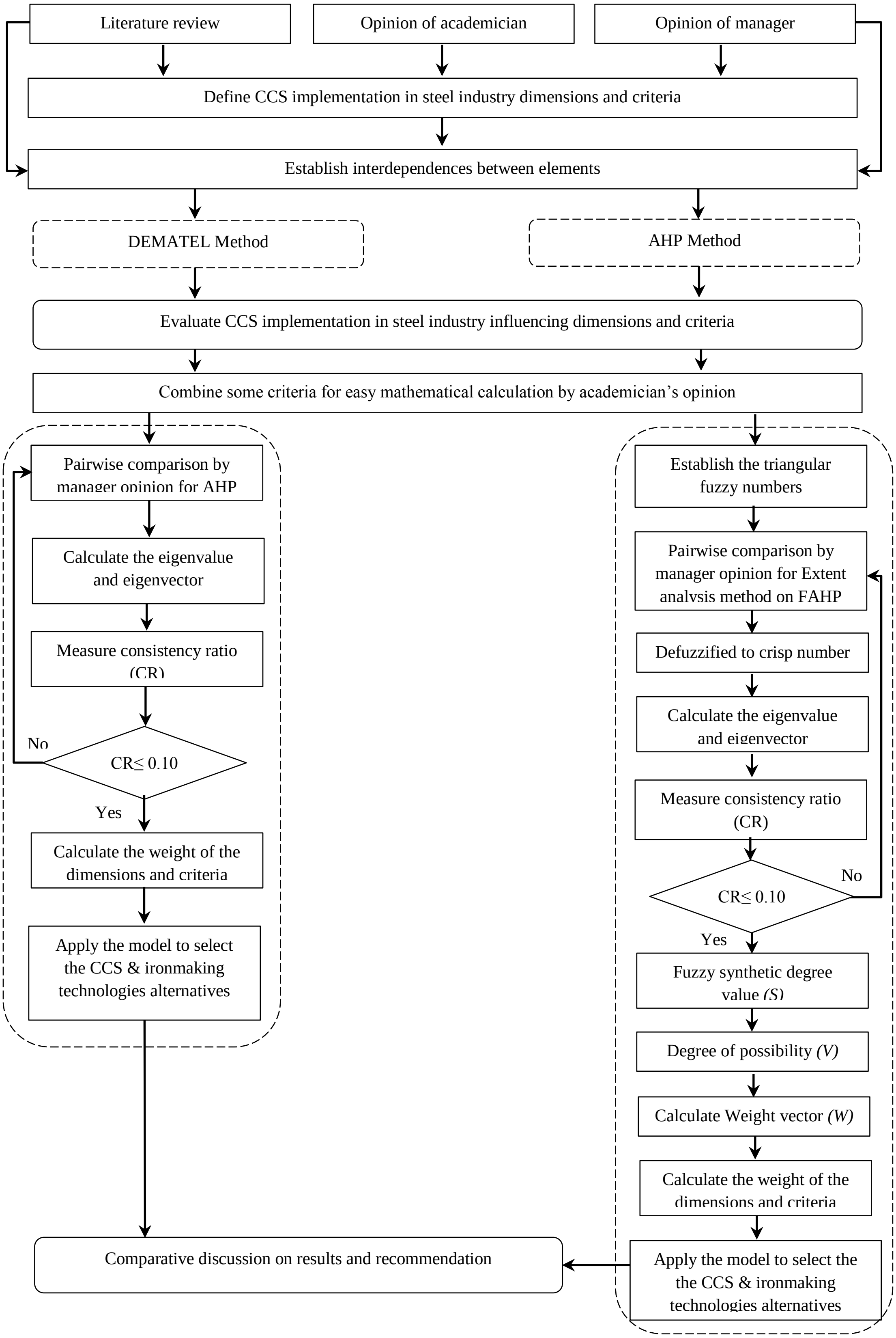


Figure 3.3: CO_2 breakthrough steelmaking technologies with CCS alternative(s) selection by DEMATEL, AHP and EFAHP

3.3.1 The Delphi method

The Delphi concept was developed from the American defense industry. Project Delphi was the name of a study undertaken by the Rand Corporation for the US Air Force in the early 1950s concerning the use of expert opinion (Robinson, 1991). Panel members remain unknown to one another and respond to a series of questionnaires. The iterative nature of the procedure generates new information for panelists in each round, enabling them to modify their assessments and project them beyond their own subjective opinions. It can represent the best forecast available from a consensus of experts (Corotis et al., 1981). The Delphi approach offers an additional advantage in situations where it is important to define areas of uncertainty or disagreement among experts. In these instances, Delphi can highlight topics of concern and evaluate uncertainty in a quantitative manner. Group evaluation of belief statements made by panel members is an explicit part of Delphi (Robinson, 1991).

The success of Delphi method depends principally on the careful selection of the panel. A group of experts was selected to provide opinions on the suitability of a certain procurement path for a given criterion. A brief overview of Delphi method application has been explained.

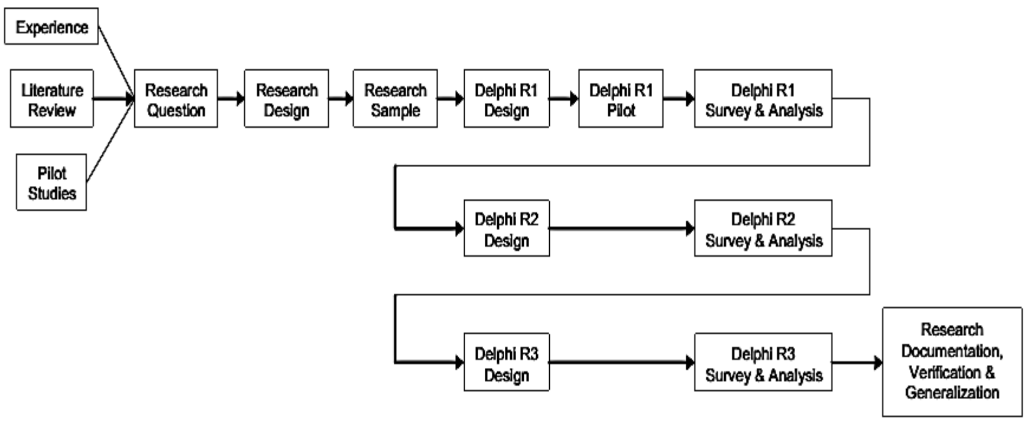


Figure 3.3: Three Round Delphi Process

3.3.2 The 2-tuple DEMATEL method

Decision-making trial and evaluation laboratory (DEMATEL) is an extended method for building and analyzing a structural model for evaluating the causal relationships among complex criteria. It is the most popular and appropriate tool to identify cause and effect relationships among the criteria and ranking the important criteria under the same dimension for long-term strategic decision making and indicate improvement scopes. The DEMATEL technique developed by the Geneva Research Centre of the Battelle Memorial Institute of Geneva between the years 1972 to 1976 (Gabus & Fontela, 1972). The basic concept of DEMATEL is a diagraph theory, which enables us to analyze the cause and effect of the system by dividing and relating the issues (Falatoonitoosi et al., 2013). This method solves the problems by visualization. It is used for various applications and issues like race, hunger, environmental production, and energy (Gabus & Fontela, 1972). In this study, a modified 2-tuple DEMATEL approach is used to ensure the relationships between and build the Influential Relation Map (IRM) among the dimensions and criteria of CO_2 capture technology and alternative iron-making technology. Besides, the proposed framework also determines the influential weights of criteria by considering hierarchy of criteria based on the results achieved by the 2-tuple DEMATEL technique.

The DEMATEL process can be summarized by the following steps:

Step 1: Calculate the initial direct-relation (Average) matrix:

Assume that we have H experts in this study and n factors (criteria) to be considered. Each respondent is asked to illustrate the degree, to which he or she believes a factor, i, affects factor j. These pairwise comparisons between any two factors are denoted by x_{ij}^{k} And give an integer score of 0-4, representing “No influence (0),”“Low influence (1),”“Medium influence (2),”“High influence (3),”and “Very high influence

(4),”separately. The scores provided by each respondent will provide a $n \times n$ nonnegative answer matrix $X^k = [x_{ij}^k]$, with $k = 1, 2, 3 \ldots\ldots H$. Thus, X^1, X^2, X^3,…… X^H, are the answer matrices for each of the H experts, and each element of $X^k = [x_{ij}^k]_{n\times n}$ is an integer denoted by x_{ij}^k. The diagonal elements of each answer matrix $X^k = [x_{ij}^k]_{n\times n}$ are all set to 0. The $n \times n$ *average* matrix ***A*** for all expert opinions could be calculated by averaging the scores of the H experts as follows:

$$a_{ij} = \frac{1}{H}\sum_{k=1}^{H} x_{ij}^k \qquad (3.1)$$

The average matrix **A** = $[a_{ij}]_{n\times n}$ is also termed the original average matrix. ***A*** show the initial direct effects that a factor utilizes on and receives from other factors. Moreover, the causal effect between each pair of factors in a system could be mapped out by drawing an influence map as shown in Figure 3.5. Each letter represents a factor in the system. An arrow from *c* to *d* shows the effect that *c* has on *d*, and the strength of its effect is 4. The structural relations among the factors of a system could be converted into an intelligible map of the system by using DEMATEL.

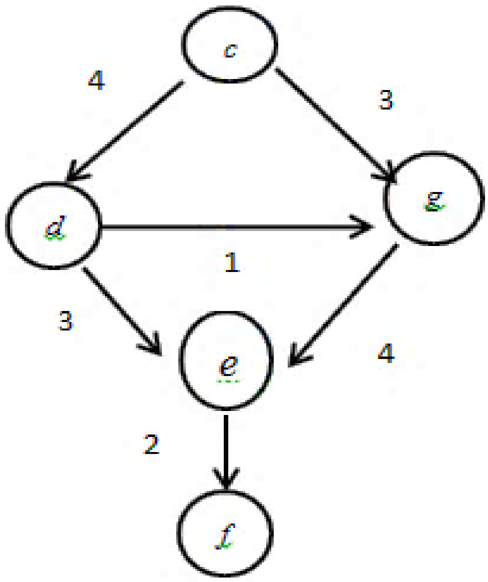


Figure 3.4: Illustration of the influence map (Lin et al., 2009)

Step 2: Calculate the direct influence matrix:

The standardized initial direct-relation matrix $\boldsymbol{D}$ is achieved by normalizing the average matrix A as follows:

$$S = max\{ max\ \sum_{j=1}^{n} a_{ij}\ , \max \sum_{i-1}^{n} a_{ij} \},$$

$$D = \frac{A}{S} \tag{3.2}$$

Since the sum of each row j of matrix $\boldsymbol{A}$ shows the direct effects that factor exert on the other factors, $max\ \sum_{j=1}^{n} a_{ij}$ denotes the factor of the highest direct influence on other factors. Similarly, since the sum of each column i of matrix $\boldsymbol{A}$ illustrates the direct effects received by factor i, $\max \sum_{i-1}^{n} a_{ij}$ represents the factor which is the most influenced factor by other factors. The positive scalar s is equal to the bigger of two extreme sums. The matrix $\boldsymbol{D}$ is acquired by dividing each element of $\boldsymbol{A}$ by the scalar. Note that each element d_{ij} of matrix $\boldsymbol{D}$ is between 0 and 1.

Step 3: Compute the total-influence matrix:

Indirect effects between factors are measured by powers of $\boldsymbol{D}$. A continuous decrease of the indirect effects of factors along the powers of matrix $\boldsymbol{D}$, namely, $\boldsymbol{D}^2$, $\boldsymbol{D}^3$ …$\boldsymbol{D}^\infty$, guarantees convergent solutions to the matrix inversion alike to an absorbing Markov chain matrix.

Note that, $D^2, D^3 \ldots D^\infty$,

$$\lim_{n\to\infty} D^m = [0]_{n\times n},$$

$[0]_{n\times n}$ is an $n \times n$ null matrix

The total relation matrix $T_{n\times n}$ is accomplished as follows:

$$T = [t_{ij}] = \sum_{m=1}^{\infty} D_i = D + D^2 + D^3 \ldots\ldots D^m$$

$$= D\ (I + D + D^2 + \cdots + D^{m-1})$$

$$= D\ (I - D)^{-1}\ (I - D)(I + D + D^2 + \cdots + D^{m-1})$$

$$= D\ (I - D)^{-1}\ (I - D^m) = D\ (I - D)^{-1}, \qquad (3.3)$$

Where ***I*** is the n × n identity matrix and ***T*** is the n × n matrix, *i*,*j* = 1,2,….*n* , D = [dij]$_{n \times n}$, $0 \leq d_{ij} < 1$.

Step 4: Build the influential relation map (IRM):

At this step, ***r*** and ***c*** as n × 1 vectors demonstrating the sum of rows and sum of columns of the total total-influence ***T*** are respectively as follows:

$$\mathbf{r} = [r_i]_{n\times1} = \left(\sum_{j=1}^{n} t_{ij}\right)_{n\times1} \qquad (3.4)$$

$$\mathbf{c} = [c_j]_{1\times n} = \left(\sum_{i=1}^{n} t_{ij}\right)_{n\times1} \qquad (3.5)$$

Where $[r_i]_{n\times1}$ denotes the sum of the *i*th row in the total matrix ***T*** and depicts the sum of the direct and indirect effects that factor *i* has on the other factors *j* = 1,2,…*n*. Similarly, $[c_j]_{1\times n}$ denotes the sum of the *j*th column in matrix ***T*** and presents the sum of direct and indirect effects that factor *j* has established from the other factors *i* = 1,2,….*n*.

The horizontal axis vector (**r** + **c**) is defined by adding ***r*** to ***c***, which shows the strength of influences that are given and received of the factor. As a result, while *i* = *j*, the sum (r_j + c_j) displays the degree of the vital role that the factor plays in the system. It is called “prominence”. Similarly, the vertical axis vector (**r** - **c**) is created by subtracting ***c*** from ***r***, which illustrates the net effect that the factor contributes to the system. If (r_j - c_j) is positive, then factor *j* has a net influence over other factors, and if (r_j - c_j) is negative, then factor *j* is being influenced by other factors on the whole. Lastly, an IRM could be acquired by mapping the ordered pairs of (**r** + **c**, **r** - **c**), that gives more essential information for problem solving.

Step 5: Determine the influential weights of criteria:

On the DEMATEL confirms the influential relationships between the dimensions and criteria; we use the causal diagram to measure the criteria weights that will be used in the decision making process (Baykasoğlu et al., 2013). The relative importance of the criteria is calculated by using the following equation:

$$w_j = \left[\left(r_j + c_j\right)^2 + \left(r_j - c_j\right)^2\right]^{\frac{1}{2}} \tag{3.6}$$

Here, Eq. (7) simply denotes the length of the vector starting from the origin to each criterion. The weight of any criterion could be normalized as follows:

$$\overline{w_j} = \frac{w_j}{\sum_{j=1}^{n} w_j} \tag{3.7}$$

Where $\overline{w_j}$ denotes the final criteria weights that would be required in the decision making process. Consequently, we could obtain the influential weight for each criterion (i.e., global influential weight) by utilizing the modified 2-tuple DEMATEL approach (Liu et al., 2015).

3.3.3 Analytic hierarchy process (AHP) method

Analytic Hierarchy Process (AHP) was originally proposed by Saaty back in the early 1970s to address the allocation of scarce resources for the military (Wang & Wang, 2014). AHP is a systematic approach to solving complex and multi-level decision-making problems (Chou et al., 2012). The approach is applicable in situations where decision-makers and experts are available. The evaluation requires criteria on multiple levels; a hierarchical evaluation process is formed. Based on the expert judgments, the criteria are compared in a pairwise fashion to assess how they contribute to the goal. Finally, alternative solutions are compared by the experts using the criteria that have been identified. Following a mathematical process, the alternative solutions are ordered in terms of their ability to attain the goal (Rezaei et al., 2013). A multi-criteria problem arises due to consideration of multiple metrics to measure the performance of the criteria under the same dimension. Several well-known increasing pressures and challenges to improve economic and environmental making methodologies can be adopted: e.g. the ELECTRE method (Figueira et al., 2005), the Data Envelopment Analysis (DEA) (Ramanathan, 2003) the Analytic Hierarchy Process (AHP) (Saaty, 1999) and PROMETHEE (Beynon, 2008).

The ELECTRE method is based on common sense techniques. However, the main disadvantage of this method is that the ranking of the final candidates depends on the choice of the threshold values, as well as on the number of available alternatives (Figueira et al., 2005). The DEA method cannot provide an actual classification of the alternatives: by using the linear programming technique, it rather carries out an efficiency evaluation, where output is the set of efficient actors. Moreover, this method evaluates the level of inefficiency accompanying with the remaining candidates. Over other methods, main advantage of the AHP method is that decision makers can make qualitative decisions based on pair-wise comparisons of the alternatives. In addition, the method can provide a rank for the different alternatives with respect to the decision maker’s preference. Experts in similar problems and analyses suggest the AHP method for use in decision making mainly because of its inherent ability to deal with qualitative and quantitative criteria pertinent to such problems.

AHP often uses a scale from “1-9” to assess the relative importance of one criteria to another (Saaty, 1999) as shown in Table 3.1. If any two criteria happen to be equally important then the relative importance for them is assigned a value of 1. If criterion j is twice as important as criterion$i$, then the relative importance a_{ij} is assigned to be a value of 2.0. If criterion j has one-fifth the importance of criterion, then, a_{ij} is set to be equal to 0.2. The relative importance of all combinations of a set of criteria then forms a pair-wise comparison matrix, A:

$$A = \{a_{ij}\} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nn} \end{bmatrix}$$

It is to be noted that if criterion *j* is twice as important as criterion i ($a_{ij} = 2.0$) then criterion *i* will be half as important as criterion *j* ($a_{ji} = 0.5$). In other words,

$$a_{ij} = \frac{1}{a_{ji}} \tag{3.8}$$

In general, when a decision-maker forms matrix *A*, he/she is likely to create some inconsistencies, i.e., not every element of the matrix will satisfy the condition of Eq. (3.5)

$$a_{ij} = a_{ik}.a_{kj} \tag{3.9}$$

where *i, j* and *k* ranges from 1 to *n*

An eigenvector method is available to find the weights (Saaty 1990). Saaty used the concept of eigenvector of the comparison matrix to find criteria and contributory factors weights. For each pair-wise comparison matrix ***A***, by using the theory of eigenvector

$$(A - \lambda_{max} I)w = 0 \tag{3.10}$$

It is possible to calculate the eigenvalue λ_{max} and the eigenvector $\boldsymbol{w} = (w_1, w_2, w_3, \ldots\ldots w_n)$ where *n* is the matrix size. Thus, weights of the criteria can be estimated. Saaty (1999) also introduced the consistency index (CI). The consistency is determined by using the following formula:

$$CI = (\lambda_{max} - n)/(n - 1) \tag{3.11}$$

Now, consistency of the judgments can be tested by computing consistency ratio (CR) of CI with the appropriate value of a random index (RI) specified by (Saaty, 1999).

$$CR = CI/RI \tag{3.12}$$

The value of CR is acceptable up to 0.1. The judgment matrix is inconsistent if it is more than 0.1. The judgments should be reviewed and improved until CR≤0.1 to obtain a consistent matrix. Random index is the CI of a randomly-generated pairwise comparison matrix shown in Table 3.2.

Table 3.1: Pairwise comparison scale for AHP preferences (Saaty, 1999)

Numerical rating	**Verbal judgments of preferences**
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely important
2,4,6,8	Immediate judgment values

Table 3.2: Random consistency index for n =10 (Saaty, 1988)

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0.00	0.00	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

**n= order of matrix*

3.3.3.1 Computational procedure of the AHP

AHP algorithm is basically composed of three steps:

Step 1:

- Develop the weights for the criteria by developing a single pair-wise comparison matrix for the criteria;
- Multiplying the values in each row together and calculating the ***n***th root of the said product;
- Normalizing the aforementioned ***n***th root of the products to get the appropriate weights; and calculating and checking the Consistency Ratio (CR).

Step 2:

- Develop the ratings for each decision alternative for each criterion by developing a pair-wise comparison matrix for each criterion, with each matrix containing the pair-wise comparisons of the performance of decision alternatives on each criterion;

- Multiplying the values in each row together and calculating the ***n*** th root of said product;
- Normalizing the aforementioned ***n*** th root of product values to get the corresponding ratings; and calculating and checking the Consistency Ratio (CR).

Step 3: Calculate the weighted average rating for each decision alternative. Choose the one with the highest score. Pairwise comparisons are made with the grades ranging from 1-9. A basic, but very reasonable assumption for comparing alternatives:

If attribute A is absolutely more important than attribute B and is rated at 9, then B must be absolutely less important than A and is graded as 1/9.

The steps of the computational procedure are shown below.

For a matrix of pairwise elements: $\begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix}$

1) Sum the values in each column of the pairwise matrix

$$= \sum_{i=1}^{n} C_{ij}$$

2) Divide each element in the matrix by its column total to generate a normalized pairwise matrix

$$X_{ij} = \frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}} = \begin{bmatrix} X_{11} & X_{12} & X_{13} \\ X_{21} & X_{22} & X_{23} \\ X_{31} & X_{32} & X_{33} \end{bmatrix}$$

3) Divide the sum of the normalized column of matrix by the number of criteria (n) used to generate weight matrix

$$W_{ij} = \frac{\sum_{j=1}^{n} X_{ij}}{n} = \begin{bmatrix} W_{11} \\ W_{12} \\ W_{13} \end{bmatrix}$$

4) Consistency vector is calculated by multiplying the pairwise matrix by weights vector as shown below.

$$\begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix} \begin{bmatrix} W_{11} \\ W_{12} \\ W_{13} \end{bmatrix} = \begin{bmatrix} Cv_{11} \\ Cv_{21} \\ Cv_{31} \end{bmatrix}$$

$$Cv_{11} = \frac{1}{W_{11}}[C_{11}W_{11} + C_{12}W_{12} + C_{13}W_{13}]$$

$$Cv_{21} = \frac{1}{W_{21}}[C_{21}W_{11} + C_{22}W_{12} + C_{23}W_{13}]$$

$$Cv_{31} = \frac{1}{W_{31}}[C_{31}W_{11} + C_{32}W_{12} + C_{33}W_{13}]$$

Then,

$$\gamma = \sum_{i=1}^{n} Cv_{ij} \ ; \quad CI = \frac{\gamma - n}{n-1} \ ; \ C_r = \frac{CI}{RI}$$

3.3.4 Fuzzy AHP (AHP) analysis and comparison with AHP method

The analytical hierarchy process (AHP) is widely used to solve multi-criteria decision making (MCDM) problems. However, as AHP uses exact numbers to represent human judgments, it is very difficult for decision makers to express the preferences using some exact value (AHP scale is 1-9) in uncertain conditions. Some assessments may be qualitative and subjective in nature, where doing pairwise comparisons using the exact numbers may not be effective. So, the decision maker needs something that can describe uncertainty in their decision. Fuzzy evaluations could be a useful alternative to handle this vagueness in decision making. To solve this problem fuzzy linguistic variables and corresponding fuzzy triangular numbers shown in Figure 3.5 can be used for comparison among the attributes. The fuzzy AHP can efficiently handle the fuzziness in the decision process to select the appropriate alternative(s) by using both qualitative and quantitative data in the multi-attribute decision making problems (R. Singh et al., 2006). Instead of nine-points scale in AHP, this approach uses triangular fuzzy numbers and then defuzzified by crisp number and calculates the weightages. Then weight vectors are calculated and normalized to get the normalized weight vector. Final priority weights of the alternatives are computed by using the different weights of criteria and attributes. CO_2 breakthrough ironmaking technologies with CCS alternatives are ranked according to the priority weights and selected as necessary.

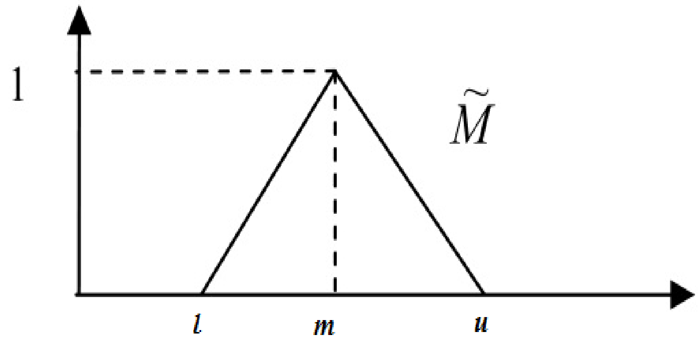


Figure 3.5: A triangular fuzzy number (Kahraman et al., 2004)

Zadeh (1965) first introduced the fuzzy set theory (Kwong & Bai, 2003) to deal with vagueness in human judgment and imprecise data in decision making through the use of linguistic terms and degrees of membership. A membership function in fuzzy sets assigns to each object a grade of membership in [0, 1]. A tilde ‘‘~’’ is used above the symbol that represents a fuzzy set. A triangular fuzzy number (TFN) $\tilde{A}$ is shown in Figure 3.6. A TFN is denoted simply as *(l, m, u)*. The parameters *l, m*, and *u* denote the smallest possible value, the most promising value and the largest possible value that describe a fuzzy event (Kahraman et al., 2004). When $l = m = u$, it is a non-fuzzy

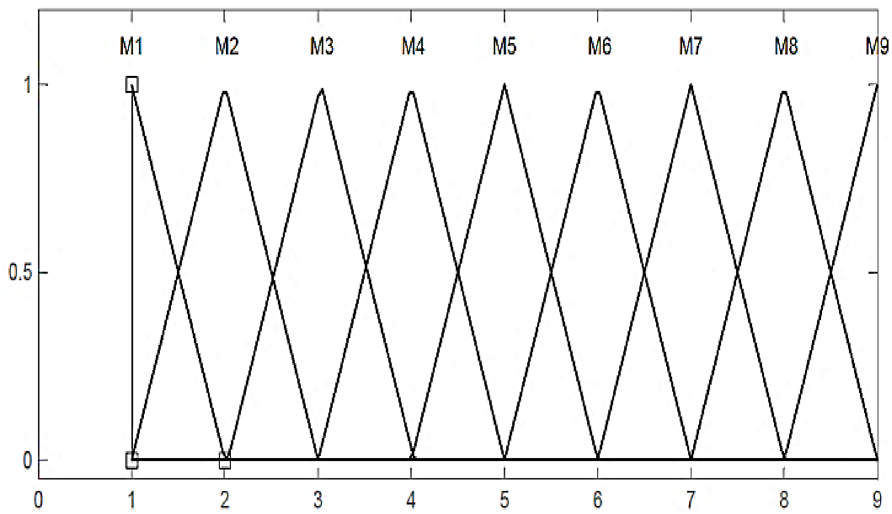


Figure 3.6: Membership functions for fuzzy linguistic variables.

number by convention (Chan & Kumar, 2007). Each TFN has linear representations on its left and right side such that its membership function can be defined as (Kilincci & Onal, 2011):

$$\mu_{\widetilde{M}} = \begin{Bmatrix} 0, x < l, \\ \frac{x-l}{m-l}, & l \leq x \leq m, \\ \frac{u-x}{u-m}, & m \leq x \leq u, \\ 0, & x > u\,. \end{Bmatrix} \tag{3.13}$$

Naturally it is easy to use fuzzy numbers in expressing qualitative assessments from decision makers. A fuzzy number can always be given by its corresponding left and right representation of each degree of membership (Kilincci & Onal, 2011)

$$\widetilde{M} = (M^{l(y)}, M^{r(y)} = (l + (m - l)y, u + (m - u)y), \;\; y \in [0,1] \tag{3.14}$$

Where, $l(y)$ and $r(y)$ denote the left side representation and the right side representation of a fuzzy number, respectively. The arithmetic operations with two fuzzy numbers M_1 and M_2 can be expressed as below.

$$M_1 + M_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2), \tag{3.15}$$

$$M_1 \otimes M_2 \approx (l_1 l_2, m_1\, m_2\,, u_1 u_2)$$

$$\lambda \otimes M_1 = (\lambda l_1, \lambda m_1, \lambda u_1), \lambda > 0, \lambda \epsilon R$$

$$M_1^{-1} \approx (\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1})$$

3.3.4.1 Computational procedure of the Fuzzy AHP

After constructing the hierarchy, next step is to determine the priority weights of the dimensions and criteria by using Fuzzy AHP approach. In order to take the vagueness into consideration the assessment of dimensions and criteria, triangular numbers *M1*, *M2, M4, M6, M8* are used to represent the assessment from equal to absolutely preferred and *M3, M5, M7* and *M9* are intermediate values. Figure 3.7 shows the membership functions of the triangular fuzzy numbers M_t= (l_t, m_t, u_t) where t=1, 2 , 3…..9 and where l_t, m_t, u_t represents the lower , intermediate and upper values of fuzzy number M_t respectively.

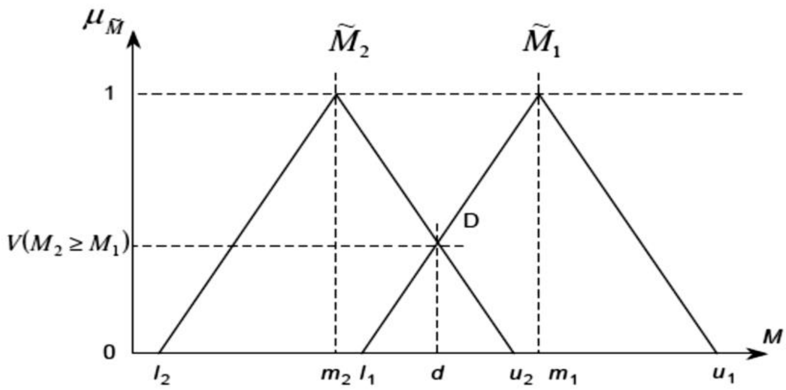


Figure 3.7: Intersection between M1 and M2 (Tolga et al., 2005)

Linguistic variables are used to make the pair-wise comparisons by the experts. Judgments by linguistic variables are converted to triangular fuzzy numbers by using membership functions shown in Figure 3.7. The linguistic variables and their corresponding triangular fuzzy numbers are shown in Table 3.3. Then the judgments from the experts are combined by using operational laws for two triangular fuzzy numbers.

Satty (1980) introduced AHP methodology and provides a consistency index to measure the inconsistencies accompanied by the judgments provided by the experts. For this, first we used the defuzzification method of fuzzy triangular numbers to convert the fuzzy comparison matrices into crisp matrices by the Eq. 3.9.

Table 3.3: Linguistic variables and their corresponding fuzzy numbers

Rating level	**Linguistic scale**	**Triangular fuzzy scale**	**Triangular fuzzy reciprocal scale**
1	Equally preferred (EP)	(1, 1, 2)	(1/2, 1, 1)
3	Moderately preferred (MP)	(1, 2, 3)	(1/3, 1/2, 1)
5	Strongly preferred (SP)	(3, 4, 5)	(1/5, 1/4, 1/3)
7	Very strongly preferred (VSP)	(5, 6, 7)	(1/7, 1/6, 1/5)
9	Absolutely preferred (AP)	(7, 8, 9)	(1/9, 1/8, 1/7)
2,4,6,8	Midpoint preference values lying between above values	(1, 2, 3), (3, 4, 5), (5, 6, 7), (7, 8, 9)	

$$M\_crisp = (4 \otimes m + l + u)/6 \tag{3.16}$$

The consistency index of each matrix is found by using $CI = (\lambda_{max} - n)/(n-1)$ and then consistency ratios are calculated by $CR = (\frac{CI}{RI})$ in crisp AHP once the fuzzy comparison matrices are converted to crisp matrices (Kwong & Bai, 2003).

3.3.5 Extent analysis method on Fuzzy AHP (EFAHP)

While a discrete scale of 1-9 is used in crisp AHP fuzzy numbers, linguistic variables are used to decide the priority of one decision variable over another whereas in fuzzy AHP (R. Singh et al., 2006). In practice, decision makers usually prefer triangular or trapezoidal fuzzy numbers because it allows a range for decision rather a single number which is difficult to choose (Kilincci & Onal, 2011). Solution methods in fuzzy AHP are different from crisp AHP as fuzzy numbers are used. Extent analysis proposed by D.Y. Chang (1996) is the most common solution method used in fuzzy AHP. This method is used to consider the extent of an object to be satisfied for the goal, that is, satisfied the extent. In the method, the ‘‘extent’’ is quantified by using a fuzzy number. On the basis of the fuzzy values for the extent analysis of each object, a fuzzy synthetic degree value can be obtained, which is defined as follows.

Let $X = \{x_1, x_2, \dots \dots . x_n)$ is an object set and $G = \{g_1, g_2, \dots \dots \dots g_m)$ be a goal set. According to the method of Chang’s (1992) extent analysis, each object is taken and extent analysis is done for each goal, g_i, respectively. Therefore, m extent analysis values for each object can be obtained, with the following signs:

$$M_{g_i}^1, M_{g_i}^2, \dots \dots \dots, M_{g_i}^m, \qquad i = 1,2, \dots \dots . n \tag{3.17}$$

Where all the $M_{g_i}^j (j = 1,2, \dots \dots m)$ are TFNs.

The steps of Chang’s extent analysis can be given as in the following manner:

Step 1: The value of fuzzy synthetic extent with respect to the ith object is defined as

$$S_i = \sum_{j=1}^{m} M_{g_i}^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1}$$

To obtain, $\sum_{j=1}^{m} M_{g_i}^{j}$, perform the fuzzy addition operation of *m* extent analysis values for a particular matrix such that

$$\sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{j=1}^{m} l_j , \sum_{j=1}^{m} m_j , \sum_{j=1}^{m} u_j \right)$$

To obtain, $\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$ perform the fuzzy addition operation of $M_{g_i}^{j}(j = 1,2, \dots \dots \dots , m)$ values such that

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{i=1}^{n} l_i \sum_{i=1}^{n} m_i \sum_{i=1}^{n} u_i \right) \tag{3.18}$$

and then compute the inverse of the vector in Eq. (3.16) such that

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{i} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \tag{3.19}$$

Step 2: The degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_{1,} u_1)$ is defined as

$$V(M_2 \geq M_1) = sup \left[\min_{y \geq x} \left(\mu_{M_1}(x), \mu_{M_2}(y) \right) \right] \tag{3.20}$$

and can be equivalently expressed as follows:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d)$$

$$\left\{ \begin{array}{ll} 1, & if\ m_2 \geq m_1 , \\ 0, & if\ l_1 \geq u_2 , \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise \end{array} \right\} \tag{3.21}$$

Where *d* is the ordinate of the highest intersection point *D* between μ_{M_1} and μ_{M_2}. In Figure 3.8.the intersection between *M1* and *M2* can be seen. To compare M_1 and M_2, require both the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$.

Step 3: The degree of possibility for a convex fuzzy number to be greater than *k* convex fuzzy numbers $M_i(i = 1,2, \dots \dots \dots . . , k)$ can be defined by

$$V(M \geq M_1, M_2, \dots \dots \dots \dots , M_K)$$

$$= V[(M \geq M_1)\ and (M \geq M_2)\ and \dots \dots \dots and (M \geq M_k)] \tag{3.22}$$

$$= \min V(M \geq M_i)\,, i = 1,2, \dots \dots \dots \dots k$$

Assume that,

$$d'(A_i) = \min V(S_i \geq S_k); \quad \text{For } k = 1,2, \dots \dots \dots \dots., n; k \neq i \tag{3.23}$$

Then the weight vector is given by

$$W' = \left(d'(A_1), d'(A_2), \dots \dots \dots \dots . d'(A_n)\right)^T, \tag{3.24}$$

Step 4: Via normalization, the normalized weight vectors are

$$W = \left(d(A_1), d(A_2), \dots \dots \dots \dots .., d(A_n)\right)^T, \tag{3.25}$$

Where W is a non-fuzzy number. This gives the priority weights of one alternative over another. Membership functions of the linguistic variables are defined by Fuzzy toolbox in MATLAB. Using this membership functions and linguistic variables expert judgments are taken and linguistic judgments were converted to fuzzy triangular numbers as defined by membership functions. By using crisp AHP method, the triangular numbers are converted into matrix and then calculate consistency ratio. Finally the matrices are solved by D.Y. Chang (1996) extent analysis method.

CHAPTER 4: DATA ANALYSIS AND RESULTS

4.1 Introduction

The assessment of alternatives ironmaking technologies with CO_2 capture technology have been analyzed based on the data collected from expert's questionnaire. The experts are from different fields of expertise having relevant experience of CCS and iron industry. All of the expert have up to 10 years of research and job experiences. Initially, the results of dimensions and criteria selection and evaluation by using Delphi and 2-tuple DEMATEL have been deliberated in subsection 4.2. Than selective criteria evaluation and alternatives selection procedure were calculated using AHP and Extent analysis on fuzzy AHP method in subsection 4.3 and 4.4.

4.2 Dimensions and criteria evaluation using 2-tuple DEMATEL

In order to select and evaluate the criteria of emerging steelmaking technologies with CCS technologies regarding engineering, economic, environmental and social, an extensive literature review related to CCS deployment in iron and steel industry has been done. Finally, with the help of circulated questionnaire to the experts and their replies, data has been collected and analyzed comprehensively using two-tuple DEMATEL technique.

First, to identify the relationship among the dimensions of engineering (D1), economic (D2), environmental (D3), and social (D4) initial direct-relation (Average) matrix A is calculated by equation 3.1 using pair-wise comparison values in terms of influences and directions between dimensions from all experts shown in Table 4.1. Then standardized the initial direct-relation matrix $\boldsymbol{D}$ which is achieved by normalizing the average matrix $\boldsymbol{A}$ using equation 3.2 shown in Table 4.2. And the total-relation matrix $\boldsymbol{T}$ of the four dimensions is derived by using equations 3.3, where threshold value is 1.179 beyond which the score of a criterion becomes unacceptable. From the $\boldsymbol{T}$ matrix, values of sum of columns and sum of rows separately denoted as $\boldsymbol{c}$ and $\boldsymbol{r}$ are calculated to find out direct and indirect effects of dimensions by equation 3.4 and 3.5. Calculations of sum of $\boldsymbol{c}$ and $\boldsymbol{r}$ are as follow:

$\mathbf{r} = [r_1]_{4\times1} = 4.995$, Similarly $\mathbf{r}_2 = 3.781$, $\mathbf{r}_3 = 5.585$, $\mathbf{r}_4 = 4.105$

$\mathbf{c} = [c_1]_{1\times4} = 4.949$, similarly $\mathbf{c}_2 = 4.266$, $\mathbf{c}_3 = 5.327$, $\mathbf{c}_4 = 3.323$

Finally the influential prominence & relation between the dimensions are depicted from the dimensions weights and normalized values by equations 3.6 and 3.7 as shown in Table 4.3. The values of weights of dimensions are as follow:

For D1, $W_j = \sqrt{\left[(9.944)^2 + (0.045)^2\right]} = 9.9442$ likewise for D2 = 8.062, D3 = 10.915, D4 = 7.469., and final weights $(\overline{W_j})$ values for dimensions D1 = 0.273, D2 = 0.222, D3 = 0.300, D4 = 0.205. Microsoft Excel 2010 was used for the calculation of all equations.

Table 4.1: Average matrix (A) of dimensions

Dimensions	D1	D2	D3	D4
D1	1.158	1.141	1.561	1.134
D2	0.993	0.741	1.089	0.959
D3	1.607	1.261	1.379	1.337
D4	1.191	1.122	1.299	0.893

Table 4.2: Direct-relation matrix (D) of dimensions

Dimensions	D1	D2	D3	D4
D1	0.000	0.211	0.474	0.158
D2	0.158	0.000	0.211	0.263
D3	0.474	0.211	0.000	0.316
D4	0.211	0.316	0.263	0.000

Table 4.3: Total-relation matrix (T) of sustainable dimensions with relevant weights

	D1	**D2**	**D3**	**D4**	$\boldsymbol{r}$	$\boldsymbol{c}$	$(\boldsymbol{r}+\boldsymbol{c})$	$(\boldsymbol{r}-\boldsymbol{c})$	$\boldsymbol{W_j}$	$\overline{\boldsymbol{W_j}}$	**Rank**
D1	1.158	1.141	1.561	1.134	4.995	4.949	9.944	0.045	9.944	0.273	2
D2	0.993	0.741	1.089	0.959	3.781	4.266	8.047	-0.484	8.062	0.222	3
D3	1.607	1.261	1.379	1.337	5.585	5.327	10.912	0.257	10.915	0.300	1
D4	1.191	1.122	1.299	0.893	4.105	3.323	7.428	0.782	7.469	0.205	4

*Threshold value: 1.179

Similarly 2-tuple DEMATEL method is used to again determine the relationship among criteria within the four dimensions. Through equations (1) to (3), the total-relation matrices of criteria under dimension of engineering (D1), economic (D2), environmental (D3), and social (D4) are shown as Tables 4.4-4.7 where average matrix

A and direct relation matrix ***D*** shown in Appendix A. Finally, influences among the criteria (prominence & relation) and their relative weights are calculated as shown in Table 4.8.

Table 4.4: Total-relation matrix (T) of engineering (D1) dimension criteria

Criteria	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**
C_1	1.114	1.515	1.380	1.280	1.466	1.353	1.180
C_2	1.537	1.756	1.766	1.639	1.917	1.677	1.480
C_3	1.493	1.807	1.584	1.630	1.842	1.589	1.516
C_4	1.325	1.728	1.593	1.323	1.642	1.434	1.328
C_5	1.564	2.022	1.835	1.670	1.840	1.779	1.631
C_6	1.637	1.994	1.767	1.636	1.982	1.583	1.516
C_7	1.453	1.794	1.771	1.589	1.889	1.606	1.364

*Threshold value: 1.608

Table 4.5: Total-relation matrix (T) of economic (D2) dimension criteria

Criteria	**C_8**	**C_9**	**C_{10}**	**C_{11}**	**C_{12}**	**C_{13}**
C_8	0.532	0.683	0.677	0.648	0.828	0.660
C_9	0.774	0.766	0.924	0.871	1.002	0.835
C_{10}	0.892	1.028	0.845	0.971	1.151	0.852
C_{11}	0.794	0.906	0.929	0.687	0.948	0.740
C_{12}	0.760	0.834	0.854	0.752	0.780	0.751
C_{13}	0.736	0.801	0.736	0.691	0.895	0.579

*Threshold value:0.809

Table 4.6: Total-relation matrix (T) of environmental (D3) dimension criteria

Criteria	**C_{14}**	**C_{15}**	**C_{16}**	**C_{17}**	**C_{18}**	**C_{19}**
C_{14}	1.408	1.330	1.422	1.347	1.555	1.751
C_{15}	1.460	1.182	1.437	1.280	1.565	1.615
C_{16}	1.243	1.098	1.060	1.111	1.314	1.354
C_{17}	1.240	1.116	1.168	0.997	1.371	1.301
C_{18}	1.610	1.402	1.506	1.455	1.467	1.624
C_{19}	1.724	1.470	1.526	1.378	1.618	1.576

*Threshold value: 1.391

Table 4.7: Total-relation matrix (T) of social (D4) dimension criteria

Criteria	**C_{20}**	**C_{21}**	**C_{22}**	**C_{23}**	**C_{24}**	**C_{25}**
C_{20}	0.869	1.019	0.899	0.838	0.830	0.979
C_{21}	1.137	0.890	0.885	0.886	0.801	1.103
C_{22}	0.933	0.846	0.636	0.757	0.696	0.850
C_{23}	0.799	0.802	0.690	0.612	0.636	0.873
C_{24}	0.862	0.820	0.783	0.721	0.558	0.825
C_{25}	1.082	1.134	0.913	1.065	0.841	0.941

*Threshold value: 0.856

According to the above empirical study, the proposed MCDM model provides some important findings. From the results of 2-tuple DEMATEL technique we can see the influential weights for each criterion as shown in Table 4.8. Results show that the criterion of energy for capture and storage (C_6) is the most important criterion with influence weight of 0.067 compared to others criteria in engineering dimension (D1), while the criterion of safe storage (C_1) is the least important one with influence weight of 0.051. Since, fuel consumption from post-combustion capture unit contributes up to 50% to the operational cost and fuel requirement is generally for solvent regeneration, somewhat for CO_2 compression, solvent circulation pumps and blowers (IEAGHG, 2013).

Table 4.8: Influences among the criteria (prominence & relation) and their relative weights

Dimensions	Criteria	r	c	$r + c$	$r - c$	Wj	$\overline{w_j}$	Rank
Engineering (D1)	C_1	9.288	10.123	19.411	-0.836	19.429	0.051	7
	C_2	11.772	12.616	24.387	-0.844	24.402	0.064	3
	C_3	11.461	11.696	23.157	-0.234	23.158	0.061	4
	C_4	10.372	10.767	21.139	-0.395	21.143	0.056	6
	C_5	12.340	12.579	24.919	-0.239	24.920	0.066	2
	C_6	14.116	11.221	25.337	0.894	25.501	0.067	1
	C_7	11.466	10.014	21.480	1.452	21.529	0.057	5
Economic (D2)	C_8	4.029	4.489	8.518	-0.460	8.530	0.022	6
	C_9	5.172	5.019	10.191	0.154	10.192	0.027	2
	C_{10}	5.747	4.966	10.712	0.781	10.741	0.028	1
	C_{11}	5.005	4.628	9.633	0.376	9.640	0.025	4
	C_{12}	4.732	5.604	10.336	-0.872	10.372	0.027	3
	C_{13}	4.438	4.417	8.855	0.021	8.855	0.023	5
Environmental (D3)	C_{14}	8.813	8.684	17.497	0.129	17.498	0.046	3
	C_{15}	8.540	7.599	16.139	0.941	16.166	0.043	4
	C_{16}	7.180	8.119	15.299	-0.939	15.328	0.040	5
	C_{17}	7.194	7.567	14.762	-0.373	14.766	0.039	6
	C_{18}	9.062	8.891	17.953	0.171	17.954	0.047	2
	C_{19}	9.292	9.221	18.513	0.071	18.513	0.049	1
Social (D4)	C_{20}	5.434	5.681	11.114	-0.247	11.117	0.029	2
	C_{21}	5.702	5.510	11.212	0.191	11.214	0.029	3
	C_{22}	4.718	4.806	9.524	-0.089	9.525	0.025	4
	C_{23}	4.413	4.880	9.293	-0.467	9.305	0.024	5
	C_{24}	4.570	4.363	8.933	0.206	8.935	0.023	6
	C_{25}	5.977	5.571	11.548	0.406	11.555	0.030	1

On the other hand, capture & storage cost (C_{10}) is considered to be the most significant criterion with influence weight of 0.028 under economic (D2) dimension, whereas operation and maintenance cost (C_9) and payback period/return on investment (C_{12}) are second and third weighty criteria respectively. The fact is that during the solvent regeneration process requires excessive thermal energy which directly impacts on fuel consumption and effects operating cost (OPEX). Additionally, corrosion of capture process equipment by oxidative and thermal degradation effects CO_2 capture cost and OPEX.

Table 4.9: Weights summary of dimensions and criteria

Criteria	Engineering (D1)	Economic (D2)	Environmental (D3)	Social (D4)	Global weights	Rank
	0.2733	**0.2215**	**0.2999**	**0.2052**		
Safe storage (C_1)	0.051				0.0140	7
Maturity/consolidation/feasibility (C_2)	0.064				0.0175	3
Compatibility with process (C_3)	0.061				0.0166	4
Ease of technology adoption (C_4)	0.056				0.0152	6
CO_2 removal efficiency (C_5)	0.066				0.0179	2
Energy for capture and storage (C_6)	0.067				0.0183	1
CO_2 concentration (C_7)	0.057				0.0155	5
Investment/capital cost (C_8)		0.022			0.0050	6
Operation and maintenance cost (C_9)		0.027			0.0059	2
Capture & storage cost (C_{10})		0.028			0.0063	1
Fuel & electric cost (C_{11})		0.025			0.0056	4
Payback period/return on investment (C_{12})		0.027			0.0060	3
Service life/plant life time (C_{13})		0.023			0.0052	5
CO_2 emission (C_{14})			0.046		0.0138	3
$CO/SO_2/Nx$ emission (C_{15})			0.043		0.0128	4
Particles emission/Non-methane volatile organic compounds (C_{16})			0.040		0.0121	5
Land use (C_{17})			0.039		0.0116	6
Eutrophication Potential (EP) (C_{18})			0.047		0.0142	2
Global Warming Potential (GWP) (C19)			0.049		0.0146	1
Public acceptance (C_{20})				0.029	0.0060	2
Job creation (C_{21})				0.029	0.0061	3
Human Toxicity Potential (HTP) (C_{22})				0.025	0.0051	4
Climate change (C_{23})				0.024	0.0050	5
Knowledge of CCS (C_{24})				0.023	0.0048	6
Policy, Politics &, Regulation (C_{25})				0.030	0.0062	1

Among the environmental (D3) criteria global warming potential (C_{19}) $\overline{w_j}$ =0.049) is considered the most significant criterion during CCS technology selection. Several studies have indicated that although CCS reduces the quantity of CO_2 emitted into the atmosphere, due to the energy penalty of CCS, extra construction material and imperfect capture technology; CO_2 is still emitted into the atmosphere. Besides, eutrophication potential (EP) (C_{18}) ($\overline{w_j}$ =0.047) is reflected to be second most pivotal factor during the selection of CCS technology. As the function of chemicals (such as NOx, SO_2, NH_3 and PO_4^{3-}) during eutrophication process occur excessive supply of nutrients to water and soil.

Likewise, in social (D4) dimension, the criterion of policy, politics and regulation (C_{25}) is measured as more vital to than other criteria with influence weight of 0.030, followed by public acceptance (C_{20}) ($\overline{\boldsymbol{w_j}}$=0.029) and job creation (C_{21}) ($\overline{\boldsymbol{w_j}}$=0.029) with similar importance. Although the IPCC has developed guidelines for storing and monitoring CO_2, the inadequacy of regulations and legislation for CCS deployment worldwide is another prime barrier to CCS development. Because of the support of governments in either monetary or legislative terms is therefore essential for its development. Hence, it is indispensable to frame national and international regulations concerning effective CCS implementation in steel industry on a large scale worldwide.

Determined by the experts, the result shown in Table 4.8 illustrates the superficial dependence existing among dimensions and criteria. Finally, the causal diagram is constructed with the vertical axis (**c - r**) named "Relation" and the horizontal axis (**c + r**) named "Prominence". The horizontal axis "Prominence" presents how much importance the factor has, whereas the vertical axis "Relation" may divide criteria into cause group and effect group as shown in Figure 5.1 and 5.2.

4.3 Alternatives evaluation using AHP method

The whole hierarchy of the selection of alternative ironmaking technologies with CCS as illustrated in Figure 4.1. Where for pair-wise comparison on AHP fourteen top most influential criteria has been selected from 2-tuple DEMATEL results to generate the weights of criteria and for the alternative selection. Surveys were conducted by distributing questionnaire among the iron and steel manufacturing company's experts to determine the importance weight of the criteria and ratings of alternatives. They were asked to use nine-scale preferences for pairwise comparisons of the relative importance of the alternatives selection criteria and to express their opinions independently on the ratings of each alternative with respect to the specified fourteen criteria.

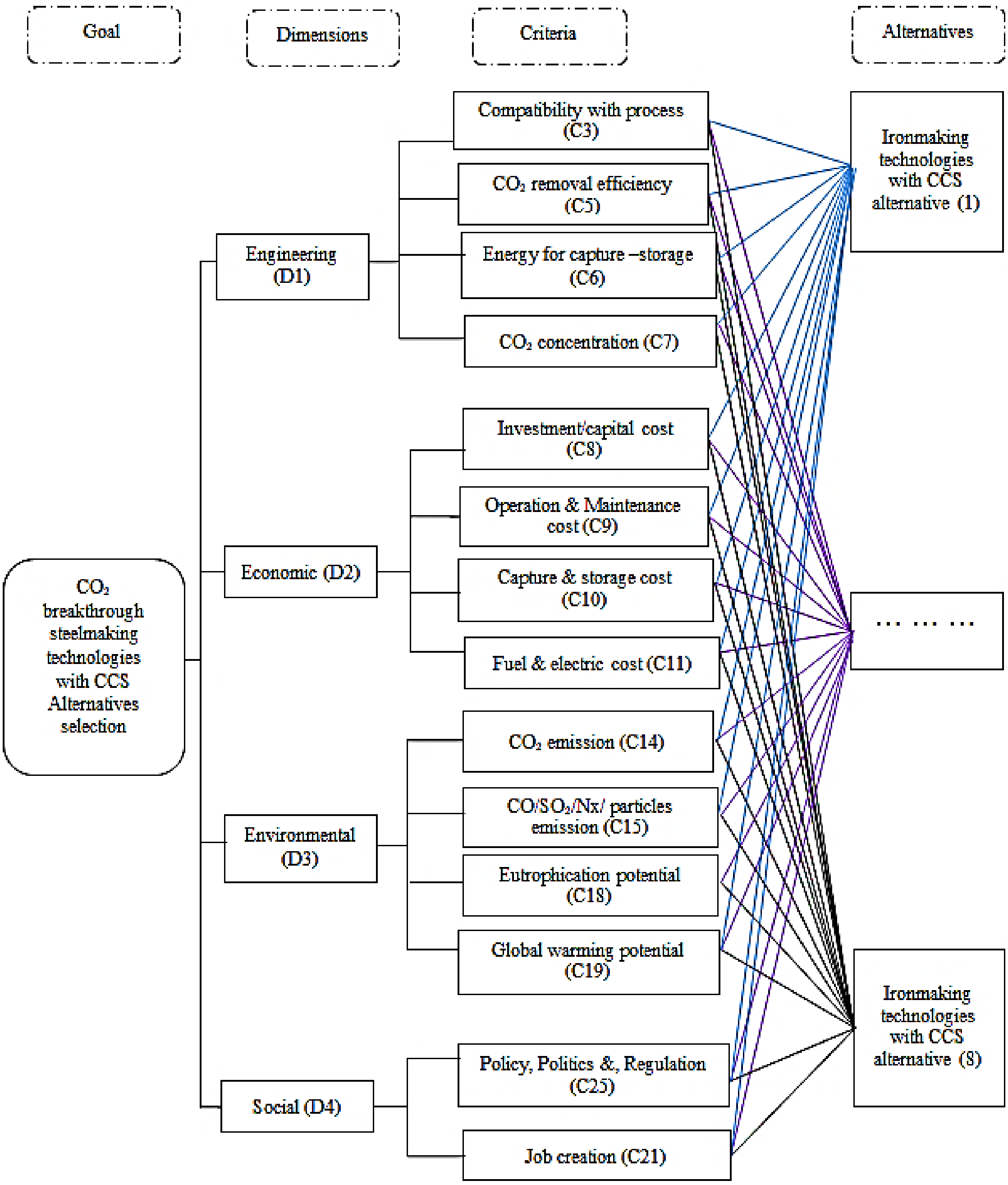


Figure 4.1: AHP structure for CO_2 breakthrough steelmaking technologies with CCS alternative(s) selection

During the data analysis, we checked the consistency of answers using the calculation methods of consistency index (CI) and consistency ratio (CR) as proposed by Saaty in the AHP data analysis. If the answers in this questionnaire were found to be inconsistent according to the CR, we contacted the respondents and asked them to explain their ranking of the criteria and alternative ironmaking technologies again after which we changed the ratings accordingly. Due to space constraints, we present here the pairwise comparison matrix of dimensions using the aggregated individual judgments as shown in Table 4.10. The steps of the computational procedure of AHP are shown below:

Table 4.10: Pairwise comparison average matrix of dimensions in AHP

Dimension	D1	D2	D3	D4
D1	1	4 1/5	3/8	4
D2	1/4	1	2/7	2 1/5
D3	2 3/4	3 4/7	1	5
D4	1/4	4/9	1/5	1

**Consistency Ratio (CR):0.08*

The normalized weights of the engineering (D1), economic (D2), environmental (D3), and social (D4) are 0.3094, 0.1130, 0.5075 and 0.0700 respectively, with a consistency ratio (*CR*) = 0.08, which is less than 0.10. Similarly, pairwise comparison matrices of these criteria results are shown in Table 4.11, where, the consistency ratio of each of the pairwise comparison judgment matrices (criteria) is less than 0.01. This clearly indicates that the pairwise comparison judgments assigned by the evaluators are consistent. Global priority weights of all criteria are used in the fourth level of the AHP model. These weights were obtained by combining the normalized local priority weights of the dimensions and criteria achieved from the third phase with respect to all the successive hierarchical structure. The global weights of each criterion were ranked according to their weight value. From the Table 4.11, it is shown that energy for capture and storage (C6) is the top most ranking in the list, with a weights value of 0.1702. In the same way, global warming potential (C19) and CO_2 removal efficiency (C5) is the second and third most influential criteria respectively.

For the selection of alternatives we evaluated eight CO_2 capture technology for each criterion separately by taking selected fourteen criteria. Based on the global weights of the criteria, each alternative's pairwise comparison matrix was solved to evaluate the best alternatives. The pairwise comparison average matrix of the eight alternatives under energy for capture and storage (C6) is shown in Table 4.12. The consistency ratio (*CR*) of this matrix is 0.054, which is less than 0.10. In the same way, the pairwise matrices of alternatives under the remaining criteria were evaluated and we checked the consistency ratio (*CR*) and found all to be less than 0.10. So the matrices are acceptable for further analysis. The eigenvalues of each matrix are shown in Table 4.13. Then we calculated the normalized score based on the global weights.

Therefore, by the following AHP procedural steps (A to D) and calculations, the ranking of CO_2 breakthrough ironmaking technologies with the combination of CO_2 capture technologies is gained. The results and final ranking for eight alternatives ironmaking processes are shown Table 4.14. Rankings of alternatives are generated by populating 14 pair wise comparison matrices. Based on the global priority weights the following alternatives; namely: 1. TGRBF with VPSA/chemical adsorption (A2-0.2410); 2. Oxygen blast furnace with PSA system (A5- 0.1611); 3. ULCORED with Cryogenic/PSA (A6-0.1562); 4. Midrex with MEA solvent (A8-0.1207) are the top four most dominant alternative technology combinations in this study. Than alternatives A3, A4, A7, are A1 are the ranked from fifth to eight respectively.

Table 4.11: Comparative ranking by DEMATEL and AHP

Dimensions	Local weights	Rank	Criteria	Local weights	Rank	Global weights	AHP Rank	DEMATEL Rank
Engineering (D1)	0.3094	2	Compatibility with process (C3)	0.0923	4	0.0285	10	10
			CO_2 removal efficiency (C5)	0.4929	1	0.1525	3	3
			Energy for capture and storage (C6)	0.3043	2	0.1762	1	4
			CO_2 concentration (C7)	0.1105	3	0.0342	9	9
Economic (D2)	0.1130	3	Investment/capital cost (C8)	0.2435	2	0.0275	11	11
			Operation and maintenance (O&M) cost (C9)	0.1131	4	0.0128	14	13
			Capture & storage cost (C10)	0.4969	1	0.0562	7	7
			Fuel & Electric cost (C11)	0.1465	3	0.0166	12	12
Environmental (D3)	0.5075	1	CO_2 emission (C14)	0.3471	1	0.0942	5	1
			$CO/SO_2/Nx$ /Particles emission (C15)	0.2185	3	0.1109	4	5
			Eutrophication Potential (C18)	0.1207	4	0.0613	6	6
			Global Warming Potential (GWP) (C19)	0.3136	2	0.1592	2	2
Social (D4)	0.0700	4	Policy, Politics &, Regulation(C25)	0.7826	1	0.0548	8	8
			Job Creation (C21)	0.2174	2	0.0152	13	14

Table 4.12: Pairwise comparison average matrix for alternative selection (for C6)

	A1	A2	A3	A4	A5	A6	A7	A8	Eigen Value
Alternative (A1)	1	3.000	3.000	3.000	5.000	3.000	3.000	1.000	0.252
Alternative (A2)	0.333	1	3.000	5.000	2.000	5.000	3.000	3.000	0.220
Alternative (A3)	0.333	0.333	1	2.000	3.000	3.000	0.333	0.200	0.086
Alternative (A4)	0.333	0.200	0.500	1	0.333	3.000	1.000	0.333	0.053
Alternative (A5)	0.200	0.500	0.333	3.000	1	3.000	1.000	1.000	0.089
Alternative (A6)	0.333	0.200	0.333	0.333	0.333	1	0.333	0.200	0.031
Alternative (A7)	0.333	0.333	3.000	1.000	1.000	3.000	1	0.333	0.089
Alternative (A8)	1.000	0.333	5.000	3.000	1.000	5.000	3.000	1	0.178

**Consistency Ratio (RC) = 0.054*

Table 4.13: Normalized weights of alternatives in AHP

	C3	C5	C6	C7	C8	C9	C10	C11	C14	C15	C18	C19	C25	C21	Normalized weights
	0.029	0.153	0.094	0.034	0.028	0.013	0.056	0.017	0.176	0.111	0.061	0.159	0.055	0.015	
A1	0.077	0.043	0.045	0.252	0.183	0.135	0.074	0.042	0.037	0.027	0.040	0.087	0.132	0.117	0.068
A2	0.265	0.353	0.232	0.221	0.190	0.199	0.186	0.169	0.251	0.221	0.259	0.203	0.193	0.107	0.241
A3	0.098	0.121	0.052	0.086	0.102	0.170	0.143	0.099	0.086	0.093	0.143	0.101	0.108	0.114	0.102
A4	0.056	0.063	0.123	0.053	0.132	0.145	0.077	0.167	0.086	0.114	0.058	0.068	0.106	0.121	0.087
A5	0.207	0.180	0.147	0.089	0.173	0.066	0.130	0.069	0.225	0.146	0.209	0.139	0.066	0.157	0.161
A6	0.088	0.151	0.244	0.032	0.027	0.160	0.188	0.282	0.114	0.152	0.119	0.208	0.174	0.107	0.156
A7	0.032	0.032	0.057	0.089	0.100	0.044	0.070	0.064	0.072	0.072	0.049	0.109	0.123	0.133	0.072
A8	0.177	0.056	0.099	0.178	0.093	0.081	0.132	0.109	0.175	0.175	0.123	0.084	0.099	0.142	0.121

Table 4.14: Normalized weights of alternatives with AHP ranking

	Alternatives	**Normalized weights**	**Rank**
A1	CBF +MEA solvent	0.0681	8
A2	TGRBF + VPSA/chemical adsorption	0.2410	1
A3	Corex + physical absorbent selexol	0.1017	5
A4	Hismelt + MEA solvent	0.0870	6
A5	OBF + PSA	0.1611	2
A6	ULCORED + Cryogenic/PSA	0.1562	3
A7	Finex + MEA solvent	0.0724	7
A8	Midrex +MEA solvent	0.1207	4

4.4 Alternatives ironmaking technology selection using EFAHP method

The detailed explanations of the EFAHP method shown in Figures 3.3 and 4.2 illustrate graphically the model and decision environment for the of CCS technology alternatives. After, the construction of the analytical hierarchy, the different priority weights of each criterion and alternative is calculated. The fuzzy comparison matrices are constructed with help of questionnaire from five-members of expert panel. Experts were most senior persons on their relevant field. The preference of one measure over another is decided by the available research and by the experience of the different experts to decide the different priority weights of each criterion and alternatives using linguistic comparison terms and their equivalent triangular fuzzy numbers (TFN) defined in Table 3.1.

Using this membership functions and linguistic variables expert judgments are taken and linguistic judgments were converted to fuzzy triangular numbers as defined by membership functions. Due to space constrains, we present here the fuzzy pairwise comparison matrices of dimensions with respect to the goal as shown in Table 4.15. To measure the inconsistencies, we used Satty inconsistence index (*CR*). For this, we first used the defuzification method of fuzzy triangular numbers to convert the fuzzy comparison matrices into crisp matrices by following equation.

$$M\_crips = (4 \otimes m + l + u)/6 \tag{3.21}$$

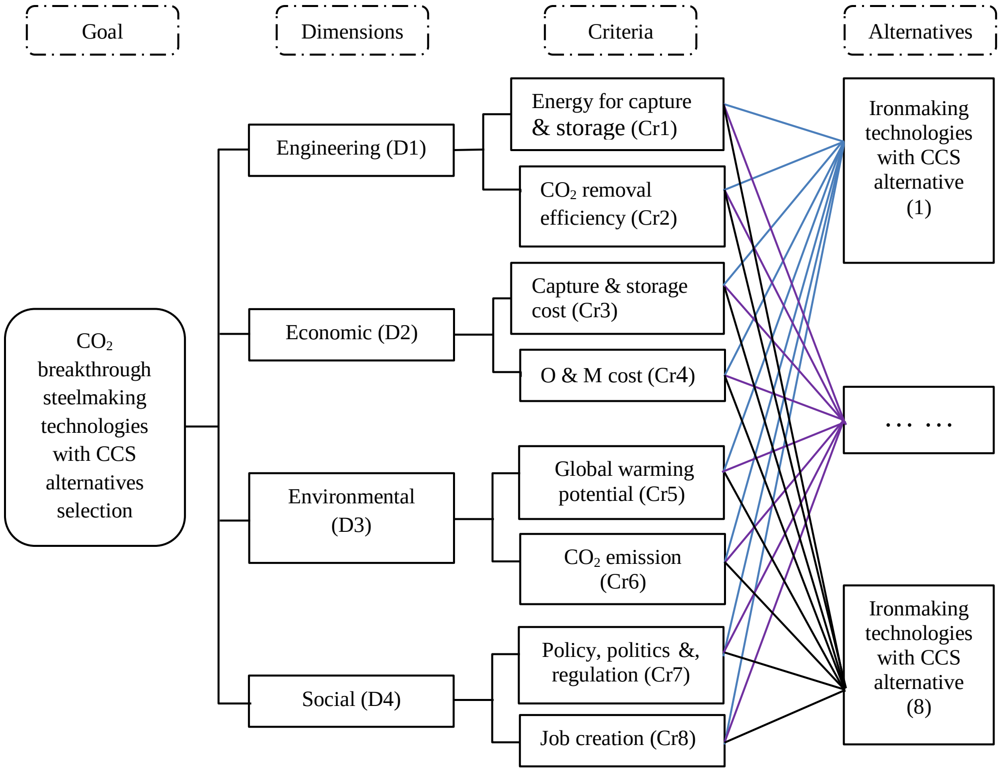


Figure 4.2: Structure of extent analysis in fuzzy AHP method for this study

The consistency index of each matrix was found by using $CI = (\lambda \max - n)/(n-1)$ and then consistency ratios were calculated by $CR = (CI/RI)$ in crips AHP once fuzzy comparison matrices were converted to crisp matrices. We found the consistency ratio of this matrix to be 0.0321 (which is less than 0.10), so the matrix is acceptable for further analysis.

After the consistency test, the extent analysis method on FAHP (EFAHP) was applied to obtain the normalized weight vector (*W*) of each dimension. The degree of possibility (*V*) is achieved by the fuzzy synthetic degree values (*Si*) of the dimensions. The degree of possibility (*V*) for dimensions along with calculated weights using Chang's extent analysis approach are shown in Table 4.16.

Table 4.15: Fuzzy evaluation matrix for dimensions (pairwise comparison)

Dimensions	**Engineering (D1)**	**Economic (D2)**	**Environmental (D3)**	**Social (D4)**
Engineering (D1)	(1,1,1)	(1, 1 ,2) (1,2,3) (3,4,5)	(1,1,2) 1/3, ½,1) (1/5,1/4,1/3)	(1/3, ½,1) (1/5,1/4,1/3) (1/6,1/5,1/4)
Economic (D2)	(½,1,1) (1/3, ½,1) (1/5,1/4,1/3)	(1,1,1)	(1,1,2) (1/5, ¼,1/3) (1/7,1/6,1/5)	(1,2,3) (3,4,5) (4,5,6)
Environmental (D3)	(½,1,1) (1,2,3) (3,4,5)	(½,1,1) (3,4,5) (5,6,7)	(1,1,1)	(3,4,5) (5,6,7) (7,8,9)
Social (D4)	(1,2,3) (3,4,5) (4,5,6)	(1/3,1/2,1) (1/5,1/4,1/3) (1/6,1/5, ¼)	(1/5,1/4,1/3) (1/7,1/6,1/5) (1/9,1/8,1/7)	(1,1,1)

Table 4.16: Degree of possibility (V) and weight (W) for dimension

	$d'(D1)$		$d'(D2)$		$d'(D3)$		$d'(D4)$
V(S1>S2)	0.763	V(S2>S1)	1	V(S3>S1)	1	V(S4>S1)	1
V(S1>S3)	0.166	V(S2>S3)	0.348	V(S3>S2)	1	V(S4>S2)	0.81
V(S1>S4)	0.935	V(S2>S4)	1.000	V(S3>S4)	1	V(S4>S3)	0.16
Weight vector (W):	**0.320**		**0.157**		**0.451**		**0.071**

The normalized weight vector (W) of the main dimension shows that the environmental dimension (0.451) has the topmost weight, followed by the engineering (0.320), economic (0.157) and social (0.071) dimensions respectively. The same calculations were done to achieve the global weights of each criterion, as shown in Table 4.17.

Similarly the values of fuzzy synthetic extent (S_j) and the degree of possibility (V) for each criterion with respect to the goal are calculated by using Eq. 3.10 to 3.14 are given followings:

$S_{En} = (0.3333, 0.6667, 1.20)$, $S_{CO2} = (0.2222, 0.3333, 0.60)$

$S_{CCS} = (0.3529, 0.625, 1.0864)$, $S_{OMC} = (0.2426, 0.375, 0.5926)$,

$S_{Glo} = (0.3836, 0.70, 1.1926)$, $S_{CO2e} = (0.2136, 0.30, 0.4817)$,

$S_{Poli} = (0.3333, 0.6667, 1.20)$, $S_{Job} = (0.2222, 0.3333, 0.60)$,

$$V(S_{En} \geq S_{CO2}) = 1, \quad V(S_{CO2} \geq S_{En}) = 0.4444$$

$$V(S_{CCS} \geq S_{OMC}) = 1, \quad V(S_{CCS} \geq S_{OMC}) = 0.4894$$

$$V(S_{Glo} \geq S_{CO2e}) = 1, \quad V(S_{CO2e} \geq S_{Glo}) = 0.1969$$

$$V\left(S_{Poli} \geq S_{Job}\right) = 1, \quad V\left(S_{Job} \geq S_{Poli}\right) = 0.4444$$

Weight vectors (W) for all criteria are calculated with the minimum degree of possibility and normalized as shown in Table 4.17.

Table 4.17: Summary of global weights of criteria

Layers	**D1**	**D2**	**D3**	**D4**	**Global Weights**
	0.320	0.157	0.451	0.071	
C1	0.957				0.306
C2	0.043				0.014
C3		0.734			0.115
C4		0.276			0.043
C5			0.325		0.147
C6			0.675		0.304
C7				0.659	0.047
C8				0.341	0.024

Table 4.18: Composite priority weights for critical success criteria

Dimensions	**Local weight**	**Criteria**	**Local weight**	**Global weight**	**Rank**
Engineering (D1)	0.3200	Energy for capture & storage (Cr1)	0.9570	0.306	1
		CO_2 concentration (Cr2)	0.5430	0.174	3
Economic (D2)	0.1570	Capture & storage cost (Cr3)	0.7340	0.115	5
		Operation & maintenance cost (Cr4)	0.2760	0.043	7
Environmental (D3)	0.4510	Global warming potential (Cr5)	0.3250	0.147	4
		CO_2 emission (Cr6)	0.6750	0.304	2
Social (D4)	0.0710	Policy, politics & regulation (Cr7)	0.6590	0.047	6
		Job creation (Cr8)	0.3410	0.024	8

After getting the weights of dimensions and eights criteria in EFAHP, experts did pairwise comparison for iron-making alternatives with CCS systems. Now the different alternatives are compared under each of the criterion separately by following the same procedure as discussed above. The matrix Eigenvalue must be normalized and then do the same process to find the weight vector of each alternative. Finally, the priority weights of each alternative iron making technology with CO_2 capture technology can be calculated by weights of the corresponding criterion. For simplicity, the weight calculations for alternatives selection are not given here because they follow the same procedure as discussed above (see in Appendix C: Table C1-C19). Table 4.19 shows the normalized score of eight alternatives.

Table 4.19: Evaluation of iron making technology alternatives with CO_2 capture technologies in normalized score

	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Normalized Score
Alternatives	0.3062	0.1738	0.1152	0.0433	0.1466	0.3044	0.0468	0.0242	
A1	0.0220	0.1032	0.0000	0.0168	0.0257	0.0259	0.0000	0.0000	0.0370
A2	0.1346	0.2399	0.2603	0.2268	0.2140	0.2138	0.2332	0.2525	0.3125
A3	0.2856	0.0849	0.1027	0.1240	0.1202	0.1201	0.1240	0.1153	0.1822
A4	0.1913	0.0513	0.0768	0.0773	0.0997	0.0924	0.1007	0.0692	0.1288
A5	0.2479	0.2049	0.2029	0.1916	0.1915	0.1833	0.1725	0.1730	0.2541
A6	0.1186	0.1394	0.1794	0.1803	0.1624	0.1612	0.1590	0.1510	0.2154
A7	0.2510	0.0513	0.0300	0.0281	0.0458	0.0550	0.0585	0.0634	0.1182
A8	0.5910	0.1250	0.1479	0.1551	0.1408	0.1484	0.1520	0.1755	0.1954

In the last step of the proposed methodology the fuzzy scores need to be ranked. To rank the fuzzy scores the method explained in Section 3 is used. The ranking results are summarized in Table 4.20. According to Table 4.20, the ‘‘TGRBF + VPSA/chemical adsorption (A2)” which has highest weight value is determined as the best alternative for the reduction of CO_2 emissions. The global weight of A2 alternatives is 0.3125, whereas 0.0382 is the lowest value for the alternative A1. The fuzzy weights of other alternatives technologies are A5 = 0.2541, A6 = 0.2154, A8 = 0.1854, A3 = 0.1304, A4 = 0.0980, and A7 = 0.0612 respectively. The ranking of CO_2 capture technologies alternative is determined as follows: [(TGRBF + VPSA/chemical adsorption) – (OBF + PSA) – (ULCORED + Cryogenic/PSA) – (Midrex +MEA solvent) – (Corex + physical absorbent selexol) – (Hismelt + MEA solvent) – (Finex + MEA solvent) – (CBF +MEA solvent)].

Table 4.20: The comparison results of iron-making technologies alternatives with CCS technologies

	Alternatives	FEAHP Global weights	EFAHP Ranking
A1	CBF +MEA solvent	0.0382	8
A2	TGRBF + VPSA/chemical adsorption	0.3125	1
A3	Corex + physical absorbent selexol	0.1304	5
A4	Hismelt + MEA solvent	0.0980	6
A5	OBF + PSA	0.2541	2
A6	ULCORED + Cryogenic/PSA	0.2154	3
A7	Finex + MEA solvent	0.0612	7
A8	Midrex +MEA solvent	0.1854	4

CHAPTER 5: DISCUSSION

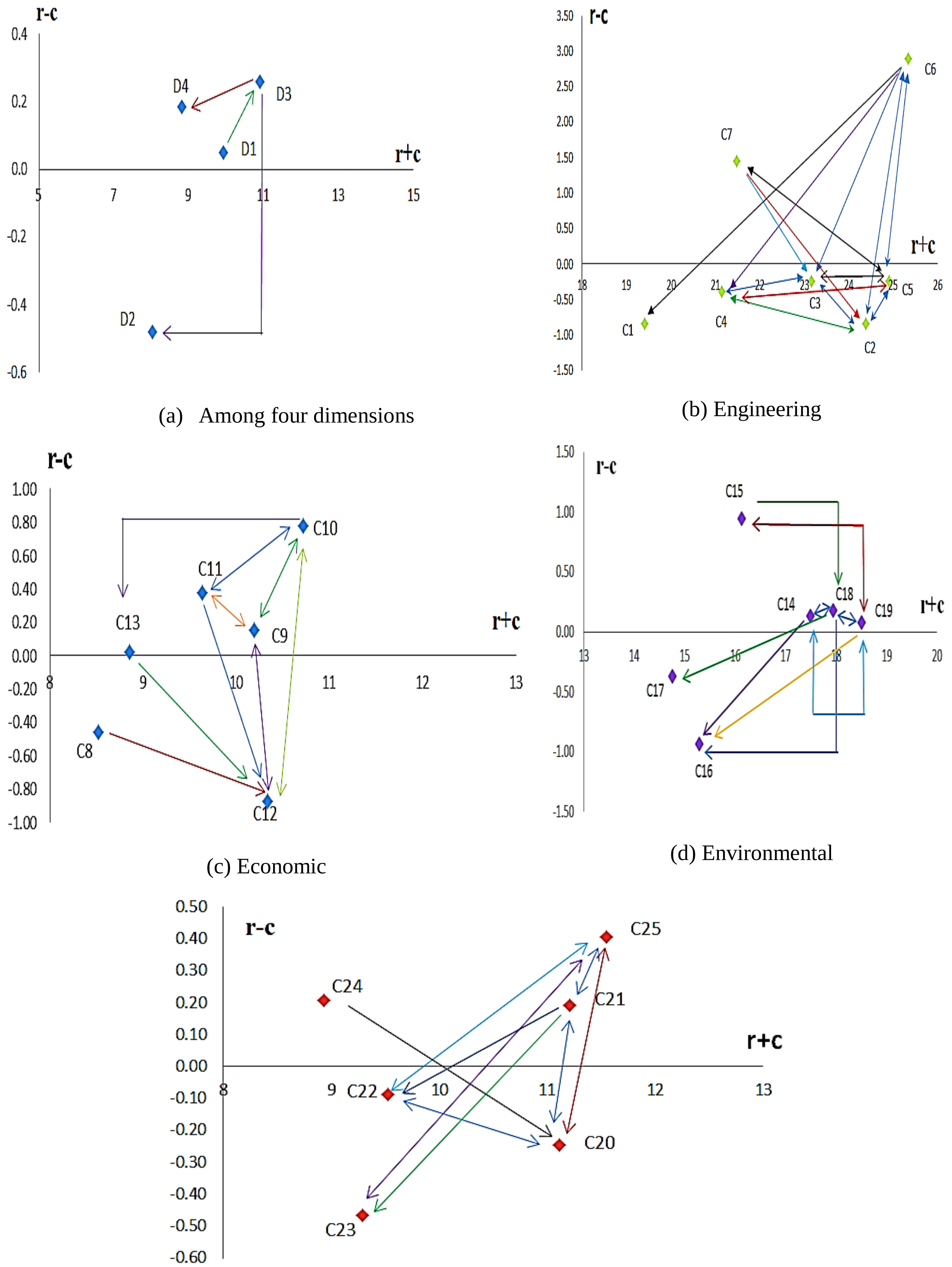
5.1 Introduction

This chapter represents the barrier/uncertainties of full scale CCS deployment in the iron and steel industry and the most important factors that need to overcome. The advantages and disadvantages of the alternative CO_2 captures technologies and CO_2 breakthrough iron making technologies have been selected. The environmental impacts of those alternative options are analyzed.

5.2 Criteria evaluation in 2-tuple DEMATEL

The interrelationship among dimensions from the Influential Relation Map (IRM) in Figure 5.1 (a) illustrates that the environmental (D3) and engineering (D1) dimensions have more influence over the other two dimensions. This findings means that decision maker should first consider these two dimensions during selection of CO_2 capture technology with alternative emerging iron-making technology. Because these are the most important aspects relate to the other aspects.

From Figure 5.1(b) in the engineering (D1) dimension, energy for capture and storage (C_6), CO_2 removal efficiency (C_5) and maturity/feasibility (C_2) are more important than other criteria. Here, C_1, $C_{2,}$ C_3, C_4 and C_5 are the net receivers, whereas energy for capture and storage (C_6) and CO_2 concentration (C_7) are net causes. Where energy for capture and storage (C_6) effects all others criteria accept CO_2 concentration (C_7). In Figure 5.1 (c), with respect to the economic (D2) dimension, capture and storage cost (C_{10}) is the most important criterion and should improve first. Here, C_{12} and C_8 are net receivers, while C_9 C_{10}, C_{11}, C_{13} are the net causes. Payback period (C_{12}) is affected by all the other criteria, but capital cost (C_8) is independent criteria.



(a) Among four dimensions

(b) Engineering

(c) Economic

(d) Environmental

(e) Social

Figure 5.1: Influential Relation Map (IRM) among the dimensions (a) and criteria of (b) engineering, (c) economic, (d) environment and (e) social

In the environmental (D3) dimension, global warming potential (C_{19}) is the most influential criterion. Eutrophication potential (C_{18}) and CO_2 emission (C_{14}) are the second and third influential criteria shown in Figure 5.1 (d). In the social (D4) dimension, policy, politics and regulation (C_{25}) is the most influential criterion. Job creation (C_{21}) and knowledge of CCS (C_{24}) are the second and third criteria respectively shown in Figure 5.1 (e). Furthermore, based on the influential relation map (IRM) we can draw an intelligent network relationship map among dimensions where criteria are inter dependent on each other. At the same time criteria in different dimensions are outer dependence with each other as shown in Figure 5.2.

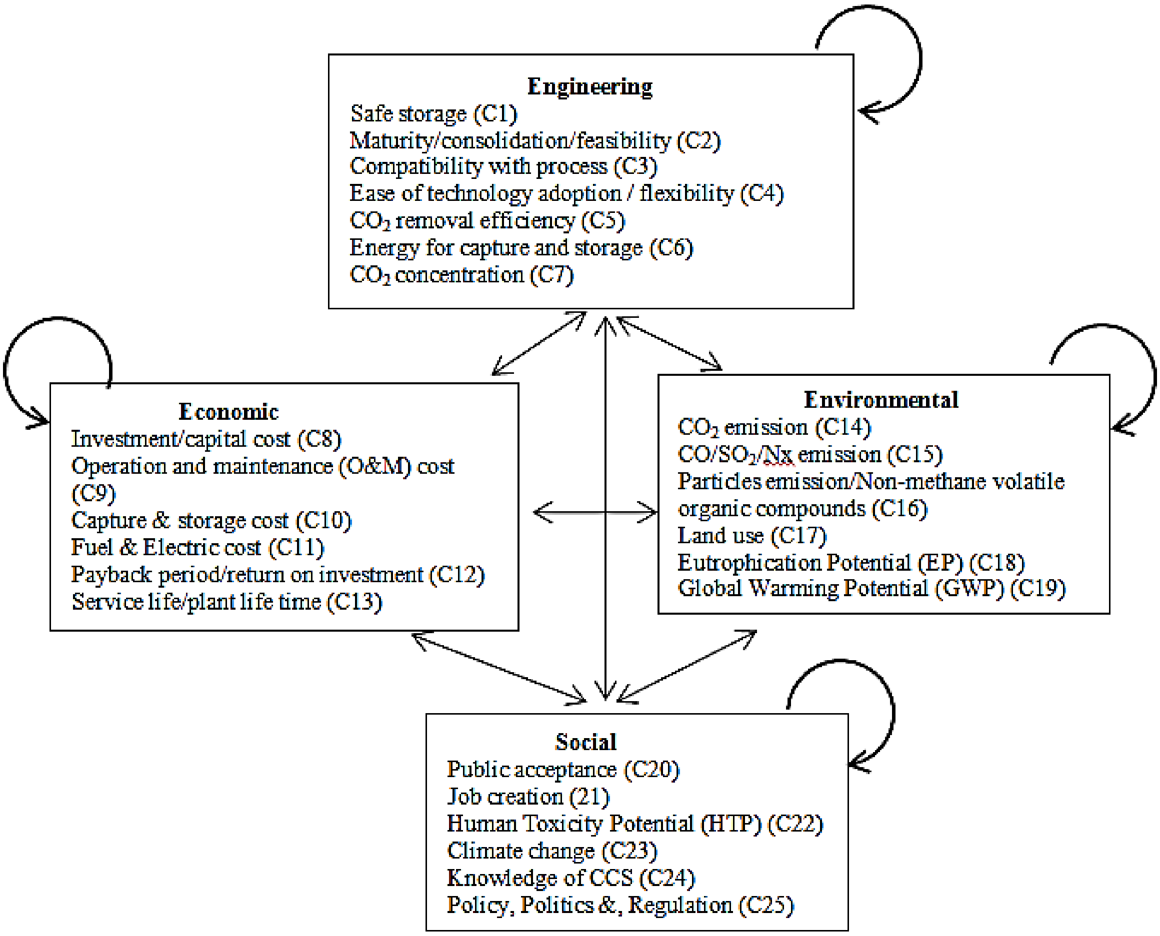


Figure 5.2: Intelligent network relationship map among dimensions including inter dependence and outer dependence loop

The study findings from Overall DEMATEL prominence-effect relationship diagram shown in Figure 5.3 are described as follows.

5.2.1 Cause group

The evaluation criteria namely energy for capture and storage (C_6), CO_2 concentration (C_7), operational and maintenance cost (C_9), capture and storage cost (C_{10}), fuel and electric cost (C_{11}), service life/plant life time (C_{13}), CO_2 emission (C_{14}), $CO/SO_2/N_x$ emission (C_{15}), eutrophication potential (C_{18}), global warming potential (C_{19}), job creation (C_{21}), knowledge of CCS (C_{24}) and policy, politics and regulatory (C_{25}) are divided into causal criteria. Because these factors have impact on the whole system, their performances can influence on the other factors. These factors can be sorted according to the degree of importance ($\boldsymbol{r} + \boldsymbol{c}$) from Table 4.8 and Figure 5.3 as follows: $C_6 > C_7 > C_{19} > C_{18} > C_{14} > C_{15} > C_{25} > C_{21} > C_{10} > C_9 > C_{11} > C_{24} > C_{13}$.

According to investigation of weight (relative importance) of the CCS technology selection with alternative emerging iron-making technology evaluating criteria in this research, energy for capture and storage (C_6) is on the top of the cause group by the highest ($\boldsymbol{c} + \boldsymbol{r}$) priority of 25.337. It indicates that energy consumption is the primary causal factor. Because, energy requirement (i.e. thermal energy) is one of the core characteristics to evaluate CO_2 capture process. The thermal energy requirement of absorbent regeneration depends on the type and amount of chemical species for instance carbamate (NH_2COO^-), carbonate (CO_3^{2-}), or bicarbonate (HCO^{3-}) in the absorbent solutions. CO_2 concentration (C_7) is the second criteria for the selection of appropriate CO_2 capture technology (Chalmers et al., 2013b). Proper method for capturing CO_2 depends on the flue gas conditions, concentration and pressure. According to experts decision (chemical engineers and scientists) the third criteria is the global warming potential (C_{19}).

5.2.2 Effect group

Factors in effect group are easily influenced by others. Safe storage (C_1), maturity/consideration/feasibility (C_2), compability with process (C_3), ease of technology adoptin/flexibility (C_4), CO_2 removal efficiency (C_5), investment/capital cost (C_8), payback period/ return on investment (C_{12}), particles emissions/non-methane volatile organic compounds (C_{16}), land use (C_{17}), public acceptance (C_{20}), human toxicity potential (C_{22}), climate change (C_{23}) are categorized into effect group. These factors can be sorted according to weights from Table 4.8 and Figure 5.3 as follows: $C_5 > C_2 > C_3 > C_4 > C_1 > C_{16} > C_{17} > C_{20} > C_{12} > C_{22} > C_{23} > C_8$. CO_2 removal efficiency (C_5) is the nearer effect group and has less influence by causal factors.

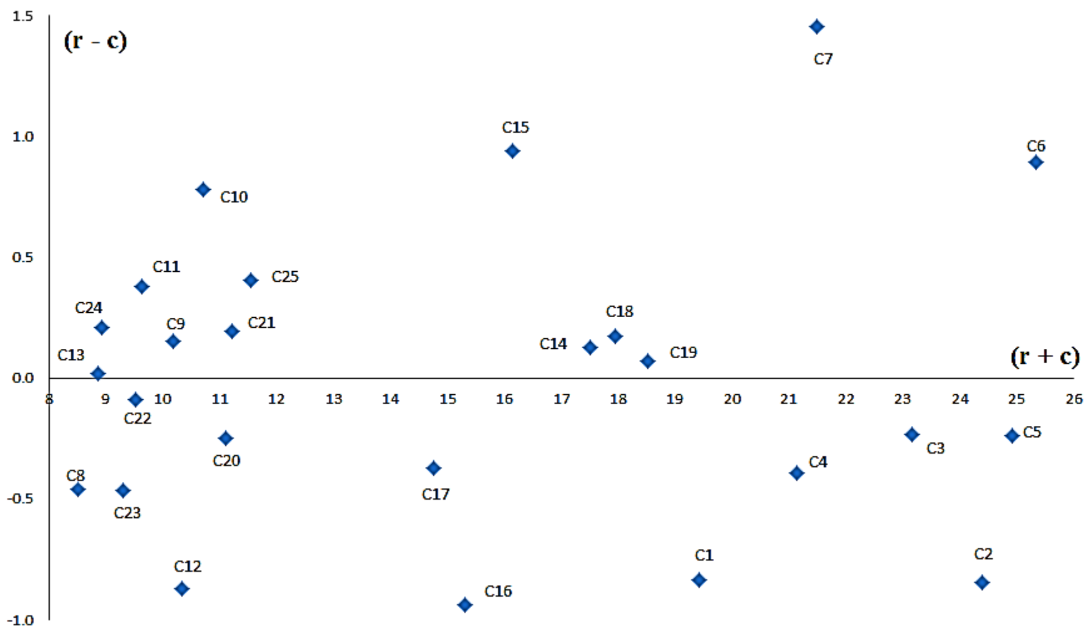


Figure 5.3: Overall DEMATEL prominence-effect relationship diagram

Finally, other barriers, namely C_2, C_3, C_4, C_1, C_{16}, C_{17}, C_{20}, C_{12}, C_{22}, and C_{23} are factors /barriers which have less influence on CCS with alternative iron-making technology when compared to other causal factors. From our result, C_8 is the least influencing criteria among all identified criteria to CCS, because capital cost is less concern when it comes into drastic reduction of GHG emissions from the world.

5.3 Comparative criteria analysis of AHP and EFAHP

Experts from both sides strongly agreed about the criteria of CO_2 emissions and energy for capture and storage. Based on the experts' opinions, Figure 5.4 shows the comparison of selected most important success criteria both in AHP and extent analysis in fuzzy AHP results. Job creation (C8) and operation and maintenance cost (C4) are considered as lower significant criteria.

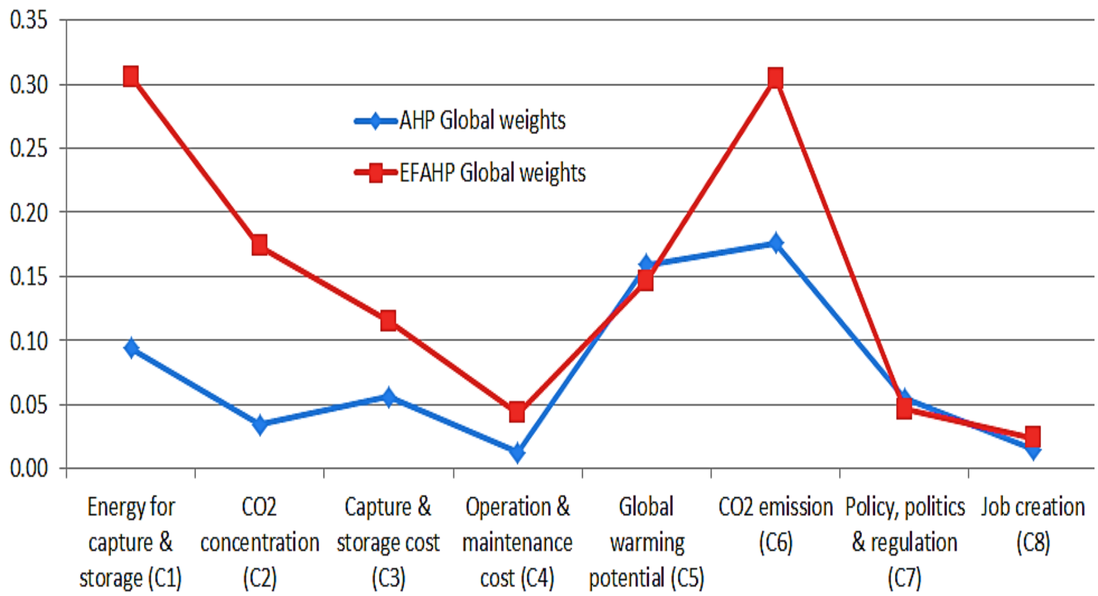


Figure 5.4: Comparative CCS criteria analysis in AHP and EFAHP

5.4 Comparison among dimensions

In hybrid multi-criteria analysis, based on experts and previous studies show that environmental and engineering aspects are far more important than social and economic aspects. Figure 5.5 demonstrates that in engineering criteria evaluation, experts from EFAHP analysis give more importance than DEMATEL analysis experts, whereas in social criteria analysis DEMATEL experts give more emphasize than EFAHP experts. However, in terms of social and engineering criteria evaluation, AHP and EFAHP experts show almost equal significance while it is far different in economic and environmental criteria.

Indeed, from the perspective of R&D, future significant environmental impacts resulting from the implementation of new CCS technologies is often considered one of the most critical decision-making factors. Although economic and industrial benefits are given priority, but in terms of drastic reduction of CO_2 emissions to combat climate change consequence of global warming, technologist and scientist should develop and deploy CO_2 capture technology in iron and steel industry by considering environmental protection. Hence, according to expert's opinion the dimension of engineering is the second most priority aspect and economic benefit is the next important aspect.

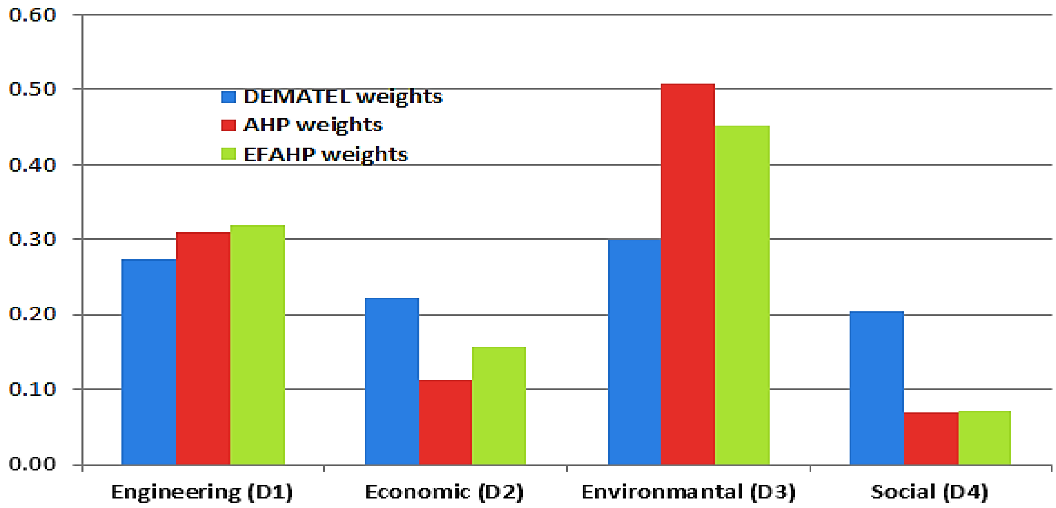


Figure 5.5: The weights of dimensions in DEMATEL, AHP and EFAHP analysis

5.5 Alternatives selection in AHP and EFAHP

In this study to evaluate the eight iron-making alternatives with CCS systems in EFAHP, eight most influential criteria have been selected from the result of the 2-tuple DEMATEL and AHP. Before that, by using fourteen criteria from the 2-tuple DEMATEL, eight ironmaking technologies were evaluated for ranking in AHP method.

From the results of AHP and EFAHP in Figure 5.6 and 5.7 respectively show that TGRBF+VPSA (A2) is the highest ranking alternatives iron making technology with CO_2 capture, followed by the ranking systems OBF + PSA (A5), ULCORED + Cryogenic/PSA (A6), Midrex + MEA solvent (A8), Corex + physical absorbent selexol (A3). In BF-BOF production rout, the integrated use of TGR-BF and CO_2 capture and storage (CCS) technologies is helpful to remove nitrogen from the TGR-BF and oxygen injection into BF also effectively recover CO_2. It effectively reduces carbon emission around 50% (Kuramochi et al., 2011). The second alternative is OBF together with PSA

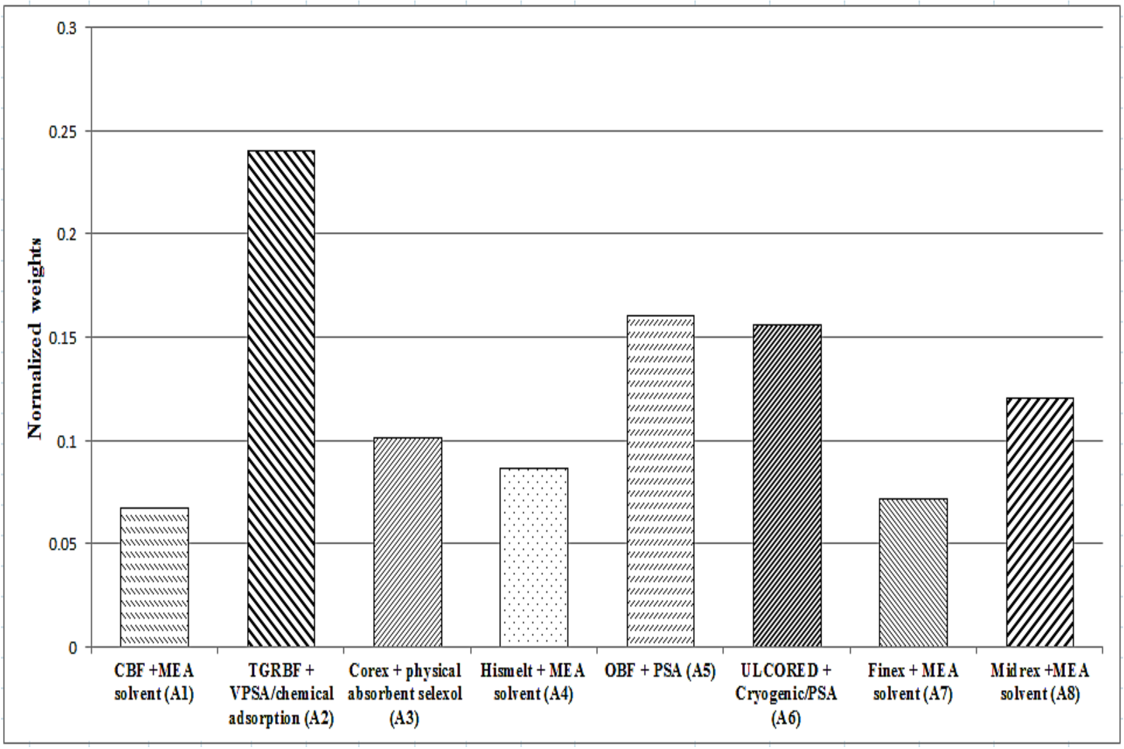


Figure 5.6: Final AHP ranking of alternatives CO_2 breakthrough ironmaking technologies with CCS

or VPSA CO_2 capture system which has several advantages to reduce CO_2 emissions, that include: higher concentration of CO_2 in top gas, higher pressure, and lower coke consumption that reduces direct CO_2 emissions. E. Tsupari et al., (2015) showed in the case of OBF there would be even more low temperature steam and hot water available for heating than in the reference case. Benefit of the additional heat from OBF and CCS processes is that the heat would probably be available with relatively constant capacity. This is, because of heat has relatively high economic value in the world.

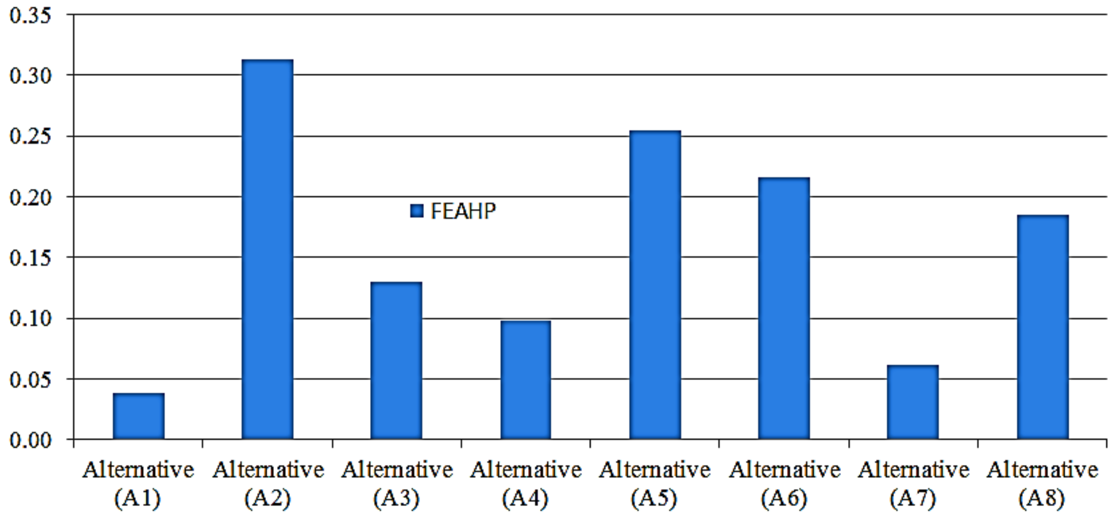


Figure 5.7: EFAHP ranking of alternatives ironmaking technologies with CO_2 capture technologies

Table 5.1: Weights of alternatives with ranking in AHP and EFAHP

	Alternative	**AHP Weights**	**FEAHP Weights**	**AHP Rank**	**EFAHP Rank**
A1	CBF +MEA solvent	0.0681	0.0382	8	8
A2	TGRBF + VPSA/chemical adsorption	0.2410	0.3125	1	1
A3	Corex + physical absorbent selexol	0.1017	0.1304	5	5
A4	Hismelt + MEA solvent	0.0870	0.0980	6	6
A5	OBF + PSA	0.1611	0.2541	2	2
A6	ULCORED + Cryogenic/PSA	0.1562	0.2154	3	3
A7	Finex + MEA solvent	0.0724	0.0612	7	7
A8	Midrex +MEA solvent	0.1207	0.1854	4	4

However, the CBF with MEA solvent (A1), a chemical absorption technology, requires high thermal energy for solvent regeneration in comparison with other capture technologies such as PSA and physical absorption with Selexol. Thus, the energy requirement highly contributes to less avoidance of the global warming potential (GWP) in the CBF+MEA (A1). Table 5.1 shows that comparative ranking in AHP and EFAHP methods (Rhee et al., 2011).

In smelting reduction route COREX with Selexol, an absorbent process shows convenient performance of CO_2 emission reduction than Finex with MEA solvent. Based on literature and experts opinions, COREX process offers lower production cost compared to CBF-based process. It also illustrates that the COREX process with CO_2 capture enables lower hot rolled coil production cost and lower specific CO_2 emissions compared to the reference BF-based process. In addition, ULCORED + Cryogenic/PSA technology is far more advantageous when the CO_2 emissions are taken into account compared to Midrex + MEA solvent. It is a direct electrolysis of iron ore (Fe_2O_3) process considered as a good alternative to the reduction reaction, releasing significant amounts of CO_2. It is basically separating iron and oxygen without adding anything in the reaction. Even though this technology is not very efficient, it is cheap. But this technology is still at different stages of the demonstration in the laboratory or small pilot plant (Tsupari et al., 2013).

5.6 Comparative discussion among alternatives

Experts from EFAHP give more importance for alternative ironmaking OBF with PSA technology (A5) than AHP experts, whereas for the alternative CBF with MEA solvent (A1) AHP experts gave much more weights value than EFAHP experts. In the case of alternatives Hismelt with combination MEA solvent (A4) and Finex with MEA solvent (A7), experts from both sides showed almost equal importance. On the other hand, during evaluation of CCS with ironmaking technologies, OBF + PSA (A5) and ULCORED + Cryogenic/PSA (A6) AHP experts gave the same weights values for both technologies, where OBF is the BF-BOF production route technology and ULCORED is the direct reducing iron production route technology shown in Figure 5.8.

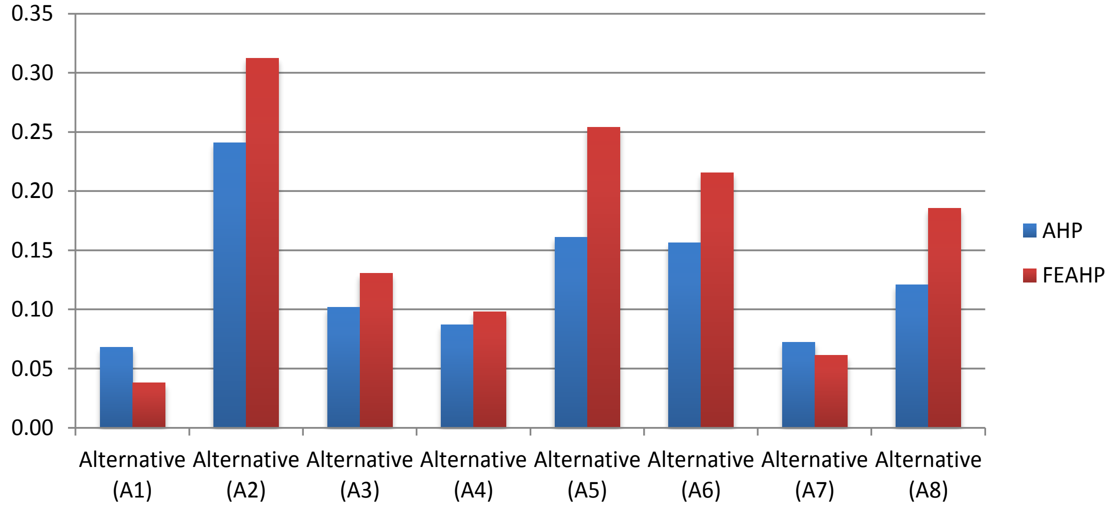


Figure 5.8: Comparison of weights of ironmaking technologies in AHP and EFAHP results

5.7 Alternatives CCS technologies analysis with criterion

According to expert's opinion, CCS alternative CBF +MEA solvent (A1) shows the fifth rank for the criterion of CO_2 concentration (C_2), whereas it is given lowest ranking for the other criteria. Because during iron production CBF emits large amount of CO_2 emissions in flue gas where conventional blast furnace combination with MEA solvent shows better performance to other CCS alternatives.

On the other hand, in smelting reduction route, Midrex +MEA solvent technology (A8) is given priority to alternative ULCORED + Cryogenic/PSA (A6) for the criteria of energy for capture & storage (C_1) and Job creation (C_8). In addition, for the criteria of energy for capture & storage (C_1), global warming potential (C_5), CO_2 emission (C_6), policy, politics & regulation (C_7), Hismelt with MEA solvent (A4) technology comparatively shows effective CO_2 emission reduction option than other CCS critical criteria shown in Figure 5.9.

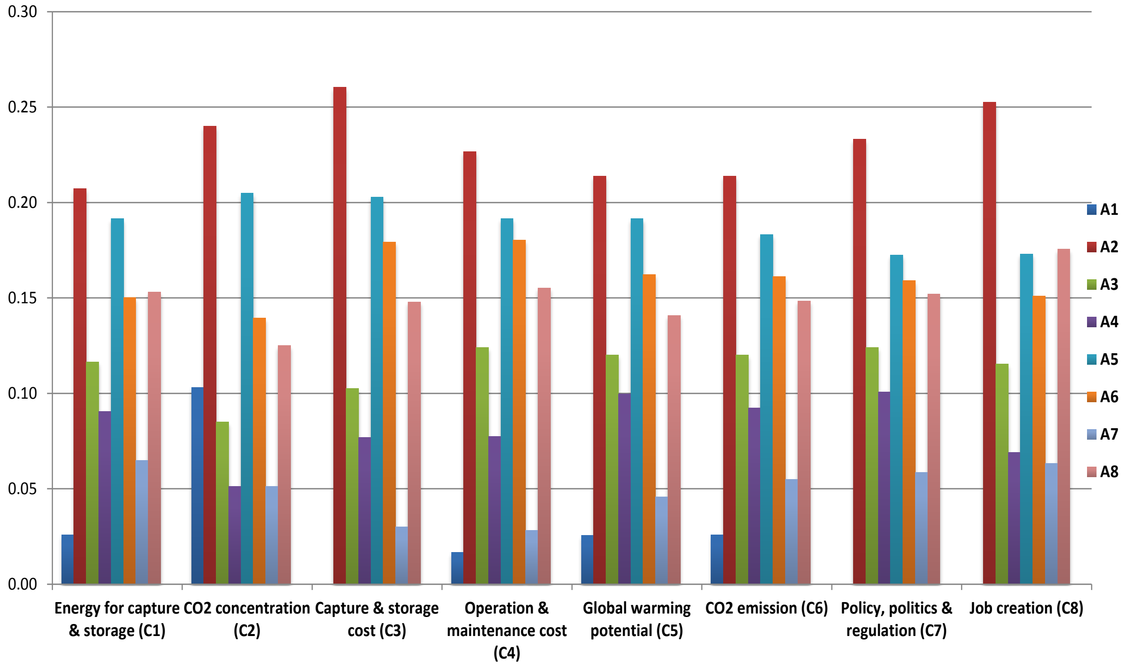


Figure 5.9: Contribution analysis of different criteria with technologies in EFAHP

CHAPTER 6: CONCLUSIONS

6.1 Summary

CCS has become an important subject of research for the academicians and practitioners in recent years. From all the sides of government policies, the organizations and customer pressure are pushing to implement CCS systems in energy-intensive industries like iron and steel industry to cut off CO_2 emissions massively from atmosphere. However, the successful accomplishment of CO_2 capture technologies in steel industry is comparatively difficult, as several critical factors and barriers are associated with the CCS. In this perspective, this study proposed a framework on fuzzy hybrid MCDM approach to predict the success of CCS implementation in iron and steel industry. This study is based on frameworks from existing literature, observations in the steel industry, and interviews with experts from iron and steel industries, CCS research institutes, universities and installation companies. The proposed model could handle the complex interactions and interdependences among dimensions and criteria and produce results that allow us to build a visible causal relationship diagram for evaluating the CCS alternatives. The model cannot only select the optimal CCS technologies for iron and steel industry but also find how to improve the gaps to achieve the aspiration level for improving existing CO_2 reduction alternatives. Therefore, the proposed MCDM model can successfully evaluate the performance of the whole CCS systems in iron and steel industry.

Humanists are often uncertain in assigning the evaluation scores. Thus these MCDM methods are performed in fuzzy environment. First, in this study, the Delphi and the modified 2-tuple DEMATEL technique used which provide a favorable solution. Because it based on graph theory that enables us to project and solve problems visually, and it can divide multiple criteria into cause group and effect group for better capture causal diagram, as well as convert the relationship between critical factors into an intelligible structural model of the system. Secondly, the AHP and FEAHP model is constructed based on the hierarchy to evaluate the best sustainable CO_2 capture technology with alternative(s) iron-making technologies for the organizations involved. Results show that in the engineering (D1) dimension, energy for capture and storage (C_6) is CO_2 removal efficiency (C_5) and maturity/feasibility (C_2) are more important than others criteria. In addition, in the economic (D2) dimension, capture and storage cost (C_{10}) is the most important criterion and should improve first, whereas global warming potential (C_{19}) is the most influential criterion in the environmental (D3) dimension. From the results of alternative technologies selection, it is seen that TGRBF+VPSA (A2) is the highest ranking alternative iron making technology with CO_2 capture. Because in BF-BOF production rout, the integrated use of TGR-BF and CCS technologies is helpful to remove nitrogen from the TGR-BF in which oxygen injection into BF also effectively recover CO_2. This alternative can effectively reduce carbon emission around 50% of total emissions.

The finding of this research would be useful for engineers, researchers, investors, steel companies, policy makers, and other interested parties to become more capable in analyzing the CCS systems and reducing emissions from iron and steel production. Besides, the results of this study help organizations to establish a system approach for selecting and evaluating sustainable iron making technologies. It is expected that this proposed model would be an effective solution for CO_2 emission reduction and sustainable green iron and steel manufacturing.

6.2 Limitations of the research

The present work has some limitations. First, the analysis process of factors and technologies depends on the respondent perspective preference weights. Therefore, pairwise evaluation matrices for critical factors assessment and technology selection need to be constructed carefully. Secondly, the data and analysis were typically based on the few numbers of experts and surveys in steel industries in the particular county. Hence, the generalization of findings may not be extended in the context of different types, sizes, regions etc. of industries. Third, it is believed that different countries (developing/developed) might have different concerns regarding success factors and alternatives for CCS implementation. In this sense, it is valuable to perform more cases study to extract new criteria for use.

6.3 Future works

Future research may be conducted by considering higher number of experts in the context of other developing/developed countries to compare the findings with this study. In addition, to reduce the inadequate reflection of the vagueness in the real world, the appropriate response measures would be proposed in future research by using multi analysis methods (fuzzy TOPSIS and fuzzy VIKOR). In this research, the only criteria and alternatives technology for CO_2 capture in the iron and steel industry are analyzed, but this model does not describe the impact of each criterion and alternative technology. In the end, a life cycle assessment (LCA) would be done in terms of environmental performance and potentials of CCS technology deployment to all stacks in an integrated steelworks.

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1. M. Abdul Quader, Shamsuddin Ahmed, Raja Ariffin Raja Ghazilla, Shmeem Ahmed, Mahidzal Dahari 2015,'A Comprehensive review on energy efficient CO_2 breakthrough technologies for sustainable green iron and steel manufacturing' *Renewable & Sustainable Energy Reviews*, Vol. 50 pp. 594–614, http://dx.doi.org/10.1016/j.rser.2015.05.026 (IF:5.901)

2. M. Abdul Quader, Shamsuddin Ahmed, RA Raja Ghazilla, Shameem Ahmed**,** "CO_2 Capture and Storage for the Iron and Steel Manufacturing Industry: Challenges and Opportunities" *Journal of Applied Science and Agriculture*, December 2014, p. 9(21): 60-67, 2014.

Revision

1. M. Abdul Quader **,** Shamsuddin Ahmed , RA Raja Ghazilla, Shameem Ahmed "Evaluation of criteria for CO_2 capture and storage in iron and steel industry using the 2-tuple DEMATEL technique" *Journal of Cleaner Production*, 2015

2. M. Abdul Quader, Shamsuddin Ahmed, Raja Ariffin Raja Ghazilla, Shameem Ahmed, 'Present needs, recent progress and future trends of energy-efficient Ultra-Low Carbon Dioxide (CO2) Steelmaking (ULCOS) program,' Renewable & Sustainable Energy Reviews, 2015.

3. M. Abdul Quader , Shamsuddin Ahmed , Raja Ariffin Raja Ghazilla 'A hybrid multi-criteria assessment of CCS systems with ironmaking processes for the sustainable iron and steel production' *Intelligent Data Analysis - An International Journal*, 2015.

4. M. Abdul Quader **,** Shamsuddin Ahmed , Raja Ariffin Raja Ghazilla, Shameem Ahmed 'A hybrid fuzzy MCDM approach to identify critical factors and CO_2 capture technology for sustainable iron and steel manufacturing' *The Arabian Journal for Science and Engineering*, 2015.

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1. M Abdul Quader, Shamsuddin Ahmed, Shameem Ahmed, "Trends of energy consumption and driving forces for mitigation of CO_2 emissions in Malaysia: A multi-sectoral analysis, IET Conference Proceedings p. 2.01 (6.) (1) 2014, http://dx.doi.org/10.1049/cp.2014.1083, presented in Processing of IET Brunei International Conference on Engineering and Technology 2014 (BICET-2014), Brunei Darussalam 1 - 3 November 2014.

Appendix A: Survey

Iron and steel industry is known as the largest energy consuming manufacturing sector, consuming 5 % of the world's total energy consumption and emitting about 6% of the total world anthropogenic CO_2. To mitigate CO_2 emission immensely, therefore, CO_2 capture and storage (CCS) is considered as one of the most promising options to achieve significant reduction in CO_2 emissions for the future costs. Reducing CO_2 emissions is not only reduces global warming, but also is beneficial in many other ways. The proposed survey intends to evaluate CO_2 breakthrough ironmaking technologies with Carbon Capture and Storage (CCS) based on an iterative pair-wise comparison process called Fuzzy Analytical Hierarchy Process (AHP) and to identify the one which is perceived to be the most effective. Enclosed is a short survey asking questions that many help us to understand this issue. No information will be gathered that could personally identify you. Thank you for your time and consideration in helping us answer these questions. This research has been approved by the University of Malaya High Impact Research (HIR) Board.

<u>Demographic Information:</u>

What is the type of your employment?

1. University ☐ 2. R&D (Research & Development) ☐ 3. Engineer (production) ☐
4. Consulting-Climate Science ☐ 5. Others please explain: -------

What is the field of you expertise?

1. Mechanical engineering ☐ 2. Chemical engineering ☐
3. Environmental and climate science ☐ 4. Others please explain: -------

Overview

In this survey, several CO_2 breakthrough ironmaking technologies with Carbon Capture and Storage (CCS) systems are evaluated through comparison and based on multiple criteria. These criteria and alternatives together with a comparison scale are elaborated below:

Criteria

In this research, twenty five sited criteria under four prominent dimensions namely engineering, economic, environmental and social are being considered for pair wise evaluation of emerging ironmaking technologies with CO_2 capture technologies:

Dimensions	Criteria /barriers	Units	Descriptions
Engineering (D_1)	Safe storage (C_1) Maturity/consolidation/feasibility (C_2) Compatibility with process (C_3) Ease of technology adoption / flexibility (C_4) CO_2 removal efficiency (C_5) Energy for capture and storage (C_6) CO_2 concentration (C_7)	Point Point Point Point % GJ/t-CO_2 % (w/w)	Protect underground sources of drinking water and other natural resources (ecosystems). Technology readiness. Suitability with each production process Technology transfer is the process of transferring skills, knowledge, technologies, and methods of manufacturing. CO_2 capture efficiency refers to the percentage of CO_2 gas that is captured from the flue gas of an iron & steelmaking industry. Basically, thermal energy requirement during the regeneration of absorbent solution. Proper technology for capturing CO_2 depending on the flue gas conditions, concentration and pressure. Higher CO_2 concentration leads high CO_2 recovery ratio.
Economic (D_2)	Investment/capital cost (C_8) Operation and maintenance (O&M) cost (C_9) Capture & storage cost (C_{10}) Fuel & Electric cost (C_{11}) Payback period/return on investment (C_{12}) Service life/plant life time (C_{13})	$ $/year $/t$CO_2$ $ $ Year	The total cost of funds used for CCS development &deployment. The O&M cost of the CO_2 capture facility, for example, steam requirement, electricity consumption for pumps and cooling tower operation, process water consumption, and chemical loss, etc. Storage cost includes all aspects of injecting and monitoring CO_2 into a geological reservoir The amount of time required for an investment to give a full return on capital costs. The period of time required to regain the funds expended in an investment. The service life of an asset is the total period during which it remains in use, or ready to be used, in a productive process.
Environmental (D_3)	CO_2 emission (C_{14}) CO/SO_2/Nx emission (C_{15}) Particles emission/Non-methane volatile organic compounds (C_{16}) Land use (C_{17}) Eutrophication Potential (EP) (C_{18}) Global Warming Potential (GWP) (C_{19})	tCO_2 t Km^2/tCO_2 (PO_4^{3-}/t steel t CO_2/t steel	CO_2 emission during pelleting, sintering, furnace combustion Different gases with CO_2 emission Most of the air pollutants, that is, SO_2, NOx, and particulate matter (PM), share the common source with CO_2 emissions by fossil fuel combustion Land used over the entire lifecycle of the plant (e.g. fuel extraction, construction, processing and delivery, operation and decommissioning) A series of chemicals such as NOx, SO_2, NH_3 and PO_4^{3-} and refers to the excessive supply of nutrients to soil and water. NH3 is the main eutrophication contributor caused by the degradation of the MEA medium used in the CO_2 capture process. The measure of an activity's impact on climate change, relation to carbon dioxide, which has a default rating of 1.
Social (D_4)	Public acceptance (C_{20}) Job creation (C_{21}) Human Toxicity Potential (HTP) (C_{22}) Climate change (C_{23}) Knowledge of CCS (C_{24}) Policy, Politics &, Regulation (C_{25})	Point Person-yr/tCO_2 Years of life lost Point Point	Public preference for the deployment or deployment of a certain CCS technology. It may be crucial to CCS development, but is uncertain. Attitudes to CCS are shaped in social interaction. "Job-years" of full time employment created over the entire life cycle of the plant. Human toxicity is mostly a function of flue gas emissions from.. (HF, NOx, SO_2, HCl and particulate matter all of which have a negative impact on human health. Awareness and understanding of CCS by the public. CCS development is intensely influenced by, political support, uncertainties, the choice and design of policies and regulations.

Alternatives

For alternative selection fourteen top most influential criteria are taken. All potential solutions to CO_2 emission reduction are categorized under the following alternatives:

	Alternatives	
	Emerging ironmaking technologies	CO_2 capture technologies
(A1)	Conventional Blast Furnace	MEA solvent
(A2)	Top Gas Recycling Blast Furnace	VPSA/chemical adsorption
(A3)	COREX	Physical absorbent selexol
(A4)	Hismelt	MEA solvent
(A5)	Oxygen Blast Furnace	PSA
(A6)	ULCORED	Cryogenic/PSA
(A7)	FINEX	MEA solvent
(A8)	MIDREX	MEA solvent

Questionnaire for DEMATEL:

Criteria comparison

Here the objective is to evaluate the aforementioned criteria through pairwise comparison to highlight the importance of different criterion compare to each other with the goal of reducing CO_2 emissions in iron and steel manufacturing sector. With this goal in mind, please evaluate the following statements:

Comparison scale:

Weights	Descriptions
0	No influence
1	Low influence
2	Medium influence
3	High influence
4	Very high influence

- Criteria under engineering dimension (D1)

	Safe storage	Maturity	Compatibility	Flexibility	CO_2 removal efficiency	Energy for capture and storage	CO_2 concen -tration
Safe storage	0						
Maturity		0					
Compatibility			0				
Flexibility				0			
CO_2 removal efficiency					0		
Energy for capture and storage						0	
CO_2 concentration							0

- Criteria under economic dimension (D2)

	Capital cost	Operation and maintenance (O&M) cost	Capture & storage cost	Fuel & Electric cost	Payback period	Plant life time
Capital cost	0					
Operation and maintenance (O&M) cost		0				
Capture & storage cost			0			
Fuel & Electric cost				0		
Payback period					0	
Plant life time						0

- Criteria under environmental dimension (D3)

	CO_2 emission	$CO/SO_2/Nx$ emission	Particles emission	Land use	Eutrophication Potential	Global Warming Potential
CO_2 emission	0					
$CO/SO_2/Nx$ emission		0				
Particles emission			0			
Land use				0		
Eutrophication Potential					0	
Global Warming Potential						0

- Criteria under social dimension (D4)

	Public acceptance	Job creation	Human Toxicity Potential	Climate change	Knowledge of CCS	Policy, Politics &, Regulation
Public acceptance	0					
Job creation		0				
Human Toxicity Potential			0			
Climate change				0		
Knowledge of CCS					0	
Policy, Politics &, Regulation						0

Questionnaire for AHP:

Selected criteria for AHP

Symbol	Description
C1	Compatibility with process
C2	CO_2 removal efficiency
C3	Energy for capture and storage
C4	CO_2 concentration
C5	Investment/capital cost
C6	Operation and maintenance (O&M) cost
C7	Capture & storage cost
C8	Fuel & Electric cost
C9	CO_2 emission
C10	$CO/SO_2/Nx$ /Particles emission
C11	Eutrophication Potential
C12	Global Warming Potential (GWP)
C13	Policy, Politics &, Regulation
C14	Job Creation

Comparison scale:

Weight	**Description**
1	Equally important
3	Moderately more important
5	Strongly more important
7	Very strongly more important
9	Dominant importance
1/3, 1/5, 1/7, 1/9	Reciprocals
2,4,6,8	Immediate judgment values

Dimensions Comparison

	Engineering(D1)	Economic (D2)	Environmental(D3)	Social (D4)
Engineering(D1)	0			
Economic (D2)		0		
Environmental(D3)			0	
Social (D4)				0

Criteria comparison

Criteria under engineering dimension (D1)

	C1	C2	C3	C4
C1	0			
C2		0		
C3			0	
C4				0

Criteria under environmental dimension (D3)

	C9	C10	C11	C12
C9	0			
C10		0		
C11			0	
C12				0

Criteria under economic dimension (D2)

	C5	C6	C7	C8
C5	0			
C6		0		
C7			0	
C8				0

Criteria under social dimension (D4)

	C13	C14
C13	0	
C14		0

Alternative comparison

Here the objective is to evaluate the aforementioned alternatives through pairwise comparison. Please evaluate the following statements based on the criterion defined for each section:

Consider the criteria is "Compatibility with process"

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is "CO_2 removal efficiency"

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider criteria is "Energy for capture and storage"

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is "CO_2 concentration"

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is “Investment/capital cost”

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is “Operation and maintenance (O&M) cost”

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is “Capture & storage cost”

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is “Fuel & Electric cost”

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is “CO_2 emission”

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is “CO/SO_2/Nx /particles emission”

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is “Eutrophication potential”

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider criteria is “Global warming potential”

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is “Policy, politics & regulation”

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Consider the criteria is “Job creation”

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0							
A2		0						
A3			0					
A4				0				
A5					0			
A6						0		
A7							0	
A8								0

Appendix B: Average matrix (A) and direct-relation matrix (D) of criteria in DEMATEL method

Average matrix (*A*) of engineering dimension criteria

	C_1	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**
C_1	0.000	1.600	1.200	1.200	1.000	1.800	1.000
C_2	1.600	0.000	1.800	1.800	2.200	1.800	1.000
C_3	1.600	1.200	0.000	2.200	1.800	1.200	2.000
C_4	1.000	2.400	2.000	0.000	1.200	1.000	1.200
C_5	1.000	2.400	1.600	1.200	0.000	2.200	2.200
C_6	2.400	2.400	1.200	1.200	2.400	0.000	1.000
C_7	1.000	1.000	2.400	1.600	2.400	1.400	0.000

Direct-relation matrix (*D*) of engineering dimension criteria

	C_1	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**
C_1	0.000	0.151	0.113	0.113	0.094	0.170
C_2	0.151	0.000	0.170	0.170	0.208	0.170
C_3	0.151	0.113	0.000	0.208	0.170	0.113
C_4	0.094	0.226	0.189	0.000	0.113	0.094
C_5	0.094	0.226	0.151	0.113	0.000	0.208
C_6	0.226	0.226	0.113	0.113	0.226	0.000
C_7	0.094	0.094	0.226	0.151	0.226	0.132

Average matrix (*A*) of economic dimension criteria

	C_8	**C_9**	**C_{10}**	**C_{11}**	**C_{12}**	**C_{13}**
C_8	0.000	1.000	1.000	1.200	2.000	1.600
C_9	1.000	0.000	2.000	2.000	1.800	2.000
C_{10}	1.600	2.200	0.000	2.400	2.600	1.200
C_{11}	1.600	2.000	2.400	0.000	1.400	1.000
C_{12}	1.600	1.600	2.000	1.200	0.000	1.600
C_{13}	1.800	1.800	1.000	1.000	2.000	0.000

Direct-relation matrix (*D*) of economic dimension criteria

	C_8	**C_9**	**C_{10}**	**C_{11}**	**C_{12}**	**C_{13}**
C_8	0.000	0.100	0.100	0.120	0.200	0.160
C_9	0.100	0.000	0.200	0.200	0.180	0.200
C_{10}	0.160	0.220	0.000	0.240	0.260	0.120
C_{11}	0.160	0.200	0.240	0.000	0.140	0.100
C_{12}	0.160	0.160	0.200	0.120	0.000	0.160
C_{13}	0.180	0.180	0.100	0.100	0.200	0.000

Average matrix (A) of environmental dimension criteria

	C_{14}	**C_{15}**	**C_{16}**	**C_{17}**	**C_{18}**	**C_{19}**
C_{14}	0.000	1.000	1.200	1.400	1.400	3.000
C_{15}	1.000	0.000	1.800	1.000	2.000	2.000
C_{16}	1.000	1.000	0.000	1.200	1.600	1.600
C_{17}	1.000	1.200	1.000	0.000	2.200	1.000
C_{18}	2.000	1.600	1.800	2.200	0.000	1.000
C_{19}	2.800	2.000	1.600	1.000	1.200	0.000

Direct-relation matrix (D) of environmental dimension criteria

	C_{14}	**C_{15}**	**C_{16}**	**C_{17}**	**C_{18}**	**C_{19}**
C_{14}	0.000	0.116	0.140	0.163	0.163	0.349
C_{15}	0.116	0.000	0.209	0.116	0.233	0.233
C_{16}	0.116	0.116	0.000	0.140	0.186	0.186
C_{17}	0.116	0.140	0.116	0.000	0.256	0.116
C_{18}	0.233	0.186	0.209	0.256	0.000	0.116
C_{19}	0.326	0.233	0.186	0.116	0.140	0.000

Average matrix (A) of social dimension criteria

	C_{20}	**C_{21}**	**C_{22}**	**C_{23}**	**C_{24}**	**C_{25}**
C_{20}	0.000	2.000	1.800	1.000	1.800	1.400
C_{21}	2.600	0.000	1.200	1.000	1.000	2.400
C_{22}	2.000	1.200	0.000	1.200	1.200	1.200
C_{23}	1.000	1.200	1.000	0.000	1.000	2.000
C_{24}	1.400	1.200	1.800	1.000	0.000	1.200
C_{25}	1.400	2.400	1.200	2.800	1.200	0.000

Direct-relation matrix (D) of social dimension criteria

	C_{20}	**C_{21}**	**C_{22}**	**C_{23}**	**C_{24}**	**C_{25}**
C_{20}	0.000	0.222	0.200	0.111	0.200	0.156
C_{21}	0.289	0.000	0.133	0.111	0.111	0.267
C_{22}	0.222	0.133	0.000	0.133	0.133	0.133
C_{23}	0.111	0.133	0.111	0.000	0.111	0.222
C_{24}	0.156	0.133	0.200	0.111	0.000	0.133
C_{25}	0.156	0.267	0.133	0.311	0.133	0.000

Appendix C: Mathematical calculations in extent analysis on fuzzy AHP

Table C1: Synthetic extent values for engineering dimension criteria

Engineering dimension	**Energy for capture and storage (C1)**	**CO_2 concentration (C2)**
Energy for capture and storage (C1)	(1, 1, 1)	(1, 2, 3)
		(4, 5, 6)
		(5, 6, 7)
CO_2 concentration (C2)	(1/3, 1/2, 1)	(1, 1,1)
	(1/6, 1/2, 1/4)	
	(1/7, 1/6, 1/5)	

$S_{En} = (2.00, 3.00, 4.00) \otimes \left(\frac{1}{6.00}, \frac{1}{4.50}, \frac{1}{3.3333}\right)$

$= (0.3333, 0.6667, 1.20)$

$S_{CO2} = (1.3333, 1.50, 2.00) \otimes \left(\frac{1}{6.00}, \frac{1}{4.50}, \frac{1}{3.3333}\right)$

$= (0.2222, 0.3333, 0.60)$

The degree of possibility of S_i with respect to S_j *(i≠j) is calculated as shown below.*

$V(\, S_{En} \geq S_{CO2}) = 1$

$V(\, S_{CO2} \geq S_{En}) = \dfrac{0.3333 - 0.60}{(0.3333 - 0.60) - (0.6667 - 0.3333)} = 0.4444$

Weight vector are calculated with the minimum degree of possibility as shown below.

$d'(S_{En}) = \min V(S_{En} \geq S_{CO2}) = 1$

$d'(S_{CO2}) = \min V(S_{CO2} \geq S_{En}) = 0.4444$

After normalization $W_G = (\mathbf{0.957}, \mathbf{0.3077})$

Table C2: Synthetic extent values for Economic dimension

Economic dimension	**CO_2 capture & storage cost (C3)**	**Operation & maintenance cost (C4)**
CO_2 capture & storage cost (C3)	(1, 1, 1)	(1, 2, 3)
		(3, 4, 5)
		(5, 6,7)
Operation & maintenance cost (C4)	(1/3, 1/2, 1)	(1, 1,1)
	(1/5, 1/4, 1/3)	
	(1/7, 1/6, 1/5)	

$S_{CCS} = (2.00, 2.6667, 3.667) \otimes \left(\frac{1}{5.6667}, \frac{1}{4.2667}, \frac{1}{3.375}\right)$

$= (0.3529, 0.625, 1.0864)$

$S_{OMC} = (1.375, 1.60, 2.00) \otimes \left(\frac{1}{5.6667}, \frac{1}{4.2667}, \frac{1}{3.375}\right)$

$= (0.2426, 0.375, 0.5926)$

The degree of possibility of S_i with respect to S_j *(i≠j) is calculated as shown below.*

$V(\, S_{CCS} \geq S_{OMC}) = 1$

$V(\, S_{CCS} \geq S_{OMC}) = \dfrac{0.3529 - 0.5926}{(0.3750 - 0.5926) - (0.625 - 0.3529)} = 0.4894$

Weight vector are calculated with the minimum degree of possibility as shown below.

$d'(S_{CCS}) = \min V(S_{CCS} \geq S_{OMC}) = 1$

$d'(S_{OMC}) = \min V(S_{CCS} \geq S_{OMC}) = 0.4894$

After normalization $W_G = (\mathbf{0.724}, \mathbf{0.2786})$

Table C3: Synthetic extent values for Environmental dimension

Environmental dimension	Global warming (C5)	CO_2 emission (C6)
Global warming (C5)	(1, 1, 1)	(1/3, 1/2, 1)
		(1/5, 1/4,1/3)
		(1, 1, 2)
CO_2 emission (C6)	(1, 2, 3)	(1, 1,1)
	(3, 4, 5)	
	(1/2, 1, 1)	

$S_{Glo} = (2.3333, 3.3333, 4.3333) \otimes \left(\frac{1}{6.0833}, \frac{1}{4.7619}, \frac{1}{3.6333}\right)$

$= (0.3836, 0.70, 1.1926)$

$S_{CO2e} = (1.30, 1.4285, 1.75) \otimes \left(\frac{1}{6.0833}, \frac{1}{4.7619}, \frac{1}{3.6333}\right)$

$= (0.2136, 0.30, 0.4817)$

The degree of possibility of S_i with respect to S_j *(i≠j) is calculated as shown below.*

$V(\, S_{Glo} \geq S_{CO2e}) = 1$

$V(\, S_{CO2e} \geq S_{Glo}) = \dfrac{0.3836 - 0.4817}{(0.30 - 0.4817) - (0.70 - 0.3836)} = 0.1969$

Weight vector are calculated with the minimum degree of possibility as shown below.

$d'(S_{Glo}) = \min V(S_{Glo} \geq S_{CO2e}) = 1$

$d'(S_{CO2e}) = \min V(S_{Glo} \geq S_{CO2e}) = 0.1969$

After normalization $W_G = (\mathbf{0.325}, \mathbf{0.675})$

Table C4: Synthetic extent values for Social dimension

Social dimension	**Policy, politics & regulation (C7)**	**Job creation (C8)**
Policy, politics & regulation (C7)	(1, 1, 1)	(1, 2, 3)
		(1, 2, 3)
		(1, 2, 3)
Job creation (C8)	(1/3, 1/2, 1)	(1, 1,1)
	(1/7, 1/5, 1/3)	
	(1/8, 1/7, 1/6)	

$S_{Poli} = (2.00, 3.00, 4.00) \otimes \left(\frac{1}{6.00}, \frac{1}{4.50}, \frac{1}{3.3333}\right)$

$= (0.3333, 0.6667, 1.20)$

$S_{Job} = (1.3333, 1.50, 2.00) \otimes \left(\frac{1}{6.00}, \frac{1}{4.50}, \frac{1}{3.3333}\right)$

$= (0.2222, 0.3333, 0.60)$

The degree of possibility of S_i with respect to S_j *(i≠j) is calculated as shown below.*

$V(\, S_{Poli} \geq S_{Job}) = 1$

$V(\, S_{Job} \geq S_{Poli}) = \frac{0.3333 - 0.60}{(0.3333 - 0.60) - (0.6667 - 0.3333)} = 0.4444$

Weight vector are calculated with the minimum degree of possibility as shown below.

$d'(S_{Poli}) = \min V(S_{Poli} \geq S_{Job}) = 1$

$d'(S_{Job}) = \min V(S_{Job} \geq S_{Poli}) = 0.4444$

After normalization $W_G = (\mathbf{0.6923}, \mathbf{0.3077})$

Synthetic extent values and weight calculation for alternatives

Table C5: Pairwise comparison matrix of alternatives selection (Energy for capture and storage)

Energy for capture and storage (C1)	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**
A1	(1,1,1)	(1/7,1/6,1/5)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1/7,1/6,1/5)	(1/3,1/2,1)	(1,2,3)	(1/5,1/4,1/3)
A2	(5 , 6, 7)	(1,1,1)	(3 ,4,5)	(6,7 ,8)	(1, 1, 2)	(5,6,7)	(7,8,9)	(2,3 ,4)
A3	(3,4,5)	(1/5,1/4,1/3)	(1,1 ,1)	(1,2,3)	(1/3,1/2,1)	(3 ,4,5)	(5,6,7)	(1/3,1/2,3)
A4	(4,5,6)	(1/8,1/7,1/6)	(1/3,1/2,1)	(1,1,1)	(1/5,1/4,1/3	(1,1,2)	(3,4,5)	(1/3,1/2,1)
A5	(5,6,7)	(1/2,1 ,1)	(1,2,3)	(3,4,5)	(1,1,1)	(3,4,5)	(7,8,9)	(2,3,4)
A6	(1,2,3)	(1/7,1/6,1/5)	(1/5,1/4,1/3)	(½,1,1)	(1/5,1/4,1/3)	(1,1,1)	(1,2,3)	(1/3,1/4,1/5)
A7	(1/3,1/2,1)	(1/9,1/8,1/7)	(1/7,1/6,1/5)	(1/5,1/4,1/3)	(1/9,1/8,1/7)	(1/3,1/2,1)	(1,1,1)	(1/8,1/7,1/6)
A8	(3,4,5)	(1/4,1/3,1/2)	(1/3,2,3)	(1,2,3)	(1/4,1/3,1/2)	(5,4,3)	(6,7,8)	(1,1,1)

Table C6: Fuzzy synthetic degree value (S_i) (Energy for capture and storage)

Energy for capture and storage (C1)	$\sum_{j=1}^{m} M_{g_i}^{j}$	$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$	$\sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$
S1 (A1)	(2.4, 3, 4.6667)	(0.01467, 0.0211, 0.0325)	(0.0352, 0.0634, 0.1514)
S2 (A2)	(4, 5.5, 9)	(0.01467, 0.0211, 0.0325)	(0.0587, 0.1162, 0.2921)
S3 (A3)	(9, 14, 19)	(0.01467, 0.0211, 0.0325)	(0.1320, 0.2958, 0.6165)
S4 (A4)	(4.6667, 8, 12)	(0.01467, 0.0211, 0.0325)	(0.0685, 0.1690, 0.3894)
S5 (A5)	(7.25, 11.3333, 15.5)	(0.01467, 0.0211, 0.0325)	(0.1064, 0.2394, 0.5029)
S6 (A6)	(3.5, 5.5, 8)	(0.01467, 0.0211, 0.0325)	(0.0513, 0.1162, 0.2596)
S7(A7)	(2.36,2.81,3.99)	(0.006,0.008,0.010)	(0.10,0.022,0.038)
S8(A8)	(16.83,20.67,24.00)	(0.006,0.008,0.010)	(0.10,0.158,0.231)

The degree of possibility of S_i with respect to S_j *(i≠j) is calculated as shown below.*

$$V(S_1 \geq S_2) = \frac{0.0587 - 0.1514}{(0.0634 - 0.1514) - (0.1162 - 0.0587)} = 0.450$$

$$V(S_1 \geq S_3) = \frac{0.1320 - 0.1514}{(0.0634 - 0.1514) - (0.2958 - 0.1320)} = 0.345$$

$$V(S_1 \geq S_4) = \frac{0.0685 - 0.1514}{(0.0634 - 0.1514) - (0.1690 - 0.0685)} = 0.251$$

$$V(S_1 \geq S_5) = \frac{0.1064 - 0.1514}{(0.0634 - 0.1514) - (0.2394 - 0.1064)} = 0.151$$

$$V(S_1 \geq S_6) = \frac{0.0513 - 0.1514}{(0.0634 - 0.1514) - (0.1162 - 0.0513)} = 0.652$$

$$V(S_1 \geq S_7) = \frac{0.0513 - 0.1514}{(0.0634 - 0.1514) - (0.1162 - 0.0513)} = 1.000$$

$$V(S_1 \geq S_8) = \frac{0.0523 - 0.1414}{(0.0634 - 0.1414) - (0.1162 - 0.0523)} = 0.100$$

Weight vector are calculated with the minimum degree of possibility as shown below.

$$\boldsymbol{d'(S_1) = \min V(0.450, 0.345, 0.251, 0.151, 0.652, 1.00, 0.100) = 0.100}$$

$$V(S_2 \geq S_1) = 1.000$$

$$V(S_2 \geq S_3) = \frac{0.1320 - 0.2921}{(0.1162 - 0.2921) - (0.2958 - 0.1320)} = 0.901$$

$$V(S_2 \geq S_4) = \frac{0.0685 - 0.2921}{(0.1162 - 0.2921) - (0.1690 - 0.0685)} = 0.809$$

$$V(S_2 \geq S_5) = \frac{0.1064 - 0.2921}{(0.1162 - 0.2821) - (0.2394 - 0.1064)} = 0.801$$

$$V(S_2 \geq S_6) = 1.000$$

$$(S_2 \geq S_7) = 1.000$$

$$(S_2 \geq S_8) = 1.000$$

Weight vector are calculated with the minimum degree of possibility as shown below.

$\boldsymbol{d'(S_2) = \min V(1.000, 0.901, 0.809, 0.801, 1.000, 1.000, 1.000) = 0.801}$

$V(S_3 \geq S_1) = 1.000$

$$V(S_3 \geq S_2) = \frac{0.0352 - 0.2921}{(0.1162 - 0.6165) - (0.0352 - 0.0634)} = 0.450$$

$V(S_3 \geq S_4) = 1.000$

$V(S_3 \geq S_5) = 0.562$

$V(S_3 \geq S_6) = 1.000$

$V(S_3 \geq S_7) = 1.000$

$V(S_3 \geq S_8) = 0.883$

Weight vector are calculated with the minimum degree of possibility as shown below.

$\boldsymbol{d'(S_3) = \min V(1.000, 0.450, 1.000, 0.562, 1.000, 1.000, 0.883) = 0.450}$

$V(S_4 \geq S_1) = 1$

$V(S_4 \geq S_2) = 0.350$

$$V(S_4 \geq S_3) = \frac{0.1320 - 0.6165}{(0.2958 - 0.3894) - (0.2958 - 0.1320)} = 0.621$$

$$V(S_4 \geq S_5) = \frac{0.1064 - 0.3894}{(0.1690 - 0.3894) - (0.2394 - 0.1064)} = 0.350$$

$V(S_4 \geq S_6) = 1$

$V(S_4 \geq S_5) = 1$

$$V(S_4 \geq S_5) = \frac{0.1164 - 0.2894}{(0.1390 - 0.3794) - (0.2494 - 0.1164)} = 0.466$$

Weight vector are calculated with the minimum degree of possibility as shown below.

$\boldsymbol{d'(S_4) = \min V(1, 0.350, 0.621, 0.8350, 1, 1, 0.466) = 0.350}$

$V(S_5 \geq S_1) = 1$

$$V(S_5 \geq S_2) = \frac{0.1320 - 0.5029}{(0.2394 - 0.5029) - (0.2958 - 0.1320)} = 0740$$

$V(S_5 \geq S_3) = 1$

$V(S_5 \geq S_4) = 1$

$V(S_5 \geq S_6) = 1$

$V(S_5 \geq S_7) = 1$

$V(S_5 \geq S_8) = 1$

Weight vector are calculated with the minimum degree of possibility as shown below.

$\boldsymbol{d'(S_5) = \min V(1, 0.740, 1, 1, 1, 1, 1) = 0.740}$

$V(S_6 \geq S_1) = 1$

$$V(S_6 \geq S_2) = \frac{0.1320 - 0.2596}{(0.1162 - 0.2596) - (0.2958 - 0.1320)} = 0.591$$

$$V(S_6 \geq S_3) = \frac{0.1320 - 0.2596}{(0.2162 - 0.2596) - (0.2958 - 0.1320)} = 0.580$$

$$V(S_6 \geq S_4) = \frac{0.0685 - 0.2576}{(0.6162 - 0.2796) - (0.1690 - 0.0685)} = 0.670$$

$$V(S_6 \geq S_5) = \frac{0.1064 - 0.2896}{(0.3162 - 0.1596) - (0.2394 - 0.1064)} = 0.681$$

$$V(S_6 \geq S_7) = 1$$

$$V(S_6 \geq S_8) = \frac{0.2064 - 0.2596}{(0.3262 - 0.2596) - (0.2594 - 0.1164)} = 0.580$$

Weight vector are calculated with the minimum degree of possibility as shown below.

$$\boldsymbol{d'(S_6) = \min V(1, 0.591, 0.580, 0.670, 0.681, 1, 0.580) = 0.4153}$$

$$V(S_7 \geq S_1) = \frac{0.1320 - 0.2596}{(0.5162 - 0.2596) - (0.2958 - 0.1320)} = 0.587$$

$$V(S_7 \geq S_2) = \frac{0.1720 - 0.1596}{(0.7162 - 0.2596) - (0.2758 - 0.1320)} = 0.290$$

$$V(S_7 \geq S_3) = \frac{0.2320 - 0.1596}{(0.3162 - 0.2596) - (0.2658 - 0.4320)} = 0.450$$

$$V(S_7 \geq S_4) = \frac{0.8320 - 0.3596}{(0.1262 - 0.2596) - (0.2458 - 0.2320)} = 0.590$$

$$V(S_7 \geq S_5) = \frac{0.2320 - 0.2586}{(0.1762 - 0.2596) - (0.3958 - 0.4320)} = 0.850$$

$$V(S_7 \geq S_6) = \frac{0.1720 - 0.2594}{(0.1562 - 0.2396) - (0.2948 - 0.1820)} = 0.267$$

$$V(S_7 \geq S_8) = \frac{0.1320 - 0.2556}{(0.2562 - 0.1596) - (0.3958 - 0.2320)} = 0.251$$

Weight vector are calculated with the minimum degree of possibility as shown below.

$$\boldsymbol{d'(S_7) = \min V(0.587, 0.290, 0.450, 0.590, 0.850, 0.267, 0.251) = 0.251}$$

$$V(S_8 \geq S_1) = 1$$

$$V(S_8 \geq S_2) = \frac{0.1320 - 0.2596}{(0.1162 - 0.2596) - (0.2958 - 0.1320)} = 0.591$$

$$V(S_8 \geq S_3) = 1$$

$$V(S_8 \geq S_4) = 1$$

$$V(S_8 \geq S_5) = \frac{0.1220 - 0.2526}{(0.1162 - 0.2596) - (0.2958 - 0.1320)} = 0.592$$

$$V(S_8 \geq S_6) = 1$$

$$V(S_8 \geq S_7) = 1$$

Weight vector are calculated with the minimum degree of possibility as shown below.

$$\boldsymbol{d'(S_8) = \min V(1, 0.591, 1, 1, 0.592, 1, 1) = 0.591}$$

After normalization $\boldsymbol{W_G = (0.026, 0.207, 0.116, 0.091, 0.191, 0.150, 0.065,}$

Table C7: Degree of possibility (V) (Energy for capture and storage)

Energy for capture and storage (C1)	$\boldsymbol{d'(A1)}$		$\boldsymbol{d'(A2)}$		$\boldsymbol{d'(A3)}$		$\boldsymbol{d'(A4)}$		$\boldsymbol{d'(A5)}$		$\boldsymbol{d'(A6)}$		$\boldsymbol{d'(A7)}$		$\boldsymbol{d'(A8)}$
V(S1≥S2)	0.450	V(S2≥S1)	1	V(S3≥S1)	1	V(S4≥S1)	1	V(S5≥S1)	1	V(S6≥S1)	1	V(S7≥S1)	0.587	V(S8≥S1)	1
V(S1≥S3)	0.340	V(S2≥S3)	0.901	V(S3≥S2)	0.450	V(S4≥S2)	0.350	V(S5≥S2)	0.740	V(S6≥S2)	1	V(S7≥S2)	0.290	V(S8≥S2)	0.591
V(S1≥S4)	0.250	V(S2≥S4)	0.809	V(S3≥S4)	1	V(S4≥S3)	0.621	V(S5≥S3)	1	V(S6≥S3)	0.4153	V(S7≥S3)	0.450	V(S8≥S3)	1
V(S1≥S5)	0.150	V(S2≥S5)	0.801	V(S3≥S5)	10.562	V(S4≥S5)	0.350	V(S5≥S4)	1	V(S6≥S4)	0.7835	V(S7≥S4)	0.590	V(S8≥S4)	1
V(S1≥S6)	0.650	V(S2≥S6)	1	V(S3≥S6)	1	V(S4≥S6)	1	V(S5≥S6)	1	V(S6≥S5)	0.5543	V(S7≥S5)	0.850	V(S8≥S5)	0.592
V(S1≥S7)	1	V(S2≥S7)	1	V(S3≥S7)	1	V(S4≥S7)	1	V(S5≥S7)	1	V(S6≥S7)	1	V(S7≥S6)	0.267	V(S8≥S6)	1
V(S1≥S8)	0.100	V(S2≥S8)	1	V(S3≥S8)	0.883	V(S4≥S8)	0.466	V(S5≥S8)	1	V(S6≥S8)	0.680	V(S7≥S8)	0.251	V(S8≥S7)	1
Weight vector *(W)*:	**0.0220**		**0.1346**		**0.2856**		**0.1913**		**0.2479**		**0.1186**		**0.251**		**0.591**

Similarly:

Table C8: Fuzzy synthetic degree value (S_i) (Capture & storage cost)

Capture & storage cost (C3)	$\sum_{j=1}^{m} M_{g_i}^{j}$	$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$	$\sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$
S1 (A1)	(4, 5.5, 9)	(0.0175, 0.0328, 0.0552)	(0.0621, 0.1257, 0.3172)
S2 (A2)	(3.3333, 4, 7)	(0.0175, 0.0328, 0.0552)	(0.0518, 0.0914, 0.2467)
S3 (A3)	(6, 11, 16)	(0.0175, 0.0328, 0.0552)	(0.0932, 0.2514, 0.5640)
S4 (A4)	(5.3333, 8.5, 13)	(0.0175, 0.0328, 0.0552)	(0.0829, 0.1942, 0.4582)
S5 (A5)	(6.8333, 10.5, 14)	(0.0175, 0.0328, 0.0552)	(0.1062, 0.24, 0.4935)

S6 (A6)	(2.8666, 4.25, 5.3333)	(0.0175, 0.0328, 0.0552)	(0.0445, 0.0971, 0.1880)
S7(A7)	(5.21, 11, 15)	(0.0175, 0.0328, 0.0552)	(0.0218, 0.0814, 0.2567)
S8(A8)	(2.145, 1.241, 6)	(0.0175, 0.0328, 0.0552)	(0.0328, 0.0614, 0.2267)

Table C9: Degree of possibility *(V)* (Capture & storage cost)

Capture & storage cost (C3)	$d'(A1)$		$d'(A2)$		$d'(A3)$		$d'(A4)$		$d'(A5)$		$d'(A6)$		$d'(A7)$		$d'(A8)$
V(S1≥S2)	0	*V(S2≥S1)*	1	*V(S3≥S1)*	1	*V(S4≥S1)*	1	*V(S5≥S1)*	1	*V(S6≥S1)*	0.919	V(S7≥S1)	0.946	V(S8≥S1)	1
V(S1≥S3)	0	*V(S2≥S3)*	1	*V(S3≥S2)*	0.394	*V(S4≥S2)*	0.341	*V(S5≥S2)*	0.780	*V(S6≥S2)*	0.689	V(S7≥S2)	0.214	V(S8≥S2)	0.568
V(S1≥S4)	0.287	*V(S2≥S4)*	1	*V(S3≥S4)*	1	*V(S4≥S3)*	0.571	*V(S5≥S3)*	1	*V(S6≥S3)*	0.987	V(S7≥S3)	0.325	V(S8≥S3)	0.624
V(S1≥S5)	0	*V(S2≥S5)*	1	*V(S3≥S5)*	0.613	*V(S4≥S5)*	0.295	*V(S5≥S4)*	1	*V(S6≥S4)*	0.965	V(S7≥S4)	0.218	V(S8≥S4)	1
V(S1≥S6)	1	*V(S2≥S6)*	1	*V(S3≥S6)*	1	*V(S4≥S6)*	1	*V(S5≥S6)*	1	*V(S6≥S5)*	0.857	V(S7≥S5)	0.185	V(S8≥S5)	0.654
V(S1≥S7)	1	*V(S2≥S7)*	1	*V(S3≥S7)*	1	*V(S4≥S7)*	1	*V(S5≥S7)*	1	*V(S6≥S7)*	0.976	V(S7≥S6)	1	V(S8≥S6)	1
V(S1≥S8)	0.182	*V(S2≥S8)*	1	*V(S3≥S8)*	1	*V(S4≥S8)*	0.890	*V(S5≥S8)*	1	*V(S6≥S8)*	0.698	V(S7≥S8)	0.115	V(S8≥S7)	1.
Weight vector *(W)*:	**0.000**		**0.260**		**0.103**		**0.077**		**0.203**		**0.179**		**0.030**		**0.148**

Table C10: Fuzzy synthetic degree value (S_i) (operation & maintenance cost)

operation & maintenance cost (C4)	$\sum_{j=1}^{m} M_{g_i}^{j}$	$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$	$\sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$
S1 (A1)	(1.8857, 2.0833, 2.4)	(0.0124, 0.0158, 0.0208)	(0.0235, 0.0331, 0.0500)
S2 (A2)	(5.7333, 7, 9.6666)	(0.0124, 0.0158, 0.0208)	(0.0714, 0.1112, 0.2016)

S3 (A3)	(14, 18, 23)	(0.0124, 0.0158, 0.0208)	(0.1744, 0.2860, 0.4798)
S4 (A4)	(6.5833, 9.8333, 13.5)	(0.0124, 0.0158, 0.0208)	(0.0820, 0.1562, 0.2816)
S5 (A5)	(14.5, 19, 23)	(0.0124, 0.0158, 0.0208)	(0.1807, 0.3019, 0.4798)
S6 (A6)	(5.2333, 7, 8.6666)	(0.0124, 0.0158, 0.0208)	(0.0652, 0.1112, 0.1807)
S7(A7)	(2.713, 7.124, 8.166)	(0.0124, 0.0158, 0.0208)	(0.1744, 0.2860, 0.4798)
S8(A8)	(5.253, 2.541, 9.666)	(0.0124, 0.0158, 0.0208)	(0.254, 0.250, 0.3798)

Table C11: Degree of possibility *(V)* (operation & maintenance cost)

Operation & maintenance cost **(C4)**	$\boldsymbol{d'(A1)}$		$\boldsymbol{d'(A2)}$		$\boldsymbol{d'(A3)}$		$\boldsymbol{d'(A4)}$		$\boldsymbol{d'(A5)}$		$\boldsymbol{d'(A6)}$		$\boldsymbol{d'(A7)}$		$\boldsymbol{d'(A8)}$
V(S1≥S2)	0.110	*V(S2≥S1)*	1	*V(S3≥S1)*	1	*V(S4≥S1)*	1	*V(S5≥S1)*	1	*V(S6≥S1)*	1	V(S7≥S1)	0.587	V(S8≥S1)	1
V(S1≥S3)	0.080	*V(S2≥S3)*	1	*V(S3≥S2)*	0.547	*V(S4≥S2)*	0.365	*V(S5≥S2)*	0.845	*V(S6≥S2)*	0.795	V(S7≥S2)	0.125	V(S8≥S2)	0.784
V(S1≥S4)	0.361	*V(S2≥S4)*	1	*V(S3≥S4)*	1	*V(S4≥S3)*	0.621	*V(S5≥S3)*	1	*V(S6≥S3)*	0.952	V(S7≥S3)	0.254	V(S8≥S3)	1
V(S1≥S5)	1	*V(S2≥S5)*	1	*V(S3≥S5)*	0.562	*V(S4≥S5)*	0.341	*V(S5≥S4)*	1	*V(S6≥S4)*	0.821	V(S7≥S4)	0.365	V(S8≥S4)	1
V(S1≥S6)	0.650	*V(S2≥S6)*	1	*V(S3≥S6)*	1	*V(S4≥S6)*	1	*V(S5≥S6)*	0.974	*V(S6≥S5)*	1	V(S7≥S5)	0.124	V(S8≥S5)	0.684
V(S1≥S7)	1	*V(S2≥S7)*	1	*V(S3≥S7)*	1	*V(S4≥S7)*	1	*V(S5≥S7)*	1	*V(S6≥S7)*	1	V(S7≥S6)	1	V(S8≥S6)	1
V(S1≥S8)	0.074	*V(S2≥S8)*		*V(S3≥S8)*	0.883	*V(S4≥S8)*	0.466	*V(S5≥S8)*	1	*V(S6≥S8)*	1	V(S7≥S8)	1.	V(S8≥S7)	1
Weight vector *(W)*:	**0.017**		**0.227**		**0.124**		**0.077**		**0.192**		**0.180**		**0.028**		**0.155**

Table C12: Fuzzy synthetic degree value (S_i) (Global warming)

Global warming (C5)	$\sum_{j=1}^{m} M_{g_i}^{j}$	$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$	$\sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$
S1 (A1)	(2.1523, 2.5833, 3.7333)	(0.0133, 0.0178, 0.0247)	(0.0287, 0.0461, 0.0922)
S2 (A2)	(3.0666, 4.5, 6.6666)	(0.0133, 0.0178, 0.0247)	(0.0409, 0.0804, 0.1647)
S3 (A3)	(12, 16, 21)	(0.0133, 0.0178, 0.0247)	(0.1602, 0.2861, 0.5189)
S4 (A4)	(6.5833, 8.8333, 12.5)	(0.0133, 0.0178, 0.0247)	(0.0878, 0.1579, 0.3088)
S5 (A5)	(12.5, 17, 21)	(0.0133, 0.0178, 0.0247)	(0.1668, 0.3040, 0.5189)
S6 (A6)	(4.1666, 7, 10)	(0.0133, 0.0178, 0.0247)	(0.0556, 0.1251, 0.2471)
S7(A7)	(3.533, 5.833, 2.5)	(0.0133, 0.0178, 0.0247)	(0.6102, 0.1861, 0.3189)
S8(A8)	(6.533, 6.833, 7.5)	(0.0133, 0.0178, 0.0247)	(0.1302, 0.2431, 0.2389)

Table C13: Degree of possibility *(V)* (Global warming)

Global warming (C5)	$d'(A1)$		$d'(A2)$		$d'(A3)$		$d'(A4)$		$d'(A5)$		$d'(A6)$		$d'(A7)$		$d'(A8)$
V(S1≥S2)	0.254	*V(S2≥S1)*	1	*V(S3≥S1)*	1	*V(S4≥S1)*	1	*V(S5≥S1)*	1	*V(S6≥S1)*	1	V(S7≥S1)	0.587	V(S8≥S1)	1
V(S1≥S3)	0.214	*V(S2≥S3)*	1	*V(S3≥S2)*	0.584	*V(S4≥S2)*	0.854	*V(S5≥S2)*	0.895	*V(S6≥S2)*	0.854	V(S7≥S2)	0.521	V(S8≥S2)	0.658
V(S1≥S4)	0.124	*V(S2≥S4)*	1	*V(S3≥S4)*	1	*V(S4≥S3)*	0.621	*V(S5≥S3)*	1	*V(S6≥S3)*	0.759	V(S7≥S3)	0.214	V(S8≥S3)	1
V(S1≥S5)	0.215	*V(S2≥S5)*	1	*V(S3≥S5)*	0.562	*V(S4≥S5)*	0.587	*V(S5≥S4)*	1	*V(S6≥S4)*	0.984	V(S7≥S4)	0.547	V(S8≥S4)	1
V(S1≥S6)	0.650	*V(S2≥S6)*	1	*V(S3≥S6)*	1	*V(S4≥S6)*	1	*V(S5≥S6)*	0.958	*V(S6≥S5)*	1	V(S7≥S5)	1	V(S8≥S5)	0.854
V(S1≥S7)	1	*V(S2≥S7)*	1	*V(S3≥S7)*	1	*V(S4≥S7)*	1	*V(S5≥S7)*	1	*V(S6≥S7)*	1	V(S7≥S6)	0.267	V(S8≥S6)	1

V(S1≥S8)	0.120	*V(S2≥S8)*	1	*V(S3≥S8)*	0.883	*V(S4≥S8)*	0.466	*V(S5≥S8)*	1	*V(S6≥S8)*	1	V(S7≥S8)	0.521	V(S8≥S7)	1
Weight vector *(W)*:	**0.026**		**0.214**		**0.120**		**0.100**		**0.191**		**0.162**		**0.046**		**0.141**

Table C14: Fuzzy synthetic degree value (S_i) (CO_2 emission)

CO_2 emission (C6)	$\sum_{j=1}^{m} M_{g_i}^{j}$	$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$	$\sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$
S1 (A1)	(2.0190, 2.3333, 3.0666)	(0.0156, 0.0138, 0.0421)	(0.0260, 0.0392, 0.0693)
S2 (A2)	(5.8666, 7.25, 10.333)	(0.0156, 0.0138, 0.0421)	(0.0756, 0.1220, 0.2337)
S3 (A3)	(12, 16, 21)	(0.0156, 0.0138, 0.0421)	(0.1547, 0.2692, 0.4750)
S4 (A4)	(7.6666, 11, 15)	(0.0156, 0.0138, 0.0421)	(0.0988, 0.1851, 0.3393)
S5 (A5)	(13.5, 18, 22)	(0.0156, 0.0138, 0.0421)	(0.1740, 0.3029, 0.4977)
S6 (A6)	(3.15, 4.8333, 6.166)	(0.0156, 0.0138, 0.0421)	(0.0406, 0.0813, 0.1395)
S7(A7)	(4.15, 4.8233, 6.326)	(0.0156, 0.0138, 0.0421)	(0.1410, 0.2129, 0.2177)
S8(A8)	(5.15, 4.821, 6.516)	(0.0156, 0.0138, 0.0421)	(0.2140, 0.5129, 0.177)

Table C15: Degree of possibility *(V)* (CO_2 emission)

CO_2 emission (C6)	$d'(A1)$		$d'(A2)$		$d'(A3)$		$d'(A4)$		$d'(A5)$		$d'(A6)$		$d'(A7)$		$d'(A8)$
V(S1≥S2)	0.250	*V(S2≥S1)*	1	*V(S3≥S1)*	1	*V(S4≥S1)*	1	*V(S5≥S1)*	1	*V(S6≥S1)*	1	V(S7≥S1)	0.587	V(S8≥S1)	1
V(S1≥S3)	0.314	*V(S2≥S3)*	1	*V(S3≥S2)*	0.578	*V(S4≥S2)*	0.432	*V(S5≥S2)*	0.857	*V(S6≥S2)*	0.857	V(S7≥S2)	0.257	V(S8≥S2)	0.694
V(S1≥S4)	0.210	*V(S2≥S4)*	1	*V(S3≥S4)*	1	*V(S4≥S3)*	0.621	*V(S5≥S3)*	1	*V(S6≥S3)*	0.968	V(S7≥S3)	0.295	V(S8≥S3)	1

V(S1≥S5)	0.124	*V(S2≥S5)*	1	*V(S3≥S5)*	0.562	*V(S4≥S5)*	0.524	*V(S5≥S4)*	1	*V(S6≥S4)*	0.887	V(S7≥S4)	0.562	V(S8≥S4)	1
V(S1≥S6)	0.650	*V(S2≥S6)*	1	*V(S3≥S6)*	1	*V(S4≥S6)*	1	*V(S5≥S6)*	1	*V(S6≥S5)*	0.754	V(S7≥S5)	0.365	V(S8≥S5)	0.847
V(S1≥S7)	1	*V(S2≥S7)*	1	*V(S3≥S7)*	1	*V(S4≥S7)*	1	*V(S5≥S7)*	0.984	*V(S6≥S7)*	1	V(S7≥S6)	0.267	V(S8≥S6)	1
V(S1≥S8)	0.121	*V(S2≥S8)*	1	*V(S3≥S8)*	0.883	*V(S4≥S8)*	0.466	*V(S5≥S8)*	0.921	*V(S6≥S8)*	0.895	V(S7≥S8)	0.435	V(S8≥S7)	1
Weight vector *(W)*:	**0.026**		**0.214**		**0.120**		**0.092**		**0.183**		**0.161**		**0.055**		**0.148**

Table C16: Fuzzy synthetic degree value (S_i) (Policy, politics & regulation)

Policy, politics & regulation (C7)	$\sum_{j=1}^{m} M_{g_i}^{j}$	$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$	$\sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$
S1 (A1)	(8, 13, 18)	(0.0168, 0.0251, 0.0370)	(0.1269, 0.3011, 0.6315)
S2 (A2)	(5.25, 8.3333, 12.5)	(0.0168, 0.0251, 0.0370)	(0.0833, 0.1930, 0.4385)
S3 (A3)	(4, 4.5, 8)	(0.0168, 0.0251, 0.0370)	(0.0634, 0.1042, 0.2807)
S4 (A4)	(3.5, 4.5, 7)	(0.0168, 0.0251, 0.0370)	(0.0555, 0.1042, 0.2456)
S5 (A5)	(3, 4.5, 6)	(0.0168, 0.0251, 0.0370)	(0.0476, 0.1042, 0.2105)
S6 (A6)	(4.75, 8.3333, 11.5)	(0.0168, 0.0251, 0.0370)	(0.0753, 0.1930, 0.4035)
S7(A7)	(2.357, 2.810, 3.986)	(0.0168, 0.0251, 0.0370)	(0.0476, 0.1042, 0.2105)
S8(A8)	(16.833, 20.667, 24.000)	(0.0168, 0.0251, 0.0370)	(0.0573, 0.1250, 0.3235)

Table C17: Degree of possibility *(V)* (Policy, politics & regulation)

Policy, politics & regulation (C7)	$\boldsymbol{d'(A1)}$		$\boldsymbol{d'(A2)}$		$\boldsymbol{d'(A3)}$		$\boldsymbol{d'(A4)}$		$\boldsymbol{d'(A5)}$		$\boldsymbol{d'(A6)}$		$\boldsymbol{d'(A7)}$		$\boldsymbol{d'(A8)}$
V(S1≥S2)	0.000	*V(S2≥S1)*	1	*V(S3≥S1)*	1	*V(S4≥S1)*	1	*V(S5≥S1)*	1	*V(S6≥S1)*	1	V(S7≥S1)	0.587	V(S8≥S1)	1
V(S1≥S3)	0.258	*V(S2≥S3)*	1	*V(S3≥S2)*	0.532	*V(S4≥S2)*	0.432	*V(S5≥S2)*	0.740	*V(S6≥S2)*	0.958	V(S7≥S2)	0.251	V(S8≥S2)	0.886
V(S1≥S4)	0	*V(S2≥S4)*	1	*V(S3≥S4)*	1	*V(S4≥S3)*	0.621	*V(S5≥S3)*	1	*V(S6≥S3)*	0.895	V(S7≥S3)	0.658	V(S8≥S3)	1
V(S1≥S5)	0	*V(S2≥S5)*	1	*V(S3≥S5)*	0.562	*V(S4≥S5)*	0.842	*V(S5≥S4)*	1	*V(S6≥S4)*	0.954	V(S7≥S4)	0.958	V(S8≥S4)	1
V(S1≥S6)	0.650	*V(S2≥S6)*	1	*V(S3≥S6)*	1	*V(S4≥S6)*	1	*V(S5≥S6)*	1	*V(S6≥S5)*	0.854	V(S7≥S5)	0.884	V(S8≥S5)	0.652
V(S1≥S7)	1	*V(S2≥S7)*	1	*V(S3≥S7)*	1	*V(S4≥S7)*	1	*V(S5≥S7)*	1	*V(S6≥S7)*	1	V(S7≥S6)	0.267	V(S8≥S6)	1
V(S1≥S8)	0	*V(S2≥S8)*	1	*V(S3≥S8)*	0.883	*V(S4≥S8)*	0.466	*V(S5≥S8)*	1	*V(S6≥S8)*	0.682	V(S7≥S8)	0.367	V(S8≥S7)	1
Weight vector *(W)*:	**0.000**		**0.233**		**0.124**		**0.101**		**0.172**		**0.159**		**0.059**		**0.152**

Table C18: Fuzzy synthetic degree value (S_i) (Job creation)

Job creation (C8)	$\sum_{j=1}^{m} M_{g_i}^{j}$	$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$	$\sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$
S1 (A1)	(3.186,4.533,6.317)	(0.0181, 0.0239, 0.0352)	(0.125, 0.2977, 0.6352)
S2 (A2)	(25.000,31.000, 41.000)	(0.0181, 0.0239, 0.0352)	(0.0820, 0.1908, 0.4411)
S3 (A3)	(12.867 ,17.250, 24.333)	(0.0181, 0.0239, 0.0352)	(0.0520, 0.0916, 0.2470)
S4 (A4)	(9.067, 11.500, 15.667)	(0.0181, 0.0239, 0.0352)	(0.0625, 0.1259, 0.3176)
S5 (A5)	(21.200, 28.000, 34.000)	(0.0181, 0.0239, 0.0352)	(0.0468, 0.1030, 0.2117)
S6 (A6)	(4.376, 5.917, 8.067)	(0.0181, 0.0239, 0.0352)	(0.0742, 0.1908, 0.4058)

S7(A7)	(2.643, 3.486, 4.283)	(0.0181, 0.0239, 0.0352)	(0.05872, 0.1584,0.6381)
S8(A8)	(16.833, 20.667, 24.000)	(0.0181, 0.0239, 0.0352)	(0.06891,0.1574,0.8951)

Table C19: Degree of possibility *(V)* (Job creation)

Job creation (C8)	$\boldsymbol{d'(A1)}$		$\boldsymbol{d'(A2)}$		$\boldsymbol{d'(A3)}$		$\boldsymbol{d'(A4)}$		$\boldsymbol{d'(A5)}$		$\boldsymbol{d'(A6)}$		$\boldsymbol{d'(A7)}$		$\boldsymbol{d'(A8)}$
V(S1≥S2)	0.954	*V(S2≥S1)*	1	*V(S3≥S1)*	1	*V(S4≥S1)*	1	*V(S5≥S1)*	1	*V(S6≥S1)*	1	V(S7≥S1)	0.740	V(S8≥S1)	1
V(S1≥S3)	0.265	*V(S2≥S3)*	1	*V(S3≥S2)*	0.457	*V(S4≥S2)*	0.542	*V(S5≥S2)*	0.888	*V(S6≥S2)*	0.752	V(S7≥S2)	0.251	V(S8≥S2)	0.951
V(S1≥S4)	0.126	*V(S2≥S4)*	1	*V(S3≥S4)*	1	*V(S4≥S3)*	0.634	*V(S5≥S3)*	0.685	*V(S6≥S3)*	0.598	V(S7≥S3)	0.587	V(S8≥S3)	1
V(S1≥S5)	0.100	*V(S2≥S5)*	1	*V(S3≥S5)*	0.574	*V(S4≥S5)*	0.274	*V(S5≥S4)*	1	*V(S6≥S4)*	0.956	V(S7≥S4)	0.694	V(S8≥S4)	1
V(S1≥S6)	0.770	*V(S2≥S6)*	1	*V(S3≥S6)*	1	*V(S4≥S6)*	1	*V(S5≥S6)*	1	*V(S6≥S5)*	0.923	V(S7≥S5)	1	V(S8≥S5)	0.695
V(S1≥S7)	1	*V(S2≥S7)*	1	*V(S3≥S7)*	1	*V(S4≥S7)*	1	*V(S5≥S7)*	1	*V(S6≥S7)*	1	V(S7≥S6)	1	V(S8≥S6)	1
V(S1≥S8)	0	*V(S2≥S8)*	1	*V(S3≥S8)*	0.840	*V(S4≥S8)*	0.428	*V(S5≥S8)*	1	*V(S6≥S8)*	0.851	V(S7≥S8)	0.895	V(S8≥S7)	1
Weight vector *(W)*:	**0.000**		**0.253**		**0.115**		**0.069**		**0.173**		**0.151**		**0.063**		**0.176**

Appendix D: 2-Tuple DEMATEL calculation for criteria evaluation

B42 Criteria: Economic

Criteria: Economic

Expart-1:

	C8	C9	C10	C11	C12	C13
C8	0.00	1.00	1.00	1.00	2.00	2.00
C9	1.00	0.00	2.00	2.00	1.00	2.00
C10	1.00	2.00	0.00	3.00	3.00	2.00
C11	2.00	2.00	3.00	0.00	2.00	1.00
C12	2.00	1.00	1.00	2.00	0.00	1.00
C13	2.00	1.00	1.00	1.00	3.00	0.00

Expart-2:

	C8	C9	C10	C11	C12	C13
C8	0.00	1.00	1.00	2.00	3.00	2.00
C9	1.00	0.00	2.00	3.00	2.00	2.00
C10	1.00	2.00	0.00	3.00	1.00	1.00
C11	1.00	2.00	3.00		1.00	1.00
C12	2.00	2.00	2.00	1.00	0.00	1.00
C13	1.00	2.00	1.00	1.00	2.00	0.00

Expart-3:

	C8	C9	C10	C11	C12	C13
C8	0.00	1.00	1.00	1.00	2.00	1.00
C9	1.00	0.00	2.00	2.00	2.00	2.00
C10	2.00	2.00	0.00	2.00	3.00	1.00
C11	2.00	2.00	3.00	0.00	1.00	1.00
C12	1.00	2.00	2.00	1.00	0.00	2.00
C13	2.00	2.00	1.00	1.00	2.00	0.00

Expart-4:

	C8	C9	C10	C11
C8	0.00	1.00	1.00	1.00
C9	1.00	0.00	2.00	2.00
C10	3.00	3.00	0.00	2.00
C11	2.00	2.00	2.00	0.00
C12	1.00	1.00	2.00	1.00
C13	2.00	1.00	1.00	1.00

Average Matrix (A)=

	C8	C9	C10	C11	C12	C13	Sum	Max. Value
C8	0.000	1.000	1.000	1.200	2.000	1.600	6.80	10.00
C9	1.000	0.000	2.000	2.000	1.800	2.000	8.80	
C10	1.600	2.200	0.000	2.400	2.600	1.200	10.00	
C11	1.600	2.000	2.400	0.000	1.400	1.000	8.40	
C12	1.600	1.600	2.000	1.200	0.000	1.600	8.00	
C13	1.800	1.800	1.000	1.000	2.000	0.000	7.60	

Direct relation Matrix (D)=

	C8	C9	C10	C11	C12	C13
C8	0.000	0.100	0.100	0.120	0.200	0.160
C9	0.100	0.000	0.200	0.200	0.180	0.200
C10	0.160	0.220	0.000	0.240	0.260	0.120
C11	0.160	0.200	0.240	0.000	0.140	0.100
C12	0.160	0.160	0.200	0.120	0.000	0.160
C13	0.180	0.180	0.100	0.100	0.200	0.000

Identity Matrix (I)=

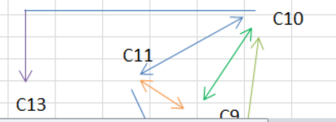
	C8	C9	C10	C11	C12	C13
C8	1.00	0.00	0.00	0.00	0.00	0.00
C9	0.00	1.00	0.00	0.00	0.00	0.00
C10	0.00	0.00	1.00	0.00	0.00	0.00
C11	0.00	0.00	0.00	1.00	0.00	0.00
C12	0.00	0.00	0.00	0.00	1.00	0.00
C13	0.00	0.00	0.00	0.00	0.00	1.00

(I-D)

	C8
C8	1.00
C9	-0.10
C10	-0.16
C11	-0.16
C12	-0.16
C13	-0.18

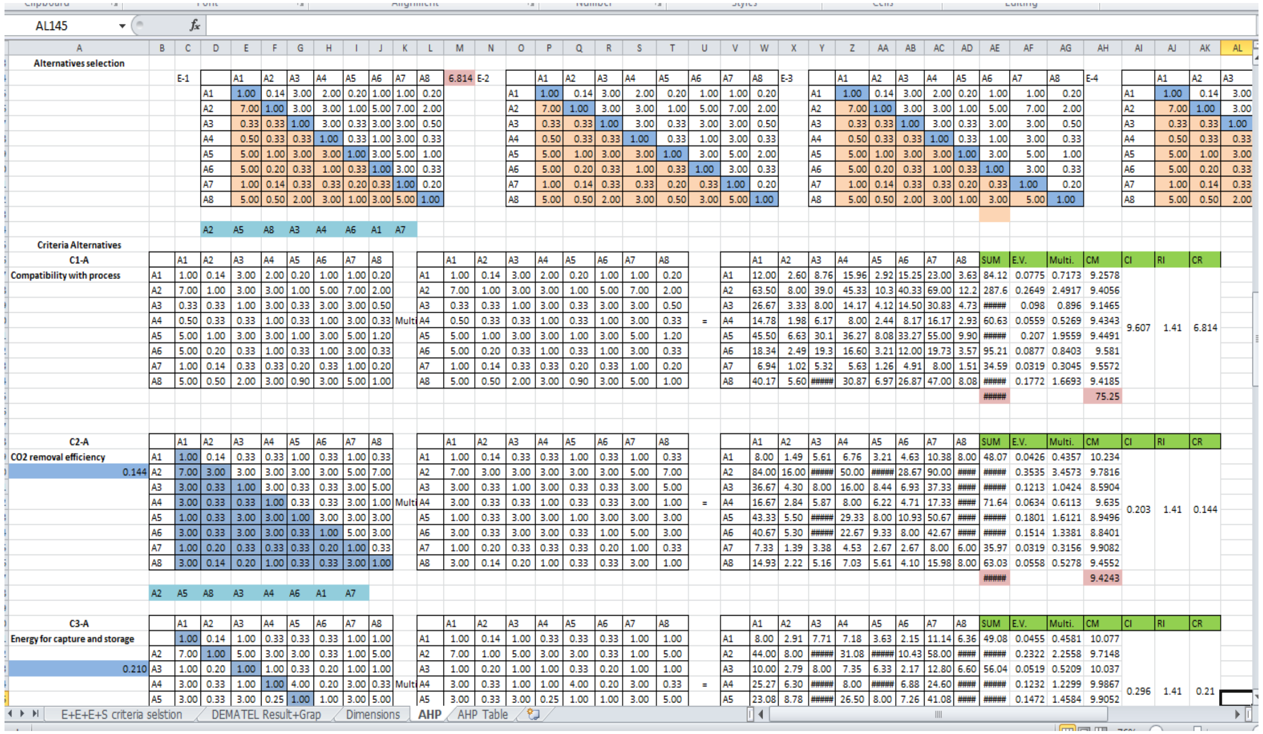
T=D*(I-D) inverse

	C8	C9	C10	C11	C12	C13	r	c	r+c	r-c
C8	0.532	0.683	0.677	0.648	0.828	0.660	4.03	4.49	8.52	-0.46
C9	0.774	0.766	0.924	0.871	1.002	0.835	5.17	5.02	10.19	0.15
C10	0.892	1.028	0.845	0.979	1.151	0.852	5.75	4.97	10.71	0.78
C11	0.794	0.906	0.929	0.687	0.948	0.740	5.00	4.63	9.63	0.38
C12	0.760	0.834	0.854	0.752	0.780	0.751	4.73	5.60	10.34	-0.87
C13	0.736	0.801	0.736	0.691	0.895	0.579	4.44	4.42	8.86	0.02



E+E+E+S criteria selstion | DEMATEL Result+Grap | Dimensions | AHP | AHP Table | Sheet1

Appendix E: AHP calculation in MS Excell 2010



Appendix F: Extent Analysis on Fuzzy AHP calculation

Step:-1: Fuzzy Evaluation Matrix (Pairwise comparism)

	A1			A2			A3			A4			A5			A6				A7	
A1	1	1	1	1/7	1/6	1/5	1/5	1/4	1/3	1/6	1/5	1/4	1/7	1/6	1/5	1/3		1/2	1	1	2
A2	5	6	7	1	1	1	3	4	5	6	7	8	1	1	2	5		6	7	7	8
A3	3	4	5	1/5	1/4	1/3	1	1	1	1	2	3	1/3	1/2	1	3		4	5	5	6
A4	4	5	6	1/8	1/7	1/6	1/3	1/2	1	1	1	1	1/5	1/4	1/3	1		1	2	3	4
A5	5	6	7	1/2	1	1	1	2	3	3	4	5	1	1	1	3		4	5	7	8
A6	1	2	3	1/7	1/6	1/5	1/5	1/4	1/3	1/2	1	1	1/5	1/4	1/3	1		1	1	1	2
A7	1/3	1/2	1	1/9	1/8	1/7	1/7	1/6	1/5	1/5	1/4	1/3	1/9	1/8	1/7	1/3		1/2	1	1	1
A8	3	4	5	1/4	1/3	1/2	1/3	2	3	1	2	3	1/4	1/3	1/2	5		4	3	6	7

	l
Total	104.

Step-4: Fuzzy synthetic degree value (S)

	Sum of 1st=a			(1/u,1/m,1/l)=b			a*b		
	l	*m*	*u*	*1/u*	*1/m*	*1/l*	*l*	*m*	*u*
S1 (A1)	3.19	4.53	6.32	0.006	0.008	0.010	0.02	0.035	0.061
S2 (A2)	30.00	36.00	43.00	0.006	0.008	0.010	0.18	0.276	0.413
S3 (A3)	13.87	18.25	25.33	0.006	0.008	0.010	0.08	0.140	0.243
S4 (A4)	9.99	12.39	16.50	0.006	0.008	0.010	0.06	0.095	0.158
S5 (A5)	22.50	29.00	35.00	0.006	0.008	0.010	0.14	0.222	0.336
S6 (A6)	4.38	6.92	9.07	0.006	0.008	0.010	0.03	0.053	0.087
S7 (A7)	2.36	2.81	3.99	0.006	0.008	0.010	0.01	0.022	0.038
S8 (A8)	16.83	20.67	24.00	0.006	0.008	0.010	0.10	0.158	0.231

Step-5: Degree of possibility (V) *[Condition: 1. if m(S1)>=m(S2) then "1"; Condition:2. if l(S2)>= u(S1) then "0" ; Condition: 3. otherwise= ((l2-u1)/(m1-u1)-(m2-l2))*

V(S1>S2)	0.450	V(S2>S1)	1.000	V(S3>S1)	1.000	V(S4>S1)	1.000	V(S5>S1)	1.000	V(S6>S1)	1.000	V(S7>S1)	0.587	V(S8>S1)	1.000
V(S1>S3)	0.340	V(S2>S3)	0.901	V(S3>S2)	0.450	V(S4>S2)	0.350	V(S5>S2)	0.740	V(S6>S2)	0.590	V(S7>S2)	0.290	V(S8>S2)	0.591
V(S1>S4)	0.250	V(S2>S4)	0.809	V(S3>S4)	1.000	V(S4>S3)	0.621	V(S5>S3)	1.000	V(S6>S3)	0.580	V(S7>S3)	0.450	V(S8>S3)	1.000
V(S1>S5)	0.150	V(S2>S5)	0.801	V(S3>S5)	0.562	V(S4>S5)	0.350	V(S5>S4)	1.000	V(S6>S4)	0.670	V(S7>S4)	0.590	V(S8>S4)	1.000