A GREEN FRAMEWORK FOR MANUFACTURING: PRODUCT, PROCESS AND SYSTEM LEVELS

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Abstract

The term green manufacturing is coined to reflect the new manufacturing paradigm that employs various green strategies (objectives and principles) and techniques (technology and innovations) to become more eco-efficient. The greening of manufacturing industry requires a holistic view spanning throughout the product, process and system level including: less material and energy consumption, reduced waste and emission as well as recycling or reuse. The aim of this research is to employ green strategies that lead towards green manufacturing via product, process and system level. This work is divided into three segments: product base, process base and system base.

In the product base segment, Life cycle inventory (LCI) is a popular measure which is computed to acquire the consumption (raw materials or energy) and emission (greenhouse gas or waste quantity) of a product system. The three main currently available methods of LCI are: Process based LCI, Input output LCI and Hybrid method method. These methods may provide different environmental impact results for the same product. In order to choose a particular method, one should know the calculation process, relative advantages and limitations for the intended purpose. These methods provide environmental impact data which are utilized in different sustainability measures. Environmental decision making is one such important LCI application. However, literatures are found where this decision making are performed on the basis of a particular impact category although a comparison based on overall environmental impact is more realistic. Different impact categories exhibit different increasing and decreasing trends simultaneously and they have different unit of measurement. In this project, a review on the LCI methods and a novel approach for using overall LCI data for environmental decision making for food products has been presented.

Under process base improvement, green energy management is one of the prime concerns for any industry. For green energy management, a renewable energy source is highly required. Waste-to-energy (WtE) can be an attractive solution for renewable energy source. The objective of this work is to propose a strategy to reduce the electricity bill for the industry under variable electricity pricing. In order to reduce the electricity bill, a fuzzy Inference System (FIS) based energy management strategy to produce electricity in low pricing period and utilize it in peak period is proposed by integrating small scale WtE and storage into industry system. Though this model is built for energy management, it indirectly works as a tool for waste management as well. The performance of the proposed model is tested with the data collected from a plastic container manufacturing industry.

Green supply chain network synthesis is one of the major system level improvements. This network is the combination of various stages such as; raw materials acquisition, processing, manufacturing, packaging, distribution and so on. Green supply chain network design is such an optimization act which combines the feasible pathways among the supply chain stages to serve environmental sustainability. However, modelling supply chain network is a complex task. Though mathematical modelling is a conventional approach to design this complex network, for larger size problem it becomes highly difficult. Furthermore, changing any variable like; materials, energy sources or process technologies etc. make this optimization even more time consuming. Process Network Synthesis (PNS) methodology based on P-graph (process Graph) is a new approach recently been adopted by practitioners for designing a sustainable supply chain network successfully. In this work, a green supply chain network is designed by P-graph approach for co-firing of bio mass in Rajshahi, Bangladesh.

Keywords : Green manufacturing, Product base, Process base, System base

Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

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CHAPTER 1: INTRODUCTION

1.1. Research Background

Green mode of manufacturing has emerged into industrial world due to several established and emerging causes such as; diminishing of conventional fuel sources, global warming, stricter environmental regulations, increasing stake holder's preference for environment friendly products and so on. Therefore transformation into green or clean is undoubtedly a well-recognized need for any industry. The term green manufacturing is defined as a new manufacturing initiative that involves numerous green strategies and techniques to become more environment friendly (Deif, 2011). This involves creating products/process/systems that consume less material and energy, substituting input materials (e.g. non-toxic for toxic, renewable for non-renewable), reducing waste and recycling or reuse. A green manufacturing framework should be aware of its production system/product impact on the environment and resources and include such impact in its overall operational planning and control. Therefore, it does not simply focus on 'technology' but also emphasizes on changes in management. The above mentioned definition set a holistic objective to be achieved for green manufacturing (Jayal et al., 2010).

For green manufacturing, there is a need to achieve optimized performance of the overall manufacturing system. It not only includes technological improvements but also requires optimizing the overall cost along with reducing energy, resource consumptions and wastes and maximizing recycling/reuse for the whole industry supply chain. This provides a win-win situation where manufacturers can improve their environmental performance along with achieving economic gains (Deif, 2011). In order to do this, the amount of resource consumption or emission or waste production should be computed for the overall product life cycle. Necessary measures should be taken to reduce these consumption or emission for one or several stages of the product life cycle to transform the industry into green. This requires identifying and developing new processes or improving the existing processes for product manufacture or sometimes implementing process controls to manufacture all green products out of that process (Jawahir and Jayal, 2011). Various green manufacturing initiatives includes: energy management system, combined heat and power system (Lund and Mathiesen, 2015), waste management system, design for disassembly (Khor and Udin, 2013), design for environment (Birch et al., 2012), optimal process design (Campatelli et al., 2014), developing new process technology (Tanzi et al., 2013) and so on. Furthermore, it also involves the “6R” approach - Reduce, Reuse, Recycle, Recover, Redesign and Remanufacture instead of conventional “3R” concept (Reduce, Reuse, Recycle) (Joshi et al., 2006).

Green manufacturing effort are also taken at the macro level or at supply chain stages such as: planning, sourcing, operations and logistics (Wang et al., 2011) to manufacture green product out of that industry system. This kind of improvement are implemented at (i) planning phase such as: location decision (Elhedhli and Merrick, 2012), storing decision etc or (ii) Sourcing phase such as: Supplier selection (Lee et al., 2009), make/ buy decision (Hall, 2000) etc., or (iii) manufacturing phase such as: production planning (Hong et al., 2012), packaging or (iv) delivery phase (route/ mode of transportation (Hoen et al., 2010).

1.2. Problem Statement

Manufacturing industries are the prime contributor of environmental pollution. They consume the highest amount of energy and also produce huge amount of emission. For example, in Taiwan, industries are responsible for 53.8% of the nation's total energy use while Chinese industrial sector is consuming approximately 70% of the country's total energy (Lu et al., 2013). According to Abdelaziz et al. (2011) the worldwide industrial energy consumption is projected to grow by an average of 1.4% per year. The increased consumption of fuel and various industrial processes cause huge amount of Green House Gas (GHGs) emission by the industries. For example, direct industrial GHG emission in 2014 is found as approximately 21% of total U.S. greenhouse gas emissions (U.S. Climate Action Report, 2014). Therefore, consumer awareness towards environment friendly products rises and environmental regulations become increasingly rigorous. As a result, environmental concern is getting more and more imperative for the industries (Bouchery et al. 2012; Zhang and Xu 2013).

An important environment contaminating factor for the industry is the product produced from it. A product produced by green manufacturing process is not fully green if it causes environment contamination during its use and disposal phase. A simple example can be a light bulb. The electricity used over the lifetime of a single incandescent bulb is much more higher than a Light Emitting Diode (LED) and Compact Fluorescent Lights (CFL) bulbs even if all of them can be made by green manufacturing process. A product consumes different amount of energy and produces different amount of waste and emission in different stages of its life cycle. A product can be said greener compared to other product when the former one has less total LCI (Life Cycle Inventory) than the later one. An example found in Brodt et al. (2013) reveals that among 1 kg paste tomato and 1 kg diced tomato produced by the same organic agricultural industry; the former one has larger total life cycle impact value.

Various industrial processes are performed in an industry to produce a product. Industrial processes need energy and most of the industries produce energy by burning conventional fossil fuel. This energy production process is the direct contributor of GHG emission. Even if some industries buy energy from other third party energy companies, still they remain as indirect emission contributor to the environment. Moreover, there are many industries whose major manufacturing process is not environmentally sound such as: iron, steel and metallurgical coke production, cement manufacturing process, ammonia production, lime production, limestone and dolomite use (e.g., flux stone, flue gas desulfurization, and glass manufacturing), soda ash production and consumption, titanium dioxide production, phosphoric acid production, ferroalloy production, silicon carbide production and consumption, food production, aluminum production, petrochemical production, nitric acid production, lead and zinc production (Benhelal et al., 2013). In addition to energy consumption and emission, waste production is another environmentally degrading process of industries. Waste is harmful without proper waste management such as: recycle or reuse.

Sometimes, environmental contamination can be performed by the industry at its operational system level or the supply chain. Supply chain is the link bridge between facility operation and transportation. Cleaner process and product cannot ensure an overall green industry if the supply chain operation is not green. Longer travel distances and energy/emission intensive vehicles lead to increased environmental impact on the delivery of products manufactured by the industries (Elhedhli and Merrick, 2012). On the other hand, the industry still remain indirect pollution contributor if the sourcing or purchasing decision is not green (Lee et al., 2009). All these are supply chain measures and there is a clear need to effectively and efficiently design eco-friendly supply chains to improve both environmental conditions and the bottom line of the organization.

From the above discussion, it is eminent that an industry needs improvement in its process, product and system level to achieve green. Improving at one level can sometimes ignore at other and cannot ensure an overall green framework for the industries. Green manufacturing is a robust area. Numerous studies cover enormous industry requirements. However, during conducting the current work, some important industry needs have been identified which motivated me to propose this project.

1.3. Organization of The Thesis

In this thesis, attempt has been taken to propose a green framework consisting of product, process and system level. This thesis is composed of three piece meal work under: product, process and system level. The chapters in thesis are organized as follows:

In chapter 2, the relevant literatures are discussed in brief. This chapter is consisting of 5 sections. The first section is a brief introduction. The second, third and fourth sections cover literatures under product level, process level and system level improvement respectively. The last section is the state of the art for the literature discussed in previous three sections.

In chapter 3, the scope of the study based on literature survey is discussed. The objectives of the study are presented in this section under scope of the study.

Chapter 4 depicts the product level improvement shown in this thesis. This chapter is divided into two parts. The first part is dedicated to life cycle inventory evolution, their mathematical deduction and application procedure. The second part shows the application of life cycle inventory. A novel framework for decision making based on Life cycle inventory is presented here.

Chapter 5 is designed for green process level improvement. This chapter presents an energy management strategy based on Waste to energy and storage.

Chapter 6 shows the system level improvement via green supply chain network synthesis. P-graph approach is adopted for this network design.

Chapter 7 shows the conclusion of the thesis. It includes the discussion and summary of the main findings of the thesis. Furthermore, it also includes the direction in which future work can be carried out.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

A plenty of studies discussing the need of a green frame work for an industry have been found in the literature. The contributions and shortcomings of these studies favored me to depict this project outline. Based on the discussion under problem statement in section 1.2, it is prominent that, study is required at three levels: Process, Product and System.

Therefore, this section has been divided into four sub sections. In first three sections, the literature has been discussed with the review on relevant previous studies and their gaps and the last section depicts the State of the art for discussion under previous three sections. Literatures on green product level improvement have been shown under section 2.2. Section 2.3 is designed for the literature related to green process level improvement for industries. Section 2.4 depicts the green system level improvement. And finally, section 2.5 shows the summary of all three sections in state of the art.

2.2. Green Product Level Improvement

The industries produce various kinds of products. A product is said to be green when it produces less environmental impact at all stages of its life cycle. For green product level improvement, the environmental impact produced by a product needs to be known. Zero environmental impact is impossible but green product level improvement entail a comparative less environmental impact. Life cycle assessment is a popular approach in order to assess the environmental impact of a product.

2.2.1. Life Cycle Assessment

In order to perform a product level improvement for green manufacturing, the product's environmental burdens are needed to be computed. This kind of computation is undergone via Life Cycle Assessment (LCA). The result of LCA can be utilized in two ways: for choosing a green product or by choosing a green process for the manufacturing to make the product green.

LCA has four steps: Goal and scope definition, Life Cycle Inventory (LCI), Life Cycle Impact Assessment (LCIA) and Life Cycle Interpretation. The LCA begins with a clear statement of the goal and scope of the study which includes all technical details i.e.: functional unit, system boundary, assumptions and limitations etc. LCI is the second step which deals with the quantification and accumulation of a products inputs i.e: raw material, energy, water consumption etc. and outputs i.e.: emission, waste etc. The next step is LCIA which is performed utilizing the result found in LCI stage to evaluate the significance of potential impacts. Finally, all these results are discussed in Life cycle interpretation stage for the purposes such as: comparison of various life cycle stages of a product or comparison among various products or process on the basis of environmental performance. Among all these steps, LCI is the most crucial and time consuming. The success of a LCA result largely depends on the LCI. Various methods of LCI are introduced by the practitioners one after another to make it easier and more accurate. Hence, the literature on various methods of LCI is discussed here in brief.

There are mainly three types of LCI techniques: Process based LCI, Input Output (IO) LCI and Hybrid method LCI. Hybrid method LCI is divided into three more types: Tiered hybrid method, IO based Hybrid method, Integrated hybrid method. Different LCI techniques have different competencies. However, in order to select a proper LCI technique for the intended study, two things must be given emphasize: (i) Acuracy; (ii) Boundary completeness (Lenzen and Crawford, 2009). Process based LCI is able to offer greater accuracy but it comes in short with system boundary completeness. On the other hand, *IO* LCI is the most suitable one for boundary completeness when the accuracy is compromised as it suffers with data uncertainty. These two LCI techniques are combined in *Hybrid method* method which may offer both accuracy and boundary completeness but it is sometimes hampered by data double counting and methodological complexity. Nevertheless, deciding on an appropriate LCI technique depends on the factors such as: objective, functional unit, availability of time, labor, money and so on. Therefore, a LCI technique which includes much detailing can provide more accurate result but consuming more time; hence it is suitable for a long term decision. In contrast, in case of taking a rough fast decision, a method requires less time but offers coarse output is a more suitable choice. Therefore, for choosing a proper LCI technique, it is also vital to know their methodological procedure, data and time requirement, advantages and disadvantages.

Different LCI methodologies with their corresponding examples are found in literature. Such as: Heijungs and Suh (2002) provides process-based LCI model; Hendrickson et al (2006) contains IO LCI model; Bullard and Pilati (1978) shows Tiered hybrid method; Treloar et al. (2001) includes IO based hybrid method LCI model; Suh and Huppes (2000) comprises integrated hybrid method. The knowledge on LCI technique and their application procedure is spreaded over diverse literatures. Although, some Reviews are available on various LCI application but they are directed towards particular area; for example: LCA of food products (Roy et al., 2009), LCA of Solid waste management (Laurent et al., 2014), LCA of Biofuel (Menten et al., 2013), LCA of Metal industry (Liu and Müller, 2012) etc. Nonetheless, a merged review on LCI is yet to report and the trend and development on various LCI methods is highly necessary.

Several examples of various LCI techniques are studied by the practitioners. Process based LCI are applied on the studies such as: Energy product (Guezuraga et al. (2012), Pharmaceutical product (Boltic et al., 2013), food products (Cellura et al., 2012) etc. IO LCI method is implemented for the study of the water foot print (Okadera et al., 2015), global carbon foot print (Fang et al., 2014), nitrogen foot print (Pierer et al., 2014), ecological foot print (Weinzettel et al., 2014) and so on. Tiered hybrid method method is adopted for some approaches such as: energy production (Chang et al., 2014, Yao et al., 2014), building energy analysis (Bullard et al., 1978), nano manufacturing (Wang and Yuan, 2014), etc. IO based Hybrid method method is effectively employed in various literatures such as: GHG intensities (Acquaye et al., 2011), energy technologies (Chang et al., 2014, Wiedmann et al., 2011), energy requirements (Jiang et al., 2014a) and so on. Integrated hybrid method is successfully adopted for different LCA analysis such as: energy consumption (Jiang et al., 2014b), emission (Bush et al., 2014), water consumption (Feng et al., 2014), etc. However, in these studies the methodologies of different LCI are barely reported. For conducting LCA for any product or process, the knowledge on data collection, appropriate method selection and reporting of assumptions and results are highly required. Moreover, for successful LCA software design and implementation, right guidelines on LCI methods are necessary.

2.2.2. Use of Life Cycle Assessment

The use of LCA or LCI is not only limited to product's life cycle environmental impact computation. Its scope is broaden by using in some more specific product level improvement measures like: Strategic Environmental Assessment (Björklund A., 2012), Environmental Key performance index (De Marco et al., 2015), Multi-Criteria Decision Analysis (Prado-Lopez et al., 2014), Design for Environment (Hernandez et al., 2012), Material Flow Analysis (Rochat et al., 2013), Life Cycle Costing (Swarr et al., 2011), Life cycle optimization (You and Wang, 2011) etc

LCA is popularly applied for comparing among various alternatives by figuring their environmental degrading indicators associated with upstream and downstream stages such as: raw material, product processing, product distribution, use, and disposal (Banos et al., 2011). Throughout this assessment, each environmental indicator caused by all stages from a specific category is summed up. Which indicators are selected usually depends on the objective of the intended study. These indicators are taken in any of the forms of LCI such as: emissions, resource consumption, water and land use, chemical consumption etc (Brodt et al., 2013) or inventory converting to corresponding LCIA such as Global energy requirement, Global warming potential, Ozone depletion potential, Photochemical oxidation, Acidification, Eutrophication, toxicity etc (Gloria et al., 2007). Along with these environmental degrading indicators some products may offer environmental benefit indicators. For example: a food product may have benefit indicators like its nutrition, calorie value, vitamins, anti-oxidant potential etc (Donno et al., 2012). However, all of these indicators' (environment degrading/ environment benefit) actually depends on the functional unit for the intended study such as: for food products it should be inventory or impacts per weight or per nutrition value or per cost or per income and so on (Cerutti et al., 2013). For example, two fruit products are compared considering the functional unit of 1ton fruit by impact/ton fruit. In this case, fruit product 1 is found to be as less environmental friendly compared to fruit product 2. Now the functional unit is changed to grower's income like impact/$1000. Consequently, fruit product 1 is found to be more environmental friendly than fruit product 2. This is because; for making make $1000 income, fruit product 2 causes more environmentally harmful impact than that of fruit product 1. Yet again, if the fruit product 2 is consist of more anti-oxidant compound than fruit product 1, then fruit product 2 becomes more environmental friendly by counterbalancing the environment degrading indicator by its benefit potential.

A single product's LCA study cannot help to make a decision on whether the product is green or not. Green or environmental decision making is a comparative measure. For this study a literature survey on the food product is conducted. Brodt et al. (2014) figure out greenhouse gas emission for a rice product. However, this study does not provide a conclusion on if the rice is green or not since a green decision should not be made from the study of a single product. Krakaya and Ozilgen (2011) analyze LCA result for energy consumption and emissions throughout the production of fresh, diced, peeled and juiced tomatoes separately. Moreover, Mohammadi et al. (2015) calculate LCA result for 82 kind of rice paddy species with seasonal variation with the aim of evaluating their green potential. Nevertheless, all these studies are unable to deliver an aggregated environmental impact result which is highly required for this kind of comparison. Another study conducted by Hall et al. (2014) show the implication of LCA for comparison among various impact categories such as: global warming potential, land use and water use for Chicken and lettuce from an industrial production and two civic productions. The result found from this study reveals that, though the water use is alike for two lettuce civic producers, the land use is greater for that of the civic producer 1. On the contrary, the civic producer 2 is emitting more Green House Gas (GHG). Hence, it is very hard to come to a conclusion on which lettuce product is comparatively greener. Again in another study the comparison among various vegetables based on LCA is reported (Cellurra et al., 2012). In this study, 1000 kilogram of packaged vegetable is considered as a functional unit. However, different food products of with same weight value do not contribute similar function in terms of nutrition, calorie value, growers income and so on. Moreover, the delivery mode and delivery distance are also significant contributor of product's LCA. A study performed by Brodt et al. (2013) depicts the comparative analysis of environmental impacts for local versus long distance delivery of 1 kg tomato products in its different forms. This study uses the graphical representation and it is limited to only three indicators, i.e; energy consumption, GHGs emissions, water use. Actually for graphical representation, the comparison becomes difficult when the number of indicators increases. Some study uses spider diagram for this kind of comparison as it is able to represent overal comparisons via one diagram. However, this representation looks clumsy for larger number of alternatives. This kind of problem can be considered as comparing among multidimensional choices which can be availed by decision making with numerical value (Sikdar 2009).

In numerous previous studies (Jeswani et al. 2010), LCA is implemented for multi-dimensional choices. Seager and Linkov (2008) combine LCA and multidimensional choices to benefit the understanding of compromises and multiple perspectives in life cycle assessment. Klein and Whalley (2015) also use LCA for multi criteria decision making for green energy option. An aggregated environmental index is the best solution for this kind of analysis. Environmental index is an excellent decision-support tool which avail easier but effective comparison for the environmental impacts among various products. This is because, this index is a one dimensional illustration and its computational complexity and representation are not affected by how bigger is impact categories pool and how many are the alternatives (Mogensen et al. 2009). However, the bigger obstacle to compute a single environmental index is: it is not possible to compare or aggregate environmental impacts across the impact categories; because different impact categories have different units (Myllyviita et al. 2014). Formulating different index for different impact categories is tedious and time consuming. Moreover, it is not useful for making an accumulated decision.

Anyway, there are some prerequisites for computing an aggregated index (Böhringer and Jochem, 2007). Firstly, A conscious selection of indicators is required which ensure that themes direct the thematic aggregation method and units direct the technical aggregation method. It reveals that, the aggregated index is ought to be a summation of all environmental indicators and the accumulation of these indicators is mathematically valid. Usually, for this accumulation, first normalization is applied to convert different impact categories into dimensionless or unit less numerical values which comply to the technical aggregation prerequisite (Böhringer and Jochem 2007). Secondly, the normalization operation is required to be treated in such a transparent way that it is subject to all-inclusive sensitivity analysis. That means, the normalized values should be a one to one representation of the original data set (Reed and Simon 1972; Ebert and Welsch 2004) such as: invariance to affine transformation and linear change of units, conformity to translational invariance. Thirdly, commensurability of the original data set must be guaranteed. Meaningfulness is the most important factor for ensuring commensurability (Ebert and Welsch, 2004). According to Ebert and Welsch (2004) a index is said meaningful when the ordering obeys unambiguity, consistency, monotonicity and separability. Though some aggregated index are found to show meaningfulness when the input data set is comprised of ratio scale data, but meaningfulness property is unfulfilled when there are interval scale data in the input data set (temperature: Celsius, Fahrenheit) (Böhringer and Jochem 2007).

Numerous computational methods for aggregated index are adopted by the practitioners. For comparing among various manufacturing processes of the same product, Sikdar (2009) introduce a metric which measures the relative distances for each process with a fixed reference process. This distance is computed by the geometric mean of the factor indicators normalized by those of the reference process. This computation method is useful until all the indicators are environmental degrading or positive indicators. However, this method suffers when any of the indicators is zero or negative (benefit indicators).In contrast, a simple Euclidian distance is invalid in this case. This is because it overlooks the influence of positive and negative differences among the processes. Moreover, it cannot handle different indicators with different units. This limitation is solved by Sikdar et al. (2012) by computing aggregated index by transforming the reference points to the alternative with minimum environmental indicators. In this study, normalized Euclidean distance is computed after this transformation. The same hierarchy can be obtained by geometric mean formula. Though for this method a different reference point is chosen and the index values are not the same. A Canberra distance measured by Brandi et al. (2014) also offers the same conclusion. Yet, this index does not show invariance under translational operation (dos Santos and Brandi 2015), it is altered into z Canberra distance (dos Santos and Brandi 2015). This index shows invariance for translational operation. It is also meaningful if all the input values are ratio scale data. Nevertheless, this method cannot conserve ratio invariance among the normalized indicators when the data is interval scale (temperature: Celsius, Fahrenheit). Therefore, in this method meaningfulness property is hampered for interval scale data. Another new method named as vector space theory is introduced by Olinto (2014) which compares environmental index of various production processes. a normed linear space is the outcome of this method which is computed via simple normalization and the ordinary Euclidean metric. Some strengths of this method is it treats positive and negative indicators similarly, and it provides a faithful representation of the original data set.

The normalization method adopted in vector space theory is highly effective for conforming to the prerequisites of aggregated index discussed before. It is a one to one representation of the original impact values (Olinto 2015). The ratio found by the normalization conforms to meaningfulness property for both ratio and interval scale data set. Moreover, the aggregated index shows robustness. This method is transparent because different alternatives with similar indicators are comparable even if they are assessed separately. This is the outcome of the fact that the comparable alternatives have the same a priori reference points which is the origin.

2.2.3. Green Process Level Improvement

Among all the process level improvement, industry's energy consumption improvement is the prominent one. This is because; the industrial sector uses the highest amount of energy for its various processes. This situation leads to the overall increase in worldwide fuel consumption. Consequently there is a rapid increase in energy price and greenhouse gas emission. Renewable energy based systems can be a solution to greenhouse gas emissions. Therefore, traditional energy supplies are being replaced by renewable sources of energy and new strategies are being planned for energy management within industries.

Energy management is a popular practice now a day. It not only reduces the increased energy cost but sometimes enhance industrial environmental practice. It is a strategy to meet energy demand when and where it is needed. This can be obtained by optimizing energy consumption pattern. This can also be useful for reducing the total cost production for the industries (Abdelaziz, Saidur et al. 2011). For attaining energy efficiency and mitigating environmental pollution, it is highly effective.

Energy management for industries is highly important when it operates under variable electricity pricing. Instead of a flat electricity bill, variable pricing causes different rates charged at different periods which depend on the time of using the electricity (peak, shoulder, off peak). The price difference can vary with the hour, day or month and also some depends on the customers' demand concentration on each period. Usually high rates are imposed on high demand period and vice versa. This is because, at high demand period, the electricity production capacity needs to be increased a lot. On the other hand, at low demand period, electricity price is low. However, industries make their production plan based on the customer demand rather than the electricity price. Therefore, industries require more electricity when their production quantity is high though electricity price can be high at different time of the day. Therefore, industry's electricity consumption cost gets bigger when industries requirement gets high at peak pricing period.

Efficient energy management can help in this case by balancing the industry's energy demand. It may either shift some demand from high price period to low price period or provide with a backup electricity source such as: alternate renewable energy source to supply energy at high pricing period or energy storage for storing energy during lower industry demand and supply it when industry demand gets higher.

Many studies have been found on energy management strategy with renewable energy and storage system. Zhang et al. introduced an energy management system for a super market using PV cell and storage(Zhang, Davigny et al. 2012). Garcia et al. presented another hybrid method model comprised of wind turbine, PV cell, hydrogen sub system and battery (García, Torreglosa et al. 2013). On the contrary, a study based on stand-alone wind-PV hybrid method system with a backup battery to supply electricity to an island is discussed by Hashimito et al.(2005). All of these energy management studies were based on commonly used renewable sources: solar, wind etc. However, their various limitations such as: dependence on weather condition, inherited intermittent nature and lack of stable power supply are also discussed (Duić 2015).

Another limitation of these common renewable energy sources (solar, wind etc.) is: they have limited scope for reducing emission. In contrast, waste as a renewable energy source becomes more favorable when its environmental waste management potential and energy management potential are considered together (Münster and Meibom 2011). It is heighted by a report published by U.S. Energy Information Administration (EIA) on 2014. The report compares among various renewable energy sources and shows that waste technology stands at the top due to its fairly steady nature and high calorific value. This study justifies the use of waste in procing renewable energy. However, in literature, waste-to-energy (WtE) has always been studied as a system of waste management though it can be considered as a reliable source of energy management well.

The higher establishment cost of WtE is the main reason for not considering WtE for energy management. Consequently, it has commonly being utilized for municipal solid waste (MSW) management in larger scale (Münster and Meibom 2011). Although, the coal's calorific value is close to that of MSW (about 10 MJ/kg), there are substantial reasons which make the establishment of WtE plants highly expensive than conventional coal-fired plants. In order to reduce this high establishment cost, many studies have been undergone (Themelis and Reshadi 2009; Mastellone, Zaccariello et al. 2010). These studies deal with the improvement of waste to energy conversion technology. As an outcome of these research, waste gasification has replaced waste combustion when the requirement is low capacity WtE plant (Ellyin and Themelis 2011). This technology improvement gives rise to some small scale WtE plant around the world. Ellyin and Themelis (Ellyin and Themelis 2011) depicts the technical, economic, and environmental features of some current world wide small-scale WtE plants.

For WtE, municipal solid waste has been popularly considered as a potential feedstock (Shareefdeen, Elkamel et al. 2015). However, these studies have overlooked the prospective benefits of industrial waste to be feed into the WtE. Industrial waste is a major byproduct of industrial processes. For example, the food processing industries convert 30% of its incoming raw materials into waste rather than a value-added product (Schaub and Leonard 1996). In another study, it is found that a large paper plant in Italy produces around 52 t of sludge output per day (Caputo and Pelagagge 2001). The treatment and disposal of this waste cause a huge amount of cost for these industries. This high cost prompts the industries to generate an alternate solution for waste management. This alternate solution is more instigated when the similarity between municipal waste and industrial waste for used as an energy source is revealed (Lupa, Ricketts et al. 2011). This study rationalizes the use of WtE in industrial waste treatment. This solution is cost effective and environmental friendly.

Usually third party WtE Company performs the function of waste treatment or energy supply. When an industry takes this service from a third party WtE company, it has to pay in two ways; for waste treatment and for electricity purchase. There still remain some other limitations. Such as: (i) Cost turn out to be bigger for frequently generated waste and fluctuating electricity demand; (ii) Transportation cost becomes prominent when no nearby WtE facility is available. (iii) Going to a third party, lacks in control and cause disintegration and higher cost of waste management and electricity consumption; (iv) Different industry produces a different type of waste and heterogeneous nature of waste creates a widely varying chemical constituency of the energy generated from these processes and affects the efficiency. All of these factors lead to the increase in expenditure of the customer industries.

Some studies have been reported on an onsite WtE facility in industries to meet up the purpose of their waste management (Villar, Arribas et al. 2012). Caputto & Pelagagge (Caputo and Pelagagge 2001) presented a techno-economic evaluation of establishing an onsite WtE plant in an Italian paper industry. Caputo et al. (Caputo, Scacchia et al. 2003) conducted a study on the technical and economic viability of combined treatment of different type of waste in an onsite WtE within an olive oil industry. However, all these studies only considers the waste management potential of WtE which saves huge land filling cost. Only waste management cannot complete the use of WtE in industries. The energy it produces can be considered as an excellent energy backup for the industries.

Industry can utilize WtE along with storage as a wonderful solution for energy management when it operates under variable electricity pricing. The storage can store the energy produced from WtE when it is low pricing period. Again, this stored energy can be supplied when the pricing period is high. This will keep the consumption on supply from main grid lower at high pricing period. This kind of guiding principle are best served by Fuzzy logic (García, Torreglosa et al. 2013; Ciabattoni, Grisostomi et al. 2014; Suganthi, Iniyan et al. 2015).

2.4. Green System Level Development

Now-a-days companies are under pressure by the customers and legislation to design their whole supply chain system in such a way as to reduce negative environmental impacts more and more. One of the major green manufacturing measures is green supply chain network synthesis. Supply chain network is synthesized to organize the processes involved in supply chain activities for production and distribution of a commodity. This network is the combination of various stages such as; raw materials acquisition, processing, manufacturing, packaging, distribution and so on. However, modeling supply chain network is a complex task. There is huge number of alternative routes among various layers forming the combination of processing, manufacturing, packaging, distribution and so on. In this project, the literature for green supply chain network synthesis is studied for the scenario of biomass supply chain in Bangladesh.

Bangladesh is one of the densely populated country and about 51% of its population have no access to electricity (Das and Hoque, 2014). Per Capita energy consumption in this country is the lowest among Indian subcontinent and its value is found as approximately 293 kg of oil equivalent in 2015 (The World Bank, 2014). Currently the production of electricity in Bangladesh is about 6000 MW and most of this generation is dependent upon conventional fuel source i.e. Natural gas, oil and coal (Hoque et al., 2014). However, supply of natural gas has been in shortage because of the lack of exploration of new gas fields and depletion of present gas reserves (Wadud et al., 2011). At present, production of natural gas in Bangladesh is about 1100 million cubic feet/per day, while about 3 million tons of petroleum products are imported every year. The only coal power plant is situated in Barapukuria which is just near to the single Coal Mine Company in Bangladesh. These coal mine company is also facing huge loss because of supplying coal to Barapukuria power plant at low price. The cost of extracting coal is $125 per ton while the selling rate is only $84 (Daily star, 2011). Therefore, the coal price has been decided to increase. All these factors influence insufficient electricity supply (Mustafa et al., 2012). Therefore, Bangladesh is suffering from loss of electricity of around 600 MW and currently around 51% of the overall population is deprived of connection to electricity grid (Huda et al., 2014). In order to overcome this situation, the government has planned to ensure the availability of electricity all over the country by the year of 2020 (Huda et al., 2014).

Another disadvantage of this conventional fossil fuel is environmental pollution. The electricity generation sector has been identified as the source of the largest carbon dioxide emissions in Bangladesh which amount to 15.6 Mt CO_2 (IEAGHG, 2008). Some largest CO_2 producing power plants are shown in Table 1 (IEAGHG, 2008).

Table 1:CO_2 Production by the power plants of Bangladesh

Sector	**Name**	**Division**	**Technology**	**Capacity**	**CO_2 emissions (kt/year)**
Power	Ashuganj	Barisal	Oil & gas fired thermal	720 MW	1502
Power	Chittagong	Chittagong	Gas engine	44 MW	914
Power	Ghorasal	Dhaka	Oil & gas fired thermal	950 MW	4731
Power	Haripur Barge	Dhaka	Oil fired	120 MW	980

			thermal		
Power	Shiddhirganj	Dhaka	gas fired thermal	260 MW	631
Power	Maghnaghat-1	Dhaka	Gas turbine	335 MW	490
Power	Maghnaghat-2	Dhaka	Oil & gas fired thermal	220 MW	392
Power	Dhaka	Dhaka	Gas engine	41 MW	327
Power	Haripur	Dhaka	Gas engine	96 MW	218
Power	Khulna	Khulna			938
Power	Golapara	Khulna	Oil fired thermal	170 MW	479
Power	Barapukuria	Rajshahi	coal fired	250 MW	2075
Power	Baghabari	Rajshahi	Oil fired thermal	110 MW	181
Power	Haripur AES	Sylhet	Gas engine	360 MW	653
Power	Shajibazar	Sylhet	Oil & gas fired thermal	183 MW	631
Power	Fenchuganj	Sylhet	Oil & gas fired thermal	97 MW	182

Some options for long-term pollution reduction technologies can be renewable energy power plant (solar, wind, hydro, nuclear etc), CO_2 sequestration, oxy-firing, carbon loop combustion and so on. Supply of some renewable energy like: solar, wind is intermittent and not available all over the year. Furthermore, building of a new power generation facility incurs a huge amount of fixed capital cost, area and resources (Beck and Martinot, 2004). On the other hand, the cost of CO_2 capture, sequestration, oxy-firing, carbon loop combustion etc. is quite high and the technology is not fully developed (Basu et al., 2011). Therefore, a renewable energy source is required which is available, cheaper and involve less technological implication.

Biomass can be considered as a potential source of renewable energy in Bangladesh. Biomass is organic matter derived from contemporary biological origin (Ahiduzzaman, 2007). All sorts of organic substances such as agricultural crops, trees, plant residues, wood, animal wastes, municipal and industrial wastes, sewage sludge etc. are some of the main sources of biomass in this country. Hassan et al. (2011) estimate bio energy potential of major crop such as rice, wheat, jute, sugarcane, mustard, coconut, lentil residues in Bangladesh. The results show that the total bio energy potential from selected crops residues is approximately 525.87 million GJ in 2009 and it is estimated to rise to 711.27 million GJ by the year 2020 (Hassan et al., 2011). In the rural area of Bangladesh, biomass is usually burnt for various purposes such as: fuel for cooking and space heating. Moreover, in some other areas biomass is either burnt for attaining high temperature or for converting to other energy sources (Halder et al., 2014). However, these technologies of burning of biomass is typically inefficient and releases over 200 volatile and particulate substances (Salje et al., 2014). Therefore, the biomass utilization process needs necessary improvement. In relation to technological selection, numerous studies have been conducted (McKendry, 2002, Sofer and Zaborsky, 2012). Various options of biomass conversion technology includes: Gasification (Buragohain et al., 2010) Combustion (Maraver et al., 2013), Pyrolysis (Shemfe et al., 2015) etc.

Some government other commercial biomass plants are planned throughout Bangladesh (Mondal et al., 2010). The first biogas plant is set up in the campus of Bangladesh Agricultural University in 1972 (Huda et al., 2014). Another 85 m^3 biogas plant is built by the Institute for Fuel Research and Development (IFRD), Bangladesh Council of Scientific Industrial Research (BCSIR) and Dhaka City Corporation (Ahmed and Bahauddin, 2012). Infrastructure Development Company Limited (IDCOL) has so far financed 9 biogas based power plants in different locations of Bangladesh and among those the largest one having a capacity of 400Kw (IDCOL, 2015). Till April 2012, more than 22,000 biogas plants have been set up in different parts of the country (Huda et al., 2014). However, the cost related to set up, operation, collection and delivery make this choice economically unsuccessful to compete with the existing petroleum-refinery technologies (Srirangan et al., 2012, Asadullah, 2014). Therefore, in order to attain better competitive advantage, a more favorable technological selection along with cost effective collection and delivery operation is highly required (Asadullah, 2014).

Actually the commercial utilization of biomass involves some constraints. Firstly, the operation of biomass conversion plant incurs huge cost due to low conversion efficiency. Secondly, setting a new plant is quite expensive (Sarkar et al., 2003). Thirdly, biomass sources are distributed over a larger area and their collection and delivery to the conversion plant is cost intensive (Turco et al., 2016); the biomass directly collected from field is less expensive than the bio mass residue collected from another industry; the bulk density of these biomass affects the number of trip required to collect them which also consequently affects transportation cost. Fourthly, the transportation of biomass causes substantial emission when the biomass sources are widely dispersed; despite being a clean energy source, the biomass supply chain cannot provide clean energy. Fifthly, different biomass has different heating value and their price is also different; so different biomass provide different energy potential at same cost, so their selection is very important. Finally, raw biomass especially agricultural biomass, is excessively wet (450 wt%), it is not feasible to store it at the place of origin (Asadullah, 2014); moreover, storing of biomass incurs some carrying cost; therefore instantaneous consumption of biomass is necessary. Therefore, considering all these requisites a near optimal supply chain solution is highly essential.

The first and second limitations can be resolved by Co-firing of biomass in existing petroleum refinery power plant (Demirbaş, 2003). It offers a great solution for emission reduction and cost effectiveness. According to Basu et al. (2011) the total reduction in CO_2 emissions would be significant if the majority of coal-fired plants operating throughout the world adopt co-firing. Co-firing can save the establishment of new biomass power plant. For a normal co-firing plant, the energy requirement for boiler operation remain identical as it is operated under the same steam load conditions (for heating or power generation), with the same heat input as that in the existing coal-fired plant. Another advantage of co-firing is its reduced costs because the cost of biomass is lower than that of fossil fuel, and escaping landfill tipping fees or other costs that would otherwise be required for disposal of unwanted biomass (Basu et al., 2011). Currently Bangladesh is having co generation facility for producing bioenergy in almost all Sugar mill industries (Sarkar et al., 2003). However, the biomass co-firing potential of existing power plant is still unnoticed.

The last four limitations can be solved by its feasible supply chain network synthesis. An effective supply chain network help to organize the chain of events associated with a product or service (Vance et al., 2012). Although, supply chains are traditionally designed and optimized for profit but the increasing environmental pollution also influence the environmental concern to be included in supply chain network synthesis (Vance et al., 2012). Supply chain network involving biomass processing is complex to model. They include a large number of alternative routes leading to a layer of combinatorial complexity. Mathematical modeling is a conventional approach to design this complex network (Kim et al., 2011, Čuček et al., 2010). However, for larger size problem it becomes highly difficult (Lam et al., 2010). Changing any variable like; materials, energy sources or process technologies etc. makes this method even more time consuming. Moreover, it only provides the optimal solution but ignores some near optimal solutions which can also be considered in special circumstances. near-optimal networks are also important because they are the most favorable and immediate replacement of the optimal network in case of interruptions from anthropogenic causes, such as warfare, route renovation etc or natural catastrophes such as earthquake. It is also well-known that mathematical modeling often encounters difficulties in determining globally optimal solutions when the objective functions are nonlinear (Fan et al., 2009).

P graph approach (Fan et al., 2009) is a new method which is successfully adopted for supply chain network synthesis. This approach is developed for solving PNS problems with software tool (Lam et al., 2011). Although, P-graphs are introduced formerly for chemical industrial processes, it is currently being used for various supply chain network designs (Tan et al., 2015). This is a directed bipartite graph, which has two vertices – one for operating units (manufacturing/processing facilities) and another for material or energy flows (raw materials, final product, emission, wastes quantity etc) (Friedler et al., 1995). Fan et al. (2009) utilized p graph to design a supply chain network incorporating three process plants, three markets, and three products under three different scenarios and show a rank order of the most favorable solutions. Lam et al. (2010) present a p graph framework for regional energy targeting and supply chain network synthesis. Siilel et al. (2011) utilize p-graph for designing an optimal network of biomass under uncertainty. Vance et al. (2012) adopt p graph for optimal design of a supply chain for providing heat and electric power derived from agricultural waste to a region with relatively limited land area.

2.5. State of the Art

The state of the art found from the literature survey discussed in previous sections is given below:

- From section 2.2, it is evident that LCA is the most prominent measure for product level development. While conducting LCA, LCI is the most crucial and time consuming step. Over past decades numerous techniques of LCI have been developed according to the aims, scope and resources for the intended purpose. However, this knowledge is fragmented over diverse studies in the literature. Although some reviews provide a view on LCI application but they are related to a particular field. Moreover, the computational structure of LCI is hardly reported. A consolidated review on the contribution of various researchers in evolution of LCI methods and their important development measures is still missing in the literature.

- LCA has many successful applications in green or sustainable manufacturing. Decision making about a green product is one of them. LCA of a product is comprised of the environmental impact caused by it at the various stage of its supply chain. Different functional unit and different environmental impact categories make this decision making a multidimensional choice. Various graphical approaches have been found for this kind of comparison but they lack in considering overall impact categories. Moreover, they are time consuming and their representation is not convenient for the readers. To solve this problem, different practitioners suggest for various aggregated measures which refer to the environmental performance of each product throughout its supply chain. Though these measures have different competencies they still lack some prerequisites of an aggregated index. Vector space theory is found to be the most competent one in this regard.

- From section 2.3, it has been seen that variable electricity pricing is a constraint on industry’s energy requirement. Without proper energy management, it may cause huge energy charge. To solve energy problem, many industries depend on third party WtE but it is not feasible and cost effective. Many previous studies are conducted on WtE based on municipal solid waste but the potential of industrial waste was overlooked. Some studies have come up with onsite small scale WtE as a solution for waste management in industries but its potential as an energy management within industry was unnoticed.

- Based on the discussion in section 2.4, it is seen that, Bangladesh is currently looking for alternative renewable energy source. The reasons behind this scenario are: inadequate electricity supply relative to increased population, scarcity of fossil fuel and higher emission to the environment. The country is abundant with various kinds of biomass resources but the inefficient consumption cannot exploit it potentially. Some biomass plants have been built around the country but they cannot compete with conventional power plants due to: low conversion efficiency, higher establishment and operating cost, higher collection and delivery cost etc. On the other hand, co-firing of biomass in a conventional power plant is found to be a cost effective and environmental friendly technological solution.

CHAPTER 3: SCOPE OF THE STUDY

3.1. Introduction

In chapter 2, the contribution and limitations of various studies under green product, process and system level development are discussed. This discussion helps to identify some gaps in this area. Initiatives have been taken to find out scope of the study and fulfill some of these gaps. In this work, a green framework consisting of product, process and system level development is presented based on the scope of study. The scopes of the study are discussed below:

3.2. Scope of the Study

• Choosing a suitable LCI technique can lower the cost, complexity and time involved in a LCA study. It also encourages a broader audience to practice and implement LCI. A consolidated review on the evolution of LCI methods can help readers to get to know the major contribution in LCI development. Furthermore, for a successful LCI method selections a knowledge on the methods and their application along with advantages and disadvantages are required. The objective of this thesis is to present a consolidated overview on the LCI evolution. Moreover a review on all the LCI methods and their modifications are presented. Some simple case studies found from literatures are also presented together to explain and compare the methods.

• An aggregated index can represent the result found from LCA via a single numerical value. This representation is highly suitable during multi criteria decision making among the products. By comparing all the methods of aggregated index from literature, vector space theory is found to be the most competent one which comply with the mathematical requirement. The objective of this work is to propose a novel frame work for computing an aggregated index based on LCA and vector space theory. This method is applied for various food products along its supply chain.

• Industry requires huge amount of energy and it converts a significant amount of its resources into waste. Therefore, it needs a twofold solution for its energy management and waste management. On the other hand, the scope of WtE needs to be broadened. In this work, a fuzzy logic based energy management strategy by incorporating a small scale WtE with energy storage in an industry is proposed. This strategy is able to save energy charges under variable electricity pricing. The objective of this thesis is to reduce electricity bill and use the waste in an effective way.

- Co-firing of biomass in coal power plant can save huge cost of setting up a new plant. Furthermore, an efficient supply chain network can reduce cost and emission. The objective of this thesis is to design feasible green supply chain network for co firing of rice residue in a coal power plant situated in Rajshahi, Bangladesh. This network is comprised of the route that incurs minimum transportation cost. Transportation cost is proportional to distance travelled. Emission is also proportional to distance travelled. Therefore, the lowest cost can also result in the lowest emission amount.

CHAPTER 4: LIFE CYCLE INVENTORY

4.1. Introduction

LCI is the most crucial phase of LCA. However, the evolution of LCI methods is yet to be documented. For applying the LCI method, one should know its mathematical deduction and proper application. Therefore, this chapter is divided into two parts: Methods of LCI and an application of LCI which is green value of food product based on LCI. In first part, the contribution of various studies in LCI evolution and procedure of applying various LCI methods with suitable examples are discussed. In second part, one application of LCI is shown via presenting a novel framework for green value of food product.

4.2. Evolution of Life Cycle Inventory Methods

The practice on LCI begins in 1960s as a methodological framework for sustainable manufacturing via measuring energy requirement and pollution prevention. The first study in this field is conducted for computing cumulative energy requirement for chemical process by Smith (1969). The method adopted is named as Process based modeling performed via Process flow diagram. Later on, Matrix method is adopted for Process based modeling in order to overcome some limitations of Process flow diagram.Some core contributions of LCA practitioners in evolution of Process based modelling along with author's observation is documented in Table 2.

Table 2: Contribution, Observation and Evolution in Process flow modelling

Reference	Contribution	Observation	Evolution
Smith (1969)	Computing cumulative energy requirement for product	• Introduction of Process flow diagram for LCI • Suitable method for single input/output system	Introduction of LCI via Process based modeling
Consoli (1993)	Iterative method for solving recurring loop	• Tedious method for solving recurring loop	Modification added to process flow diagram

Heijungs(1994)	Introduction of matrix method for product system	• Can solve system with multiple input/output simultaneously	Introduction of Matrix method in LCI
Heijungs and Frischknecht (1998)	Treatment of cut-off and allocation for Matrix method	• Give an idea on when allocation is necessary	Various allocation procedure for matrix based LCI
Heijungs and Suh (2002)	Discussion on basic model for LCI, Various treatment i.e. hollow process, cut-off, pseudo-inverse, refined method of matrix based LCI; Connecting matrix method with other LCI techniques; uncertainty analysis	• A complete guidance for process based LCI(Process flow diagram and Matrix method) • Connecting process based LCI and other LCI techniques	Various modification added to process based LCI(Process flow diagram and Matrix method)
Lu(2006)	Surplus flow vector in matrix method	• Different method of allocation for matrix method	Modification added to matrix method
Tan et al. (2008); Heijungs (2010); Cruze et al.(2014)	Fuzzy based Matrix LCI; Sensitivity coefficients for matrix LCI; Least square technique based Matrix LCI	• Dynamic LCI techniques • Advanced method of allocation	Recent Extension of Process based modeling

However, one of the drawback of this method is, it remains quite detail due to intensive data collection requirement. Therefore, the time and cost for this method are judged in case of a rapid decision making. On the other hand, ignoring some data from the upstream and downstream process can cause truncation error which seriously hamper some practices like long term decision for policy making; comparative assessment between two systems etc. The shortcomings of process based LCI sometimes motivate the practitioners to utilize IO analysis for LCI (Matthews and Small,2000).

The first introduction of IO analysis in environmental application was performed by Leontief (1970). Since then this technique is popularly adopted for environmental analysis. One of the key benefits of this method is avoiding truncation error as it considers the whole product supply chain in an economy. LCI based on IO is quite faster than Process based modeling as this takes data from already available input output database like: national economic accounts Some core contribution of practitioners in evolution of IO LCI along with author's observation is documented in Table 3.

Table 3: Contribution, Observation and Evolution in IO LCI

Reference	Contribution	Observation	Evolution
Leontief (1970)	Introduction of Input Output analysis in environmental application	• Connecting economic IO model to environmental application	Foundation for IO LCI
Leontief and Ford (1971); Folk and Hannon (1973); Cumberland and Korbach (1973);	Air pollution, on energy and labor, waste	• IO analysis popularly adopted for various environmental application	Wide application of IO model in environmental field
Lave (1995)	A step-by-step procedure for conducting input output LCI	• Discussion of limitations of process based LCI • Computational structure for IO based LCI	Development of IO based LCI methodology
Joshi(1999)	Six models of IO based LCI; Incorporation of products use phase and End-of-life phase in IO based LCI	• Flexible models for various cases of IO based LCI • Guidelines for	Modification of IO based LCI

		disaggregation in IO model	
Lenzen(2000); Tan et al. (2007); Lloyd and Ries (2007)	Monte Carlo simulation, Fuzzy set theory, Stochastic modeling for reducing uncertainty.	• Increasing accuracy and reliability of IO based LCI • Making more robust computation process	Extension of IO based LCI

The limitation of this method is IO databases are not available at the necessary level of detail. Therefore, this method lacks in process specificity such as raw material selection and process redesign (Finnveden et al., 2009). Another disadvantage is IO database includes out-of-date data because most of them are compiled with 3-5 years' time lag. It is also notable that IO table only consists the data of pre use stages and it also cannot provide accurate results for LCA when upstream processes are heavily dependent upon imports. Attempts to overcome these disadvantages, while combining with the advantages of Process oriented modeling, Hybrid method analyses were introduced since 1970's (Peters et al., 2010, Yao et al., 2014).

Hybrid method LCI is first introduced when practitioners find that indirect energy consumption is equally important as direct energy consumption for net energy analysis to produce a product. Moriguchi et al. (1993) extends this approach and introduces Tiered hybrid method analysis. Tiered hybrid method calculations are conducted in two different ways: (i) Processes around the production and consumption stages are modeled by Process based modeling and processes in further upstream and downstream are modeled by IO LCI i.e. Yao et al. (2014) or (ii) the principle processes are modeled by IO LCI and processes not covered by the IO table are modeled by Process based modeling (Wang and Yuan, 2014). Some core contribution of practitioners in evolution of Tiered hybrid method along with author's observation is documented in Table 4:

Table 4: Contribution, Observation and Evolution in Tiered Hybrid method

Reference	Contribution	Observation	Evolution
Bullard and Pilati (1976)	Aggregating process based and IO based model for computing	• A new method by Combining strength of process based and IO based	Foundation of hybrid method method

	summation of direct and indirect energy requirement of product	LCI	
Moriguchi et al. (1993)	Adding use phase and End-of-Life phase in LCI	• Extension of system boundary • More reliable solution	Introduction of Tiered hybrid method
Hondo and Sakai (2000)	Computing LCA by employing process modeling for far upstream processes(not covered by the national IO table) while applying IO analysis for the remaining sectors	• Complete upstream system boundary in case of imported goods	Modification of Tiered hybrid method
Suh and Huppes, (2002)	Introducing Missing inventory estimation tool(MIET)	• Increase the resolution of Tiered hybrid method LCI along with expanded system boundary	Extension of Tiered hybrid method
Stromman et al.(2009); Lenzen and Crawford (2009)	Algorithms, structural path analysis for solving double counting problem	• Increase accuracy of the method • Reduce data overlapping	Extension of Tiered hybrid method

This method is quite straight forward but sometimes suffers from data double counting. In order to solve double counting problem, another method is introduced by Treloar (1997) which is named as IO based hybrid method.

IO based hybrid method is performed via extracting particular paths from IO matrix and substituting these paths with Process based modeling data. Usually the direct input into a process or product is substituted by process based data. Some core contribution of practitioners in evolution of IO based hybrid method along with author's observation is documented in Table 5:

Table 5: Contribution, Observation and Evolution in IO based hybrid method

Reference	Contribution	Observation	Evolution
Treloar (1997)	Extraction of particular path from IO table and substituting them with process based data	• Solves problems of double counting • More expanded system boundary	Introduction of IO based hybrid method
Joshi (1999)	Six methods for extended input output LCI	• Effective method of disaggregation • Inclusion of Use and End-of-Use phase	Modification of IO based hybrid method
Crawford (2008)	Includes the capital inputs (machineries) in IO based hybrid method, 22% increase in LCI result than previous IO based hybrid method method	• Extension of system boundary • More accurate result suitable for comparison	Modification of IO based hybrid method

However, the disaggregating procedure is the most complex part of the IO based hybrid method. Furthermore, this method suffers from the same uncertainty problem suffered by IO based LCI due to not updated IO data and lack of newer technologies information (Jiang et al., 2014a). Therefore, for reducing uncertainty in IO-based hybrid method by interconnecting IO table at upstream and downstream cut-offs, another Hybrid method method emerge which is named as Integrated hybrid method.

The Integrated hybrid method analysis devised by Suh and Huppes (2000) and Suh (2004a) is the most sophisticated form of hybrid methodization at the matrix level. This model is derived from a make and use framework for both the Process based and the IO based system by linking them through flows crossing the border between the two systems via downstream and upstream cut-off matrices. Some core contribution of practitioners in evolution of Integrated hybrid method along with author's observation is documented in Table 6:

Table 6: Contribution, Observation and Evolution in Integrated Hybrid method

Reference	Contribution	Observation	Evolution
Suh and Huppes (2000); Suh (2004a)	Introduction of Integrated hybrid method	• A special form of hybrid method in matrix form • More computational accuracy	Introduction of Integrated hybrid method
Suh (2004b), Tukker et al. (2006).	Commercial and noncommercial LCA software tools ; Integrated Product Policy (IPP) in Europe	• Popular adoption of Integrated hybrid method for various environmental application	Adoption of Integrated hybrid method
Peters and Hertwich (2006)	Contribution of downstream cut off matrix in the inputs of IO table depending on how much portion of the economy is occupied by process sector	• More clear explanation of the elements of downstream cut off matrix in integrated hybrid method model in Suh (2004a)	Modification of Integrated hybrid method
Suh (2006)	Reprents a detail method to identify the significance of elements in downstream cut off matrix	• Argument on Peters and Hertwich (2006) explanation of downstream cut off • Helps data collection for downstream cut off matrix	Modification of Integrated hybrid method

Williams et al. (2009)	Truncation uncertainty at boundary between process based and IO based system, suggest iterative method for reducing uncertainty	• Identification and guidelines for reducing uncertainty	Extension of Integrated hybrid method
Lee and Maa (2013)	Develop cut off criteria to minimize truncation uncertainty	• Increase reliability of integrated hybrid method	Extension of Integrated hybrid method

This approach enables a consistent allocation and avoids double counting. However, due to higher computational complexity, data and time requirement, this method is adopted for long term decision making.

LCI has evolved significantly over the past three decades to become more systematic and robust tool for sustainability practices. Different LCI methods entail different level of computational complexity and data requirement. In section 4.3, the significant methodological development of each method and their numerical examples are presented.

4.3. Various Life Cycle Inventory Method

In the following sections, three principal methods of LCI, with different modifications are elaborated. The numerical examples are also shown for these methods. This section can provide guidelines on each method for how much data they require, how to make assumptions and how to perform the calculations. As huge number of LCA software are available in market, this knowledge also help the practitioners to choose, use and further development of LCA software. Moreover, this may aid scientific validation of future extension and modification in LCI methodology.

4.3.1. Process based modeling

Process based modeling is the straight forward approach of inventory compilation via process analysis. There are two methods in this category. They are:

4.3.1.1. Process Flow Diagram

Process flow diagram shows how processes of a product system are interconnected through commodity flows. Using plain algebra, the amount of commodities for fulfilling a certain functional unit is obtained, and by multiplying the amount of environmental interventions generated to produce them, the LCI of the product system is calculated. Let us consider the simple product system of a toaster shown in Fig. 1 (Suh and Huppes, 2005).

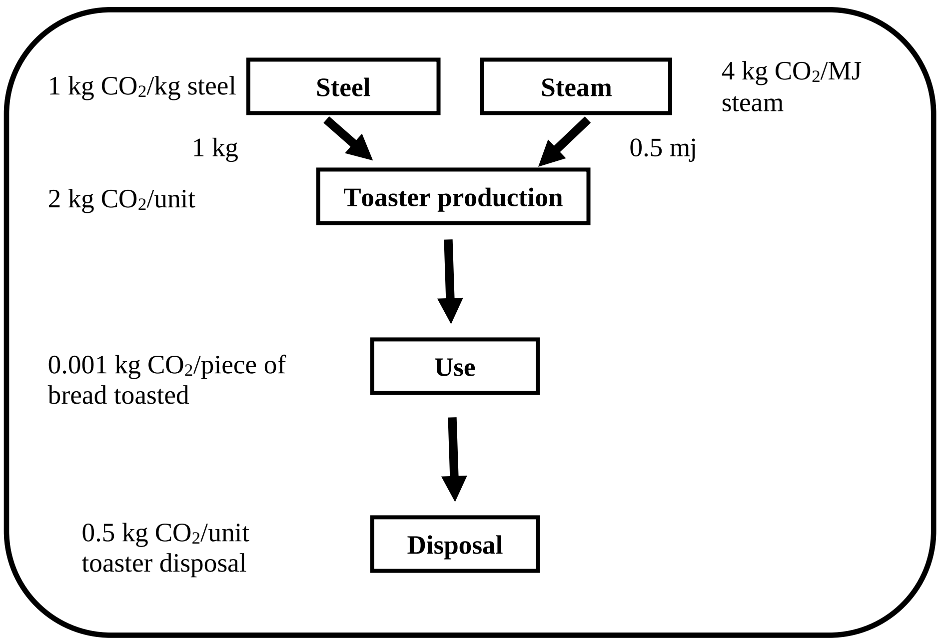


Fig. 1. Process flow diagram of Simplified Product System of a toaster (Suh and Huppes, 2005).

This is a single product system with no recurring loop. One can calculate the amount of environmental intervention as follows (Suh and Huppes, 2005):

$$\left(\frac{1\ kg\ CO_2}{kg\ steel}.1\ kg\ steel\right)+\left(\frac{4\ kg\ CO_2}{MJ\ steam}.0.5\ MJ\ steam\right)+\left(\frac{2\ kg\ CO_2}{unit\ toaster\ prod.}.1\ unit\ toaster\ prod.\right)+\left(\frac{0.001\ kg\ CO_2}{piece\ of\ toast}.1000\ piece\ toast\right)+\left(\frac{0.5\ kg\ CO_2}{unit\ toaster\ disposed}.1\ unit\ toaster\right)=6.5\ kg\ CO_2 \quad (1)$$

For a simple product system like Fig. 1, *Process flow diagram* method works fine. But in reality industrial processes have multiple input streams or generate multiple output streams. Usually only one of the outputs is of interest for LCA study being conducted. So, allocation problem comes into consideration (Suh and Huppes, 2005).

One allocation is done for "avoided burdens" or "avoided impacts" (Azapagic and Clift, 1999). This is performed to include "credits" for the avoided environmental burdens by subtracting them from the total burdens in the system. i.e., in above example, the toast prepared by the toaster also releases heat into the environment and so reduces the demand for heat produced from other sources. Another allocation problem may occur for open-loop recycling. i.e.; for above example; if steel from disposed toaster is recycled and used again in producing another toaster, the system boundaries can be expanded to include the life cycle of the toaster containing recycled steel. Therefore, allocating environmental burdens need to consider multiple product flow diagrams to correctly estimate the environmental burden for a particular product under study. Therefore, this method becomes very time consuming.

These limitations accentuate the necessity of a method which can express the multiple product systems with a vast range of equations and can solve them simultaneously. This introduces the *Matrix method* for *Process based modeling*.

4.3.1.2. Matrix method

Matrix method expresses the whole product system with vast range of linear equations and solves them simultaneously. It can be applicable for product system with multiple input/output, internal looping, recycling etc.

Let us consider the commodity flows for the processes are arranged in the coefficient matrix $\boldsymbol{A}$, and the environmental flows are arranged in the environmental load matrix $\boldsymbol{B}$. In matrix $\boldsymbol{A}$, the inputted flows are expressed by negative coefficients and outputted flows by positive ones. The boundary condition for the commodity flow is expressed by the vector $\boldsymbol{\alpha}$. Therefore, the process vector $\boldsymbol{p}$ can be derived as (Heijungs and Suh, 2002):

$$\boldsymbol{A}.\boldsymbol{p} = \boldsymbol{\alpha} \tag{2}$$

$$\boldsymbol{p} = \boldsymbol{A}^{-1}.\boldsymbol{\alpha} \tag{3}$$

A is a square matrix, and $\boldsymbol{A}^{-1}$ is the inverse matrix of ***A***. Items in the system boundary vector $\boldsymbol{\alpha}$ are the absolute values of the commodity flows, which cross the system boundary. Each item in the vector ***p*** is the scaling factor corresponding to one unit process. Then, the final environmental load vector $\boldsymbol{\beta}$ can be obtained by using the environmental load matrix ***B*** as follows (Heijungs and Suh, 2002):

$$\boldsymbol{\beta} = \boldsymbol{B}.\boldsymbol{p} \tag{4}$$

$$\boldsymbol{\beta} = \boldsymbol{B}.\boldsymbol{A}^{-1}.\boldsymbol{\alpha} \tag{5}$$

According to Heijungs and Suh (2002) matrices ***A*** and ***B*** are also called as technology matrix and intervention matrix respectively and vectors $\boldsymbol{\alpha}$, $\boldsymbol{p}$, $\boldsymbol{\beta}$ are also called as final demand vector, scaling vector and inventory vector respectively. For example, a product system of aluminum can is shown in Fig. 2 (Lu, 2006).

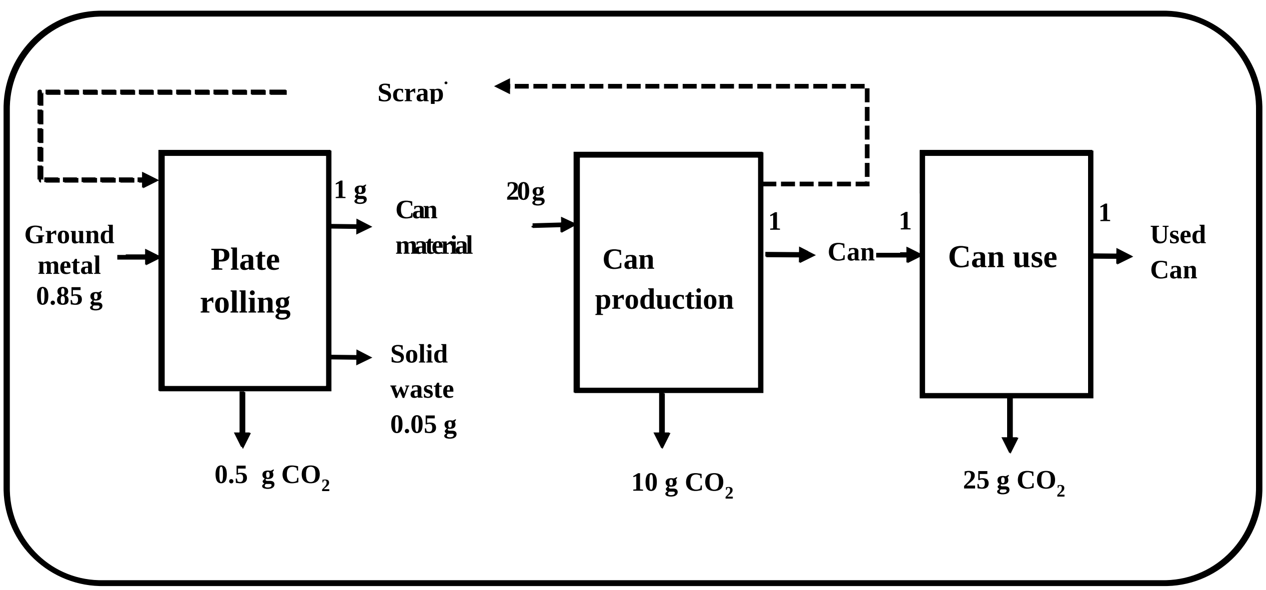


Fig. 2. Aluminum can product system (Lu, 2006).

In this case study (Lu, 2006), CO_2 and solid waste are considered to be environmental loads, and the other flows are all considered as commodity flows. The functional unit is given by '*1 used can*', and the finally cumulative solid waste and CO_2 are expected to calculate. If the coefficient matrix is constructed where rows represent all the economic flows and columns represent the three processes (Plate rolling, Can production, Can use), the technology matrix is as follows (Lu, 2006):

$$
A= \begin{array}{r} \\ \boldsymbol{ground\ metal} \\ \boldsymbol{scrap} \\ \boldsymbol{can\ material} \\ \boldsymbol{can} \\ \boldsymbol{used\ can} \end{array}
\begin{array}{c} \begin{array}{ccc} \boldsymbol{plate\ rolling} & \boldsymbol{can\ prod.} & \boldsymbol{can\ use} \end{array} \\
\begin{bmatrix} \mathbf{-0.85} & \mathbf{0} & \mathbf{0} \\ \mathbf{-0.2} & \mathbf{4} & \mathbf{0} \\ \mathbf{1} & \mathbf{-20} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} & \mathbf{-1} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} \end{bmatrix} \end{array} \tag{6}
$$

This is a rectangular matrix. For applying Eq. (2) the matrix need to be square. This problem can be solved by several ways. The first one is automatic cut-off (Marvuglia et al., 2010). In automatic cut off only the functional flow is included and other flows for which production data are not available are cut off from the calculation.

For example shown in Fig. 2, if ***'1 used can'*** is considered as a functional unit and only functional flows are arranged in matrix $\boldsymbol{A}$ the technology matrix $\boldsymbol{A}$ can be formulated as follows (Lu, 2006):

$$
A= \begin{array}{r} \boldsymbol{can\ material} \\ \boldsymbol{can} \\ \boldsymbol{used\ can} \end{array}
\begin{bmatrix} \mathbf{1} & \mathbf{-20} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} & \mathbf{-1} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} \end{bmatrix} \tag{7}
$$

Then the boundary conditions of the functional flow can be established by giving value to the functional unit and setting others to zero. Here functional unit is **"*1 used can*".** Hence, by putting 1 for ***"1 used can"*** and setting zero for others, the boundary vector $\boldsymbol{\alpha}$ is constructed as follows (Lu, 2006):

$$\boldsymbol{\alpha} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{1} \end{bmatrix} \tag{8}$$

So, by using Eq. (3) the process vector $\boldsymbol{p}$ can be calculated as (Lu, 2006):

$$\boldsymbol{p} = \begin{bmatrix} \mathbf{20} \\ \mathbf{1} \\ \mathbf{1} \end{bmatrix} \tag{9}$$

Now, the environmental load matrix $\boldsymbol{B}$ considered for $\boldsymbol{CO_2}$ is calculated as follows (Lu, 2006):

$$\boldsymbol{B} = \boldsymbol{CO_2}[\mathbf{0.5} \quad \mathbf{10} \quad \mathbf{25}] \tag{10}$$

By using the Eq. (5), the final environmental load vector $\boldsymbol{\beta}$ is derived as (Lu, 2006):

$$\boldsymbol{\beta} = [\mathbf{45}] \tag{11}$$

However, automatic cut-off can affect the LCA result by under estimating the inventory values. Therefore allocation method becomes more preferable.

Ground metal and scrap has been found to be two other product flows in this system. Therefore, the coefficient matrix $\boldsymbol{C}$ for these products can be written as (Lu, 2006):

$$\boldsymbol{C} = \begin{matrix} \boldsymbol{ground\ metal} \\ \boldsymbol{scrap} \end{matrix} \begin{bmatrix} \mathbf{-0.85} & \mathbf{0} & \mathbf{0} \\ \mathbf{-0.2} & \mathbf{4} & \mathbf{0} \end{bmatrix} \tag{12}$$

By multiplying ***C*** with process vector ***p*** found in Eq. (3) the amount of total ground metal and total scrap for **'*1 used can*'** production can be found as follows (Lu, 2006):

$$\boldsymbol{p}' = \begin{bmatrix} \mathbf{-17} \\ \mathbf{0} \end{bmatrix} \tag{13}$$

As in matrix $\boldsymbol{p'}$ is the coefficient for scrap metal is zero, so scrap is completely recycled inside the system and no environmental load data is needed for it. It is also found that, ***17 g*** ground metal is needed for ***1 Aluminum can*** production. Now let us consider the production process of 1 g ground metal shown in Fig.3 (Lu, 2006).

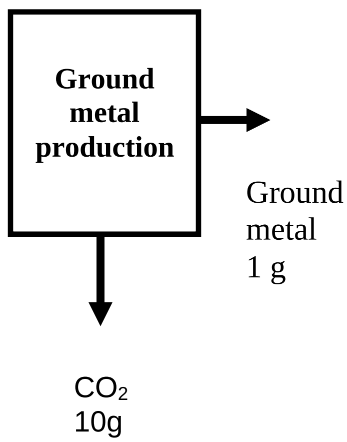


Fig. 3. Ground metal production (Lu, 2006)

Then the ***CO_2*** for ground metal can be calculated as follows (Lu, 2006):

$$\boldsymbol{\beta}' = [\mathbf{17}][\mathbf{10}] = \mathbf{170} \tag{14}$$

Therefore, total ***CO_2*** is given by Eq. (15) as follows (Lu, 2006):

$$\boldsymbol{\beta_{total}} = \mathbf{45}\ \boldsymbol{g}\ \mathbf{+170\ g=215\ g} \tag{15}$$

The value of environmental intervention found in Eq.(15) is better estimation than the underestimated value found in Eq. (11) with automatic cut-off.

However, the rectangular technology matrix can also be treated by some more other methods. Marvuglia et al.(2010) investigated the use of Least Squares Techniques (TLS) to estimate process vector for rectangular technology matrices. Marvuglia et al.(2012) continued the exploration on the same data set, using an iterative approach to the generalized total least squares methods.

Nevertheless, whatever the allocation method followed, process oriented modeling needs a lot of primary and axillary process data. It makes this method complicated and time consuming. On the other hand, cut off method is also criticized for underestimating inventory data of higher-order upstream stages. Therefore *IO* LCI is adopted by some practitioners because it delivers the simple and faster solution with more expanded system boundary.

4.3.2. Input Output (IO) LCI

IO LCI method takes data from input output databases. This method considers far upstream stages into LCI calculation, so provide better result than process oriented modeling.

Let us consider a consumption matrix $\boldsymbol{C}$ is consist of $\boldsymbol{C_{ij}}$ which is the (in monetary value) output from industry $\boldsymbol{i}$ which is needed to produce one unit (in monetary value) of output of industry **j**. If there are n number of industries in the overall economy and each produces $\boldsymbol{x_i}$ units, the production vector $\boldsymbol{p_i}$ is defined by Eq.(16) (Hendrickson et al., 1998):

$$\boldsymbol{p_i} = \begin{bmatrix} \boldsymbol{x_1} \\ \boldsymbol{x_2} \\ \cdots \\ \cdots \\ \cdots \\ \boldsymbol{x_n} \end{bmatrix} \tag{16}$$

If the consumption by the industries is $\boldsymbol{C.p}$ and $(\boldsymbol{p} - \boldsymbol{C.p})$ is the available output for external use. This available output can be expressed as follows (Hendrickson et al., 1998):

$$(\boldsymbol{p} - \boldsymbol{C}.\boldsymbol{p}) = (\boldsymbol{I} - \boldsymbol{C}).\boldsymbol{p} \tag{17}$$

Then the demand $\boldsymbol{d}$ for the output of the industry $\boldsymbol{I}$ can be expresses as (Hendrickson et al., 1998):

$$\boldsymbol{d} = \begin{bmatrix} \boldsymbol{d_1} \\ \boldsymbol{d_2} \\ \dots \\ \dots \\ \dots \\ \boldsymbol{d_n} \end{bmatrix} \tag{18}$$

If the demand is exactly met without any surplus or shortage (Hendrickson et al., 1998),

$$(\boldsymbol{I} - \boldsymbol{C}).\boldsymbol{p} = \boldsymbol{d} \tag{19}$$

If $(\boldsymbol{I} - \boldsymbol{C})$ is invertible, Eq.(20) can be expressed as (Hendrickson et al., 1998):

$$\boldsymbol{p} = (\boldsymbol{I} - \boldsymbol{C})^{-\mathbf{1}}.\boldsymbol{d} \tag{20}$$

If $\boldsymbol{E_{dir}}$ consists of the direct environmental impacts per dollar of output for each industrial sector then the vector of total environmental outputs $\boldsymbol{r}$ can be expressed as (Hendrickson et al., 1998):

$$\boldsymbol{r} = \boldsymbol{E_{dir}}.\boldsymbol{p} \tag{21}$$

$$\boldsymbol{r} = \boldsymbol{E_{dir}}.(\boldsymbol{I} - \boldsymbol{C})^{-\mathbf{1}}.\boldsymbol{d} \tag{22}$$

Let us discuss a simple example given by Kitzes (2013) where the economy consists of two sectors: ***Manufacturing*** and ***Agriculture***. The Input-Output table for this economy is given in Table 7:

Table 7: Input-Output table with two economic sectors (Kitzes, 2013).

	Ag.	Ma.	Final demand	Total output

Ag.	8	5	3	16
Ma.	4	2	6	12
Value added	4	5		
Total input	16	12		

The consumption matrix ***C*** is formulated as follows :

$$\boldsymbol{C} = \begin{matrix} & \boldsymbol{Ag.} & \boldsymbol{Ma.} \\ \boldsymbol{Ag.} & \mathbf{8/16} & \mathbf{5/12} \\ \boldsymbol{Ma.} & \mathbf{4/16} & \mathbf{2/12} \end{matrix} \tag{23}$$

Therefore, the demand ***d*** vector will be

$$\boldsymbol{d} = \begin{bmatrix} \mathbf{3} \\ \mathbf{6} \end{bmatrix} \tag{24}$$

The identity matrix ***I*** is

$$\boldsymbol{I} = \begin{bmatrix} \mathbf{1} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} \end{bmatrix} \tag{25}$$

So, the production vector ***p*** can be found by

$$\boldsymbol{p} = \begin{bmatrix} \mathbf{16.1613} \\ \mathbf{12.0968} \end{bmatrix} \tag{26}$$

Now environmental factor matrix $\boldsymbol{E_{dirs}}$ for $\boldsymbol{CO_2}$ production for each industry is

$$\boldsymbol{E}_{\mathbf{dirs}} = [\mathbf{0.5} \quad \mathbf{0.33}] \tag{27}$$

So, the total environmental output ***r*** is calculated as

$$\boldsymbol{r} = [\mathbf{8.08} \ \ \mathbf{3.99}] \tag{28}$$

Therefore, the total $\boldsymbol{CO_2}$ production for each industry is ***8.08t*** and ***3.99t*** respectively or in total ***12.07t*** for the overall economy.

In practical situation, the economy is consisted of numerous sectors. Therefore, a large input-output table representing the overall economy is too detailed to understand, and too extensive to use in making further numerical computation (Fisher, 1958). So, Fisher(1958) suggest specific criteria and procedures for "good" aggregation of a given input output table. The criteria are proposed on the basis of similarity of coefficient or homogeneity of input structure.

However, aggregated *IO* data is blind to individual processes. Consequently, it cannot be used to guide technological or consumer choices at a product level. This aggregation uncertainty is estimated in various literatures (Lloyd and Ries, 2007, Vinodh and Rathod, 2014, Heijungs and Lenzen, 2014, Bouwmeester and Oosterhaven, 2013). Another problem of IOA is it captures the upstream environmental burdens associated with raw materials acquisition and manufacturing stages, but not those associated with product use and end-of-life options.

4.3.3. Hybrid method

Linking *Process based* and *IO based* analysis, combining the strengths of both are generally called *Hybrid method* method (Suh and Huppes, 2005). There are three types of *Hybrid method* methods which are widely used in different LCA computations (Alexander and Franchetti, 2012):

1. Tiered hybrid method or process based hybrid method

2. IO based hybrid method

3. Integrated hybrid method

4.3.3.1. Tiered Hybrid method

In *Tiered hybrid method*, process data from main process modules are calculated by process oriented modeling and the added to the far upstream data which are calculated by *IO* analysis.

Let us consider, ***E*** is a *IO* environmental matrix and B is the process based environmental matrix; ***C*** is the *IO* technology matrix and **A** is the process based technology matrix; ***d*** is the *IO* final demand vector and ***p*** is the process based demand vector. If ***I*** is the identity matrix, the general structure of *Tiered hybrid method* analysis is given as (Alexander and Franchetti, 2012);

$$\boldsymbol{M_{tiered}} = \boldsymbol{B}.\boldsymbol{A^{-1}}.\boldsymbol{P} + \boldsymbol{E}.(\boldsymbol{I} - \boldsymbol{C})^{-\boldsymbol{1}}.\boldsymbol{d} \qquad (29)$$

Let us discuss a simple Example of production of a toy taken from Cruze (2013):

In this example, the main process consists of two modules $\boldsymbol{S_{4'}}$ and $\boldsymbol{S_{5'}}$. $\boldsymbol{S_{5'}}$ denotes the target module, and it receives the output processed by $\boldsymbol{S_{4'}}$. The net output for $\boldsymbol{S_{4'}}$ is ***5.375*** and net input and output for $\boldsymbol{S_{5'}}$ is ***2.5*** and ***6*** respectively. $\boldsymbol{S_{4'}}$ is dependent on the output comes from industry $\boldsymbol{S_3}$. $\boldsymbol{S_3}$ is interconnected with two other industries within the economy. The overall system is shown by a network in **Fig.** 3 (Cruze, 2013).

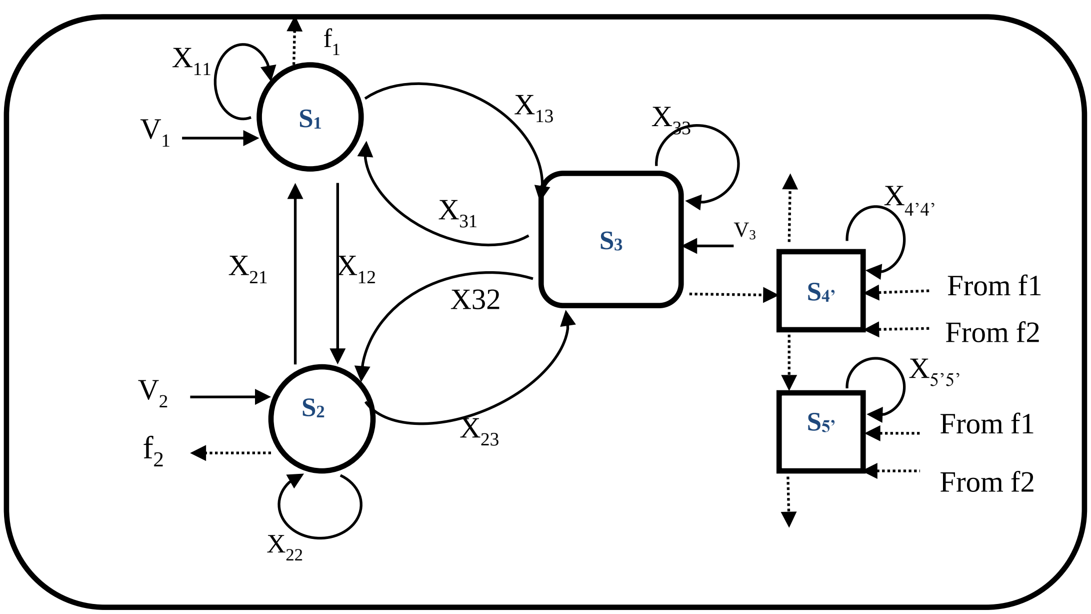


Fig.4. The hybrid network for process modules and industries (Cruze, 2013).

In **Fig. 4**, ***S_1***, ***S_2*** and ***S_3*** nodes describe the three industries, ***$S_{4'}$*** and ***$S_{5'}$*** shows two process modules and the arrows denotes all flows among them. ***f1***, ***f2*** describe the final demand and ***V_1***, ***V_2***, ***V_3*** describes the value added to the industry. Table 8 represents an aggregated input output table showing transactions between industries ***S_1***, ***S_2*** and ***S_3*** , their final demand, gross input and gross output.

Table 8: Aggregated industry by industry transactions table (Cruze, 2013)

	S_1	S_2	S_3	Final demand	Gross output
S_1	150	250	150	220	770
S_2	300	210	220	140	870
S_3	250	222	295	243	1010
Value Added	70	188	345		
Gross Inputs	770	870	1010		

Some additional information about the pollutant emission and producer price of goods are also given in the Table 9 below:

Table 9: Price and emission data for the toy example (Cruze, 2013)

sector	Pollutant 1	Pollutant 2	Pollutant 3	Emission factor 1	Emission factor 2	Emission factor 3	Producer price of good
S_1	30	30	30	0.039	0.039	0.039	$1
S_2	28	28	28	0.032	0.032	0.032	$1
S_3	41	505	100.3	0.041	0.500	0.099	$2
$S_{3'}$	20	492.5	100	0.020	0.500	0.102	$2
$S_{4'}$	12	5.5	0.2	1.091	0.500	0.018	$2
$S_{5'}$	9	7	0.1	0.643	0.500	0.007	$2

Emission factors are calculated as emission of a particular pollutant (shown in Table 7) per unit of gross output (shown in Table 8).

Now, as any input required by $S_{4'}$ is out of the boundary of this process , therefore input and output for S_1, S_2 and S_3 are omitted in process technology coefficients matrix ***A***. Considering the input and output for $S_{4'}$ and $S_{5'}$, matrix ***A*** is written as follows (Cruze, 2013):

$$\boldsymbol{A} = \begin{bmatrix} \mathbf{5.375} & \mathbf{-2.5} \\ \mathbf{0} & \mathbf{6} \end{bmatrix} \tag{30}$$

The data for pollutant 1 is found from Table 3 which is written in environmental matrix ***B*** as follows:

$$\boldsymbol{B} = [\mathbf{12} \quad \mathbf{9}] \tag{31}$$

The functional unit is "***1 single toy***". So, the process based demand vector ***p*** for $S_{4'}$ and $S_{5'}$ is written as:

$$\boldsymbol{p} = \begin{bmatrix} \mathbf{0} \\ \mathbf{1} \end{bmatrix} \tag{32}$$

Now the *IO* technology matrix ***C*** for upstream inputs of $S_{4'}$ is formulated. In matrix ***C***, the columns represent physical input requirement of $S_{4'}$ and $S_{5'}$; and rows represent the contributing economic sectors S_1, S_2, S_3 and the matrix is shown below:

$$\boldsymbol{C} = \begin{bmatrix} \mathbf{0.25} & \mathbf{1.75} \\ \mathbf{0.25} & \mathbf{1.75} \\ \mathbf{5} & \mathbf{0} \end{bmatrix} \tag{33}$$

And the *IO* final demand vector ***d*** is:

$$\boldsymbol{d} = [\mathbf{0.311} \quad \mathbf{0.311} \quad \mathbf{0.775}]^{\boldsymbol{T}} \tag{34}$$

The environmental matrix $\boldsymbol{E}$ showing the value of pollutant 1 for $\boldsymbol{S_1}$, $\boldsymbol{S_2}$ and $\boldsymbol{S_3}$ is shown below:

$$\boldsymbol{E} = [\mathbf{30} \quad \mathbf{28} \quad \mathbf{41}] \tag{35}$$

So, the total calculated *Tired hybrid method* inventory for pollutant 1 is calculated by using Eq.(29) as follows:

$$\boldsymbol{M_{tiered}} = \boldsymbol{B}.\boldsymbol{A}^{-1}.\boldsymbol{P} + \boldsymbol{E}.(\boldsymbol{I} - \boldsymbol{C})^{-1}.\boldsymbol{d} = \mathbf{2.43} + \mathbf{0.221} = \mathbf{2.652} \tag{36}$$

Therefore, at price of ***$2*** the total *tired hybrid method* inventory of pollutant 1 for producing "***1 single toy***" is ***2.652*** unit.

However, in *Tiered hybrid method* method, there is no signification rule for determining the boundary between process and *IO* based modeling. Furthermore, due to overlapping between process and *IO* based data, double counting of inventory may also occur. These two problems are solved by practitioners via introducing *IO* based *hybrid method* for LCI calculation.

4.3.3.2. IO based hybrid method

In IO based *hybrid method* method, the direct inputs to a specific product or process being studied are calculated using process analysis. Further upstream indirect processes accounted for are determined by either further applications of process analysis or *IO* analysis when the process data are unavailable or is considered too time consuming to collect relative to the significance of the process in question. Generally, the *IO based hybrid method* approach is carried out by disaggregating specific sector in IO.

Let us consider, $\boldsymbol{A_{eio-adj}}$ is original sectors of the economy, $\boldsymbol{A_u}$ is upstream process flow, $\boldsymbol{A_d}$ is downstream process flow and $\boldsymbol{A_{proc-\$}}$ is intra-process activity. Then the expanded direct requirements matrix for *IO based hybrid method* is given by (Cruze, 2013):

$$\boldsymbol{A_{IOH}} = \begin{bmatrix} \boldsymbol{A_{eio-adj}} & \boldsymbol{A_u} \\ \boldsymbol{A_d} & \boldsymbol{A_{proc-\$}} \end{bmatrix} \tag{37}$$

If, $\boldsymbol{b_{eio}}$ is share of emissions due to parent sector and $\boldsymbol{b_{proc-\$}}$ is share of emission due to process then each vector of emissions must also be disaggregated as given by (Cruze, 2013):

$$\boldsymbol{b_{IOH}} = [\boldsymbol{b_{eio}} \quad \boldsymbol{b_{proc-\$}}] \tag{38}$$

Let, $\boldsymbol{T_{IOH}}$ is a vector represented as follows (Cruze, 2013):

$$\boldsymbol{T_{IOH}} = \boldsymbol{I} - \boldsymbol{A_{IOH}} \tag{39}$$

If $\boldsymbol{f_{IOH}}$ is the price of inputs in monetary terms then the final inventory $\boldsymbol{r_{IOH}}$ is given by Eq.(40) as follows (Cruze, 2013) :

$$\boldsymbol{r_{IOH}} = \boldsymbol{b_{IOH}} \boldsymbol{T_{IOH}^{-1}} \boldsymbol{f_{IOH}} \tag{40}$$

Let us again consider the toy example which is already discussed for *Tiered hybrid method* in section 3.3.1. *IO based hybrid method* inventories require disaggregation of specific sector in IO (Cruze, 2013). If $\boldsymbol{S_3}$ is considered as an aggregated form of $\boldsymbol{S_{3'}}$, $\boldsymbol{S_{4'}}$ and $\boldsymbol{S_{5'}}$, the disaggregation of Table 7 is shown in Table 10 (Cruze, 2013):

Table 10: Disaggregated transaction table (Cruze, 2013)

	S_1	S_2	$S_{3'}$	$S_{4'}$	$S_{5'}$	Final demand	Gross output
S_1	150	250	148	0.25	1.75	220	770
S_2	300	210	218	0.25	1.75	140	870
$S_{3'}$	245	220	274	10	0	236	985
$S_{4'}$	3	0	1.75	0.25	5	1	11
$S_{5'}$	2	2	2	0	2	6	14
Value added	70	188	341.25	0.25	3.5		

Gross input	770	870	985	11	14

Now from original input-output table shown in Table 7, the original input-output matrix for industries S_1, S_2 and $S_{3'}$ is devised by calculating their required dollar input from particular industry per unit gross output they produce. The original input-output matrix $A_{eio-adj}$ is shown in Eq. (41)

$$A_{eio-adj} = \begin{bmatrix} \frac{150}{770} & \frac{250}{770} & \frac{150}{770} \\ \frac{300}{870} & \frac{210}{870} & \frac{220}{870} \\ \frac{250}{1010} & \frac{222}{1010} & \frac{295}{1010} \end{bmatrix} \quad (41)$$

From Table 9, the upstream process flow vector A_u for process modules $S_{4'}$ and $S_{5'}$ is calculated by dividing their required dollar input from S_1, S_2 and $S_{3'}$ by their gross dollar input. Therefore, the upstream process flow vector A_u is shown in Eq.(42)

$$A_u = \begin{bmatrix} \frac{0.25}{11} & \frac{1.75}{14} \\ \frac{0.25}{11} & \frac{1.75}{14} \\ \frac{10}{11} & \frac{0}{14} \end{bmatrix} \quad (42)$$

From Table 9, the downstream process flow A_d for $S_{4'}$ and $S_{5'}$ is calculated by dividing their output to industries S_1, S_2 and $S_{3'}$ by gross dollar output needed by these industries. Therefore, the downstream process flowA_d is shown in Eq.(43)

$$A_d = \begin{bmatrix} \frac{3}{770} & \frac{0}{870} & \frac{1.75}{985} \\ \frac{2}{770} & \frac{2}{870} & \frac{2}{985} \end{bmatrix} \quad (43)$$

$\boldsymbol{A_{proc-\$}}$ is the process technology matrix converted to input-output matrix. From Table 9, Matrix $\boldsymbol{A_{proc-\$}}$ is constructed as follows:

$$\boldsymbol{A_{proc-\$}} = \begin{bmatrix} \frac{\mathbf{0.25}}{\mathbf{11}} & \frac{\mathbf{5}}{\mathbf{14}} \\ \frac{\mathbf{0}}{\mathbf{11}} & \frac{\mathbf{2}}{\mathbf{14}} \end{bmatrix} \quad (44)$$

Therefore, the disaggregated direct requirements matrix is formed as follows:

$$\boldsymbol{A_{IOH}} = \begin{bmatrix} \boldsymbol{A_{eio-adj}} & \boldsymbol{A_u} \\ \boldsymbol{A_d} & \boldsymbol{A_{proc}} \end{bmatrix} = \begin{bmatrix} \mathbf{0.193} & \mathbf{0.287} & \mathbf{0.150} & \mathbf{0.023} & \mathbf{0.125} \\ \mathbf{0.390} & \mathbf{0.241} & \mathbf{0.221} & \mathbf{0.023} & \mathbf{0.125} \\ \mathbf{0.318} & \mathbf{0.252} & \mathbf{0.278} & \mathbf{0.909} & \mathbf{0.000} \\ \mathbf{0.004} & \mathbf{0.000} & \mathbf{0.002} & \mathbf{0.023} & \mathbf{0.357} \\ \mathbf{0.003} & \mathbf{0.002} & \mathbf{0.002} & \mathbf{0.000} & \mathbf{0.143} \end{bmatrix} \quad (45)$$

So, matrix $\boldsymbol{T_{IOH}}$ is shown as follows:

$$\boldsymbol{T_{IOH}} = \boldsymbol{I} - \boldsymbol{A_{IOH}} \quad (46)$$

Now, the emissions information must be disaggregated as well and values taken for emission factor 1 from Table 8, the new vector of emission $\boldsymbol{b_{IOH}}$ is calculated as;

$$\boldsymbol{b_{IOH}} = [\boldsymbol{b_{eio}} \quad \boldsymbol{b_{proc-\$}}] = [\mathbf{0.039} \quad \mathbf{0.032} \quad \mathbf{0.020} \quad \mathbf{1.091} \quad \mathbf{0.643}] \quad (47)$$

Now, at price of **$2**, the *IO based hybrid method* inventory of Pollutant 1 is calculated as Eq. (48)

$$\boldsymbol{r_{IOH}} = \boldsymbol{b_{IOH}} \boldsymbol{T_{IOH}^{-1}} [\mathbf{0} \quad \mathbf{0} \quad \mathbf{0} \quad \mathbf{0} \quad \$\mathbf{2}]^{\boldsymbol{T}} = \mathbf{2.628} \quad (48)$$

For *IO based hybrid method,* LCI of Pollutant 1 is calculated as **2.628** units for every unit at price of **$2** which is greater than the result found for *Tiered hybrid method* analysis.

However, in this method, the process specific data is also collected via input output table which may increase the probability of data uncertainty. In order to remove this limitation, *Integrated hybrid method* is evolved.

4.3.3.3. Integrated Hybrid method

Integrated hybrid method is the matrix inversion method of *hybrid method* analysis. The technology matrix consists of a typical process-based technology matrix, upstream and downstream cut-off matrices, and adjusted direct requirements matrix derived from the make and use tables in which economic flows corresponding to process modules have been subtracted. The upstream cut-off matrix holds the inputs into the processes that are not covered by the process database, expressed in monetary units per physical unit while the downstream cut-off matrix holds the deliveries of process outputs to input-output sectors, expressed in physical units per monetary unit.

Let us consider $\boldsymbol{C_u}$ is upstream cut off matrix, $\boldsymbol{C_d}$ is downstream cut off matrix, $\boldsymbol{A_{EIO-adj}}$ is adjusted direct requirements matrix and $\boldsymbol{T_{proc}}$ is typical process-based technology matrix. Threfore the mixed-units technology matrix for this method is shown in Eq.(49) (Cruze, 2013):

$$\boldsymbol{T_{Int}} = \begin{bmatrix} \boldsymbol{I - A_{EIO-adj}} & \boldsymbol{-C_u} \\ \boldsymbol{-C_d} & \boldsymbol{T_{proc}} \end{bmatrix} \tag{49}$$

If $\boldsymbol{Q_u}$ is upstream flows from the economy into the process and $\boldsymbol{\hat{p}}$ is dollar value of inputs received by the process from the economy, the upstream requirement matrix is given as follows (Cruze, 2013):

$$\boldsymbol{C_u} = \boldsymbol{\hat{p}Q_u} \tag{50}$$

If $\boldsymbol{A_d}$ is disaggregated technical coefficient and $\Delta_{\boldsymbol{p}}$ is price of process module, then the downstream cut off matrix is given by (Cruze, 2013):

$$\boldsymbol{C_d} = \Delta_{\boldsymbol{p}}^{-\boldsymbol{1}}\boldsymbol{A_d} \tag{51}$$

If $\boldsymbol{b_{eio-adj}}$ is adjusted emissions corresponding to the economic sectors and $\boldsymbol{b_{proc}}$ is emission from the process module, then the vector of emissions $\boldsymbol{b_{int}}$ for the *Integrated hybrid method* inventory is also disaggregated and is represented in Eq.(52) (Cruze, 2013):

$$\boldsymbol{b_{int}} = [\boldsymbol{b_{eio-adj}} \quad \boldsymbol{b_{proc}}] \tag{52}$$

If $\boldsymbol{f_{Int}}$ is scaling factor, the inventory is calculated by Eq.(53) as follows (Cruze, 2013):

$$\boldsymbol{r_{Int}} = \boldsymbol{b_{Int}}\boldsymbol{T_{Int}}\boldsymbol{f_{Int}} \tag{53}$$

Let us again consider the toy example of previous sections. Like *IO based hybrid method* inventory, the *Integrated hybrid method* inventory requires disaggregation of the input output plus process specifics. From Table 9 the upstream inputs (into the process) from $\boldsymbol{S_{4'}}$ and $\boldsymbol{S_{5'}}$ to $\boldsymbol{S_1}$, $\boldsymbol{S_2}$ and $\boldsymbol{S_3}$ are measured as Eq.(54)

$$\boldsymbol{C_u} = \boldsymbol{\hat{p}Q_u} = \begin{bmatrix} \mathbf{0.250} & \mathbf{1.750} \\ \mathbf{0.250} & \mathbf{1.750} \\ \mathbf{10.000} & \mathbf{0.000} \end{bmatrix} \tag{54}$$

Downstream cutoffs (from process to the rest of the economy) are measured in terms of units of physical terms per dollar of purchasing sector output. From Table 4, the downstream cutoff $\boldsymbol{C_d}$ is expressed as Eq. (55)

$$\boldsymbol{C_d} = \Delta_p^{-1}\boldsymbol{A_d} = \begin{bmatrix} \mathbf{0.0019} & \mathbf{0.0000} & \mathbf{0.0009} \\ \mathbf{0.0013} & \mathbf{0.0011} & \mathbf{0.0010} \end{bmatrix} \tag{55}$$

Therefore, the mixed unit vector of emissions $\boldsymbol{b_{int}}$ is

$$\boldsymbol{b_{int}} = [\boldsymbol{b_{eio-adj}} \quad \boldsymbol{b_{proc}}] = [\mathbf{0.390} \quad \mathbf{0.032} \quad \mathbf{0.020} \quad \mathbf{12} \quad \mathbf{9}] \tag{56}$$

Now if the scaling vector is $[\mathbf{0} \quad \mathbf{0} \quad \mathbf{0} \quad \mathbf{0} \quad \mathbf{1}]$, the resulting inventory of Pollutant 1 is

$$\boldsymbol{r_{Int}} = \boldsymbol{b_{Int} T_{Int}^{-1}} [\mathbf{0 \quad 0 \quad 0 \quad 0 \quad 1}]^{\boldsymbol{T}} = \mathbf{2.628} \tag{57}$$

Therefore, *integrated hybrid method*, LCI of Pollutant 1 is calculated as **2.628** units for every unit at price of **$2** which is identical to the result found for *IO based hybrid method* analysis.

Based on the above discussion, a comparative analysis can be done among all LCI methods. *Matrix method* is superior to the *Process flow diagram* method particularly for the most simplified systems. Pure *IO* LCI can be most suitable for faster result. However, when *Process based modeling* and *IO* LCI is compared with *Tired hybrid method* analysis, the latter provides more reliable result with system completeness. However, in *Tiered hybrid method* method the connection between *Process* and *IO* is made externally which may cause double counting. In contrast, the *IO based hybrid method* analysis shows higher resolution for the *IO* based system and does not have problems of overlap. With information on the monetary value only for cut-off flows and with improved availability of environmentally extended input output data, *Integrated hybrid method* method becomes the best choice though the method is quite expensive.

The advantages, limitations and some suitable field of application of these LCI methods are shown in Table 11. This may help to choose an appropriate method for intended purpose.

Table 11: Advantages, limitations and some suitable application of various LCI methods

LCI method	Advantages	Limitations	Suitable application

Process Flow Diagram	• necessary level of detail • best result for single product system • Easier to understand	• Not suitable for larger system /multiple input/output/recycling • time consuming for huge data • truncation error	• LCI for Single product system(Kulak et al., 2015) • LCI for production chain without recycling (Suh and Huppes, 2005) • sustainable process selection(Nucci et al., 2014)
Matrix method	• Effective for larger system/multiple input/output/recycling • necessary level of detail	• time consuming for huge data • truncation error • Mathematical expertise required	• Raw material selection(Ocampo et al., 2015) • Process selection/redesign(Wang and Work, 2014)
IO LCI	• no requirement of unit process data. • calculate upstream or indirect environmental impacts • less truncation error/time /complexity.	• not covering entire life cycle; • Lack in necessary level of detail • data uncertainty • Un-updated/coarse data • Not suitable for import/export	• Make/ buy decision (De Benedetto and Klemeš, 2010) • LCI for larger system boundary(emission at national/ regional level)(Tan et al., 2012) • Foot print/benchmarking(Chang et al., 2015)

Tiered Hybrid method	• simplest • more complete boundary than process based modeling • less data uncertainty	• Double counting • interaction between process based and IO based isnot assessed • lack of dynamic representations	• LCI in case of Imports/exports (Hondo et al., 1996) • LCI until product consumption stage (Junnila and Horvath, 2003)
IO based Hybrid method	• considers capital inputs(i.e.; machineries) • provides more comprehensive inventory assessment than Tiered hybrid method • No double counting	• disaggregating of IO table complex • Uncertainty is higher due to not updated IO data and lack of newer technologies information • recurring flows between the main system and use and end-of-life phase are not properly described • misleading results in case of imports	• New product development (Sharrard et al., 2008) • LCA requiring larger system boundary(i.e: including capital inputs, indirect energy etc)(Guan et al., 2016) • Design for environment (González-García et al., 2011)
Integrated Hybrid method	• the consistent mathematical framework • most accurate environmental impacts among all	• complexity of use • High data requirement • Time consuming • Double counting	• New product development with time and data availability (Jang et al., 2015) • New process/technology implementation (Wiedmann et al., 2011)

LCI results are further utilized in various methods under green product level development. Sometimes these results are utilized directly or sometimes they are converted to life cycle impact values or other mathematical interpretation. Among all the further application of LCI, decision making or choosing a green product is a prominent one. In section 4.4, a novel framework has been presented for applying LCI in decision making about green product.

4.4. Green Value of Food Product Based on LCI

The food industry has been detected as one of the major user of various energy and resources as well as producer of waste and emissions throughout its life cycle from the farming process through manufacturing until distribution. For example, at the farm stage, the dominant Green House Gases (GHGs) are nitrous oxide (N_2O) and methane (CH_4). Furthermore, Carbon dioxide (CO_2) emissions arise from power generation, manufacture of synthetic fertilizers and transportation (Garnett 2011). According to European Commission, the food system is responsible for up to 29% of global warming generated by the consumer economy in industrialized nations (Brodt et al. 2013). These kind of environmental contamination leads to the worldwide crises like dioxin pollution, classical swine fever, and avian influenza etc. These alarming situations have fuelled the consumer's concerns about sustainability of food production systems (Wognum et al. 2011). Furthermore, other stakeholders i.e., the government, policy makers and financial organizations are also emphasizing the practice of environmental sustainability in food sectors.

In response to stake holder's demand for environment friendly products and services, food manufacturing organizations have begun to implement green practices to enhance environmental sustainability. According to Green et al. (2012), environmental sustainability is a supply chain imperative rather than an organizational imperative. Environmental pollution caused by one stage of supply chain reduces the environmental sustainability of the end product of that overall chain. There are multiple stages in a supply chain affected by multiple factors. For example, sourcing of tomato from a remote producer in comparison to a nearer producer always causes more emission in transportation due to long distance delivery. However, if the remote producer does organic farming, the emission in farming stage will be lower. On the other hand, due to more product handling (long distance delivery), food waste production during transportation can be higher for remote producer than the nearer one. This kind of decision making related to multiple criteria and multiple alternatives is very common for green supply chain.

In Green Supply Chain Management (GSCM), the evaluation of environmental impacts of products throughout life cycle stages is very important (Lam et al., 2015).

4.4.1. Methodology

This work has two parts. First is LCA and the second is determining green value with vector space theory. The step-by-step methodology is shown in flow chart in Fig. 5

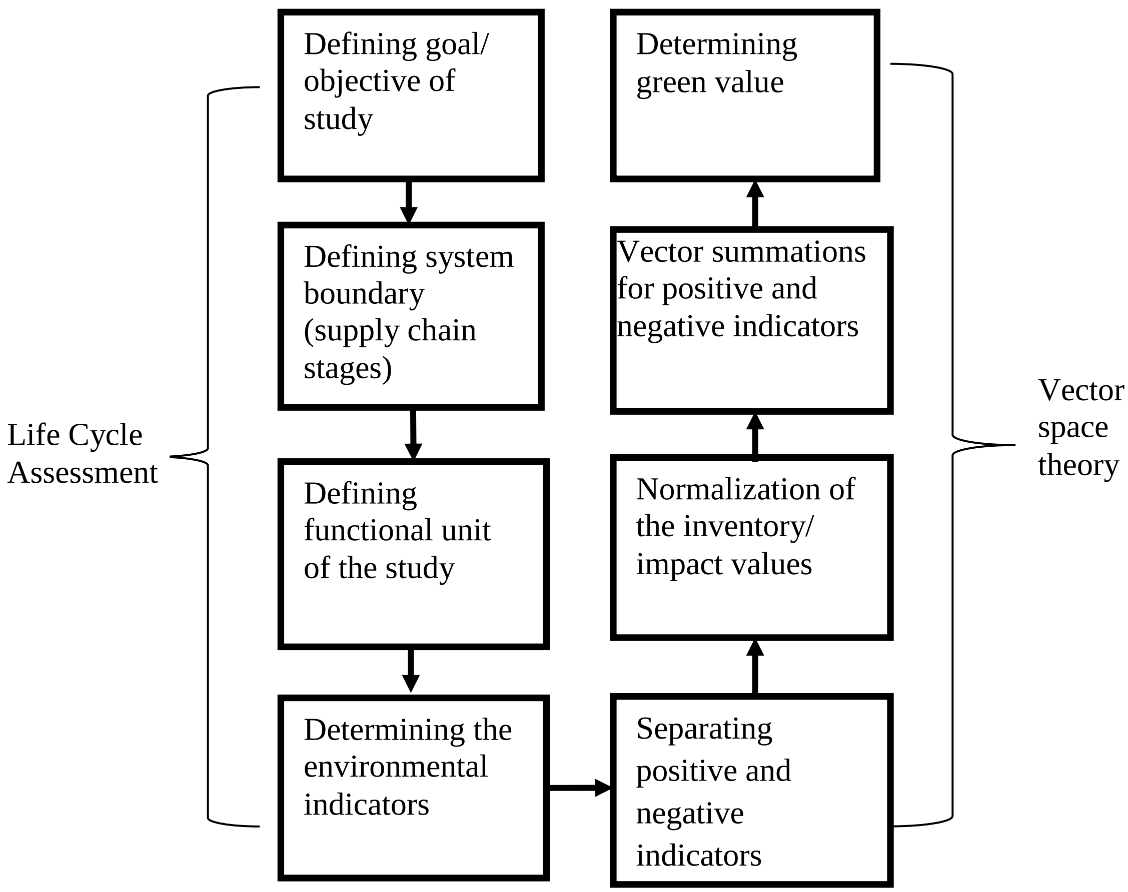


Fig.5 Flow chart for computing green value

The method for LCA is largely conformed to internationally accepted standards (ISO 14000) for Life cycle assessment methodology (Brodt et al. 2014). The first step is to determine the goal of the study. The goal needs to state clearly and without ambiguity which is the application, what are the reasons, why the study is carried out (Klemeš and De Benedetto 2013). After that, the system boundary needs to be determined. System boundary means which supply chain stages are included in the study. Usually the stages involved in a food supply chain are: cultivation, delivery to distribution center, packaging, end use. However, in some study, the production of capital equipment, raw material transportation to the field and the end use phase are not included. Defining the functional unit is an important step here. The environmental impact depends heavily on the functional unit chosen (Mogensen et al. 2009; Cerutti et al. 2013). For this paper, the LCA values have been collected from previous studies. After collecting the LCA data, the green index of the food supply chain is determined by using *vector space theory*. The lower the green value, the more green is the supply chain.

4.4.1.1. Vector Space Theory

In order to determine the aggregated sustainability index for various chemical processes, the vector space theory is first introduced by Olinto (2014). Vector space theory considers each supply chain values as a vector, whose components are the indicators of the environmental factors. These vectors construct a matrix and the aggregated metric for this matrix is measured by its norm. Here this norm is termed as *green value* of the supply chain.

Positive and negative indicators in the matrix represent distinct categories. The former are the adverse environmental impact categories and the latter are the added benefits that transform the supply chain towards green. Hence, positive indicators are defined such that a smaller indicator is more favorable than a larger one. On the other hand, larger the negative indicators, smaller is the green value. The present formalism treats both categories separately and delivers an aggregated green value for these.

The next stage is *Normalization*. Normalization transforms different physical dimensional indicator into dimensionless values into a coherent scale (Olinto 2014). The normalization of these indicators should be performed in a transparent way (Böhringer and Jochem 2007). Olinto (2014) utilizes the normalization on a scale of [0,1]. Let us consider there are $\boldsymbol{m}$ different indicators and $\boldsymbol{n}$ supply chains arranged in a $\boldsymbol{m} \times \boldsymbol{n}$ array, $\boldsymbol{A}[\boldsymbol{a_{ij}}]$, whose rows correspond to the indicators, columns correspond to the food supply chains, and the element $\boldsymbol{a_{ij}}$ is the physical indicator-**i** from **j**-supply chains where $\boldsymbol{i} = \boldsymbol{1}, \boldsymbol{2}, \boldsymbol{3}, \ldots \boldsymbol{m}$ and $\boldsymbol{j} = \boldsymbol{1}, \boldsymbol{2}, \boldsymbol{3}, \ldots \boldsymbol{n}$. The normalization transformation maps the array $\boldsymbol{A}[\boldsymbol{a_{ij}}]$ into a $\boldsymbol{m} \times \boldsymbol{n}$ matrix $\boldsymbol{M}\ [\boldsymbol{x_{ij}}]$ of dimensionless indicators by applying a constant normalization parameter $\boldsymbol{s_i}$ on the set of $\boldsymbol{i}$-indicators where, $\boldsymbol{T}: \boldsymbol{A}[\boldsymbol{a_{ij}}] \rightarrow \boldsymbol{M}[\boldsymbol{x_{ij}}]$. On a scale of [0,1], the summation of normalized maximum and minimum indicators in a particular row should be 1. So it can be written as

$$\boldsymbol{x_i}^{\boldsymbol{max}} + \boldsymbol{x_i}^{\boldsymbol{min}} = \boldsymbol{1} \tag{58}$$

$$\frac{\boldsymbol{a_i}^{\boldsymbol{max}} + \boldsymbol{a_i}^{\boldsymbol{min}}}{\boldsymbol{s_i}} = \boldsymbol{1} \tag{59}$$

$$\boldsymbol{s_i} = \boldsymbol{a_i}^{\boldsymbol{max}} + \boldsymbol{a_i}^{\boldsymbol{min}} \tag{60}$$

Therefore, the normalization transformation $\boldsymbol{T}(\boldsymbol{a_{ij}})$ can be written as

$$\boldsymbol{T}(\boldsymbol{a_{ij}}) = \boldsymbol{a_{ij}}/(\boldsymbol{a_i}^{\boldsymbol{max}} + \boldsymbol{a_i}^{\boldsymbol{min}}) \tag{61}$$

This T should be invariant to affine transformation. According to Reed and Simon (1972) a map $\boldsymbol{T : C \rightarrow Y}$ where $\boldsymbol{C}$ is a convex subset of **X** and **Y** is vector spaces, is called an **affine linear map** on $\boldsymbol{C}$ if

$$\boldsymbol{T}(\boldsymbol{tx} + (\boldsymbol{1} - \boldsymbol{t})\boldsymbol{y}) = \boldsymbol{tTx} + (\boldsymbol{1} - \boldsymbol{t})\boldsymbol{Ty}, \boldsymbol{all}\ \boldsymbol{x}, \boldsymbol{y} \in \boldsymbol{C}\ \mathit{and\ all}\ \boldsymbol{0} \leq \boldsymbol{t} \leq \boldsymbol{1}. \tag{62}$$

In present case, the indicator $\boldsymbol{a_{ij}} \in \left[\boldsymbol{a_i^{min}}, \boldsymbol{a_i^{max}}\right]$ and $\boldsymbol{a_{ij}}$ is a convex set which can be expressed as (Olinto 2015)

$$\boldsymbol{a_{ij}} = \boldsymbol{\lambda_{ij}}\, \boldsymbol{a_i^{max}} + (\mathbf{1} - \boldsymbol{\lambda_{ij}})\boldsymbol{a_i^{min}}, \qquad (\mathbf{0} \le \boldsymbol{\lambda_{ij}} \le \mathbf{1}) \tag{63}$$

$$\boldsymbol{T}(\boldsymbol{a_{ij}}) = \boldsymbol{T}\left(\boldsymbol{\lambda_{ij}}\, \boldsymbol{a_i^{max}} + (\mathbf{1} - \boldsymbol{\lambda_{ij}})\boldsymbol{a_i^{min}}\right) \tag{64}$$

Hence, $$\boldsymbol{T}\left(\boldsymbol{\lambda_{ij}}\, \boldsymbol{a_i^{max}} + (\mathbf{1} - \boldsymbol{\lambda_{ij}})\boldsymbol{a_i^{min}}\right) = \boldsymbol{\lambda_{ij}}\, \boldsymbol{T}(\boldsymbol{a_i^{max}}) + (\mathbf{1} - \boldsymbol{\lambda_{ij}})\boldsymbol{T}(\boldsymbol{a_i^{min}}) \tag{65}$$

$or,$ $$\boldsymbol{T}\left(\boldsymbol{\lambda_{ij}}\, \boldsymbol{a_i^{max}} + (\mathbf{1} - \boldsymbol{\lambda_{ij}})\boldsymbol{a_i^{min}}\right) = \boldsymbol{\lambda_{ij}}\, \boldsymbol{x_i^{max}} + (\mathbf{1} - \boldsymbol{\lambda_{ij}})\boldsymbol{x_i^{min}} \tag{66}$$

$$Therefore, \qquad \boldsymbol{T}(\boldsymbol{a_{ij}}) = \boldsymbol{x_{ij}} \tag{67}$$

Therefore, transformation T is isomorphic (Reed and Simon 1972). It maps the array $\mathbf{A}[\boldsymbol{a_{ij}}]$ into $\boldsymbol{m} \times \boldsymbol{n}$ matrix $\mathbf{M}$ $[\boldsymbol{x_{ij}}]$ of dimensionless indicators such that,

$$\frac{\boldsymbol{a_{ij}}}{\boldsymbol{a_{ik}}} = \frac{\boldsymbol{x_{ij}}}{\boldsymbol{x_{ik}}} \quad (\boldsymbol{a_{ij}}\boldsymbol{a_{ik}} > 0) \tag{68}$$

Since the normalization parameter remains constant for each indicator, eqn (68) is unchanged of linear change of unit such that

$$\boldsymbol{T}(\boldsymbol{t_i}\boldsymbol{a_{ij}}) = \frac{\boldsymbol{t}_{\,i}\boldsymbol{a_{ij}}}{\left(\boldsymbol{t_i}\boldsymbol{a_i^{max}} + \boldsymbol{t_i}\, \boldsymbol{a_i^{min}}\right)} \; where\ \boldsymbol{t}_{\,i}\ is\ a\ constant \tag{69}$$

$$= \frac{\boldsymbol{aij}}{\left(\boldsymbol{a_i^{max}} + \boldsymbol{a_i^{min}}\right)} = \boldsymbol{T}(\boldsymbol{aij}) \tag{70}$$

Though a nonlinear change of unit changes the result, however eqn (68) still remains unchanged.

$$\frac{\boldsymbol{T}\left(\boldsymbol{a}_{ij}+\boldsymbol{t}_{i}\right)}{\boldsymbol{T}(\boldsymbol{a}_{ik}+\boldsymbol{t}_{i})}=\frac{\left(\frac{\boldsymbol{a}_{ij}+\boldsymbol{t}_{i}}{\boldsymbol{a}_{i}^{max}+\boldsymbol{t}_{i}+\boldsymbol{a}_{i}^{min}+\boldsymbol{t}_{i}}\right)}{\left(\frac{\boldsymbol{a}_{ik}+\boldsymbol{t}_{i}}{\boldsymbol{a}_{i}^{max}+\boldsymbol{t}_{i}+\boldsymbol{a}_{i}^{min}+\boldsymbol{t}_{i}}\right)} \quad where\ \boldsymbol{t}_{i} is\ a\ constant \tag{71}$$

$$\frac{\boldsymbol{T}\left(\boldsymbol{a}_{ij}+\boldsymbol{t}_{i}\right)}{\boldsymbol{T}(\boldsymbol{a}_{ik}+\boldsymbol{t}_{i})}=\frac{\boldsymbol{a}_{ij}+\boldsymbol{t}_{i}}{\boldsymbol{a}_{ik}+\boldsymbol{t}_{i}} \tag{72}$$

Therefore, eqn (68) remains same for ratio scale and interval scale data. Therefore, the ratiofound in eqn (68) is meaningful for both ratio scale and interval scale dataset.

The set of indicators in matrix M can be considered as vectors in n dimensional Euclidean space (Olinto 2014). Therefore, green value of a supply chain is to be determined by Euclidian distance or norm as follows:

$$\boldsymbol{G}_{j}=\left(\sum_{j}\boldsymbol{x}_{ij}{}^{2}\right)^{1/2} \tag{73}$$

The metric associated with the norms (distance between two vectors) satisfies translational invariance (Hunter and Nachtergaele, 2001).

In a food supply chain there can be negative indicators or beneficial indicators. In order to handle negative indicators, it is convenient to split the matrix $\boldsymbol{A}[\boldsymbol{a}_{ij}]$ into positive and negative indicators,

$$A[a_{ij}] = A'[a_{ij} \geq 0] + A''[a_{ij} \leq 0] = A'[a_{ij} \geq 0] - A''[a_{ij} \geq 0] \tag{74}$$

Now $A''[a_{ij} \leq 0]$ has only positive entries and all indicators vary within the same interval [0, 1], i.e., within the $\boldsymbol{n}$-dimensional unit hypercube in the positive octant. In matrix $\boldsymbol{A}'_{j}$, value correspond to $\boldsymbol{a_{ij}} \leq \mathbf{0}$ be replaced by zero and in matrix $\boldsymbol{A_j''}$, value correspond to $\boldsymbol{a_{ij}} \geq \mathbf{0}$ are replaced by zero. The green value given by the Euclidean norm in eqn(73) applied to eqn (74) expression then reads,

$$G_j = G_j' - G_j'' \tag{75}$$

Since both G_j' and G_j'' are positive, the overall green value G_j does not increase rather decreases due to negative indicators (benefit indicator). The smaller the green value G_j, the more favorable is the supply chain. G_j can be positive or negative. If negative, it means that the benefit overwhelms the environmental harms.

The difference between the method of Olinto (2014) and the method applied in this study are two: Firstly, Vector space theory applied by Olinto (2014) for determining overall sustainability of a specific process. However, here vector space theory is applied for assessing the environmental sustainability of the overall supply chain where the LCA data are collected and aggregated for all stages of the supply chain. Secondly, for assessing a single process, Olinto (2014) did not consider the impact of functional unit. However, in current study, a fixed functional unit is selected for each case study and how changing of functional unit can change the value of environmental sustainability is also shown. The methodology has been applied for three case studies and the results found have been compared with the previous results reported.

4.4.2. Demonstration case study

The preceding formalism is applied in three cases of food supply chains with different goals. The first case treats seven categories of life cycle inventories for six canned tomato supply chains from three different locations; three of which are for diced tomato and three are for paste tomato. The second case deals with the comparison of 12 different categories of life cycle impact of five different protected crops in an agricultural industry located in southern Italy. The third case compares the environmental impact of three traditional apple cultivars with commercial cultivar Golden delicious in Northern Italy for multi-functional unit. The first case shows the similarity and relevance of results found in present study and the original case study. In second case, a problem with more number of environmental indicators has been chosen for different products where the functional unit has been revised and different ordering than the original study has been reported here. Case 1 and 2 contains only positive indicators. For these two cases, the similar ordering can also be found by Sikdar et al. (2012). However, to clarify the effect of functional unit on ordering given by green value, the third case has been shown for same product with different functional unit. To show the effect of negative indicators some benefit indicators value have also been included in this case to show how they can change the value and ordering of environmental sustainability (green value).

Case 1

Brodt et al. (2013) have compared the environmental impacts of six canned tomato product supply chains. They considered three production area and two types of products (diced and paste) for each area. They are: *California conventional (diced tomato), California conventional (paste tomato), Michigan conventional (diced tomato), Michigan conventional (paste tomato), California organic (diced tomato), California organic (paste tomato).*

Their research goal is to assess the potential of regional food supply chain by comparing to national scale food supply chain when the product is shipped at long distances. The functional units are chosen as a *kilogram of canned, consumer-ready tomato paste* at a retail warehouse or distribution center in Michigan, and a kilogram of canned, consumer-ready diced tomatoes at a retail warehouse or distribution center in Michigan. This study considers the following supply chain stages: *tomato farming, post-harvest transport, tomato processing for diced and paste, tomato packaging, transport to retail distribution center in Michigan*.

In our current study, the vector space theory is applied for this case study. The key inventory categories considered here are: *GHG emissions, energy consumption, water consumption, land use, chemical use, gasoline use, diesel use*. Here Nitrogen consumption is only considered under chemical use category because it is one of the major source of pollution and the mass percentage for nitrogen consumption is quite higher than other chemical used (Brodt et al., 2013). All life cycle inventory amounts have been transferred for functional unit of 1 kg of tomato. The data set is shown in Table 12.

Table 12: Life cycle inventory for canned tomato (for functional unit=1 kg of tomato)

Indicator/ 1 kg tomato	Michigan conventional (diced)	California organic (diced)	California conventional (diced)	Michigan conventional (paste)	California organic (paste)	California conventional (paste)
GHG emission(kg CO_2 equivalent)	0.74	0.79	0.79	1.52	1.44	1.44
Energy consumption(MJ)	9.4	10.87	11.15	19.5	19.6	20.32
Water consumption (m^3)	0.020	0.096	0.101	0.021	0.096	0.102
Land use (ha)	1.35E-05	1.18E-05	1.11E-05	1.35E-05	1.18E-05	1.11E-05
Chemical use (kg N)	0.002	0.003	0.002	0.002	0.003	0.002
Gasoline(l)	0.0002	8.24E-05	0.0002	0.0002	8.24E-05	0.0002
Diesel(l)	0.004	0.008	0.006	0.004	0.008	0.006

By eqn. (61) the normalized value for Table 22 has been shown below in Table 13.

Table 13: Normalized life cycle inventory of canned tomato

Indicator/ 1 kg tomato	Michigan conventional (diced)	California organic (diced)	California conventional (diced)	Michigan conventional (paste)	California organic (paste)	California conventional (paste)
GHG emission ($kgCO_2$ equivalent)	0.327	0.349	0.349	0.673	0.637	0.637
energy consumption (MJ)	0.316	0.366	0.375	0.656	0.659	0.684
Water	0.168	0.783	0.831	0.168	0.783	0.832

consumption (m^3)						
Land use (ha)	0.549	0.478	0.451	0.549	0.478	0.451
Chemical use (kg N)	0.413	0.587	0.488	0.413	0.587	0.488
Gasoline(l)	0.736	0.264	0.605	0.736	0.264	0.605
Diesel(l)	0.319	0.681	0.498	0.319	0.681	0.498

By using eqn (73) the normalized values found in Table 23 are utilized to calculate the green value of 6 supply chains. The lower the green value, the more green is the supply chain. The green values are shown in Table 14 as follows:

Table 14: Green value of tomato for functional unit=1 kg equivalent canned tomato

Green value for 1 kg tomato supply chain	Michigan conventional (diced)	California organic (diced)	California conventional (diced)	Michigan conventional (paste)	California organic (paste)	California conventional (paste)
Green value	1.162	1.405	1.418	1.424	1.599	1.619

The hierarchical order of the green values of these supply chains found is: California conventional (paste tomato)> California organic (paste tomato)> Michigan conventional (paste tomato)>California conventional (diced tomato)> California organic (diced tomato)>Michigan conventional (diced tomato). This result is comparable to the study conducted by Brodt et al. (2013). Brodt et al. (2013) utilized three graphs to show the energy consumption, GHGs emission and water use separately. However, from their result, it was not clear that aggregately which supply chain was greener. From this study, if the green values are considered, it can be seen that, Michigan diced tomato supply chain is the most green and California paste tomato supply chain is the least. The long distance transportation required to send California product to Michigan distribution center makes California organic diced tomato supply chain the second most green as the long distance transportation causes higher energy use and GHG emission. This supply chain is greener than California diced tomato supply chain as Organic agriculture reduces energy use and GHG emission by decreasing agrochemical needs. The green value also shows that, tomato paste production supply chains irrespective of the regions are less greener and this result also supports the argument presented by Brodt et al. (2013) which is the environmental impacts of paste are approximately twice as great as those of diced tomatoes on a per kg basis, primarily due to the larger quantity of tomatoes required. Therefore, the hypothesis of the original study is fulfilled by the Green value found in this present study. Moreover, this depicts better illustration of LCA data for decision making.

Case 2

Another study conducted by Cellura et al. (2012), who assesses the life cycle environmental impact of different protected crops: tomatoes, cherry tomatoes, peppers, melons and zucchinis in an agricultural industry located in southern Italy. As this study considers more factors (12 factors) compared to Brodt et al. (2013) it is not very easy to rank the supply chains from the result found from Cellura et al. (2012) by graphical representation.

The goal of this study is to assess the impact of typologies of greenhouses on crops eco profile. The original study considers functional unit of 1000 kg packaged vegetable. However, here different kind of vegetables is considered and they are not comparable in weight basis. Therefore, the functional unit is revised and chosen as $18 \times 10^3\ kcal$ equivalent crops. The data has been converted for this amount of functional unit. The supply chain stages considered here are: raw material delivery to the cultivation site, cultivation stage, and transportation to local companies, packaging and delivery to customers, use and end-of-use. The environmental impact assessment data for this case study is shown below in Table 15:

Table 15: Environmental impact of protected crops (for functional unit= $18 \times 10^3\ kcal$ equivalent crops)

Column1	melon	Pepper	Zuchhini	Tomato	Cherry tomato
Global energy requirement[GJ]	12.72	10.08	29	16.2	23

Global warming potential[kgCO2eq]	756.575	512.68	1571	740	1245
Ozone depletion potential[kg CFC eq]	0.000302	0.000224	0.00045	0.00043	0.00051
Photochemical oxidation[kg C2H4 eq]	0.265	0.168	0.5	0.3	0.5
acaidification [kg SO2 eq]	5.936	3.864	13	5.7	9.8
Eutrophication kgPO4 e	2.279	1.904	6.7	2.1	3.7
Human toxicity (kg 1,4-DB)	449.758	476.224	1746.4	430.4	769
aquatic ecotoxicity (kg 1,4-DB)	216.664	246.848	932.3	194.5	421.8
marine ecotoxicity (ton 1,4-DB)	344.023	378.896	1307.7	313.1	611.1
terrestrial ecotoxicity (kg 1,4-DB)	2.915	2.688	9.7	2.9	4.8
Water Consumption [m3]	78.334	62.608	172.4	88.9	77.7
Wastes [kg]	149.354	73.024	210	178.4	293.6

By using eqn (61) and eqn (73) just as case 1, the normalized value and green values for each supply chains are shown in Table 16.

Table 16: Normalized environmental impact and green value of protected crops

Indicator/$18 \times 10^3\ kcal$ equivalent crop	melon	Pepper	Zuchhini	Tomato	Cherry tomato
Global energy requirement[GJ]	0.325486	0.257932	0.74206755	0.4145343	0.588536336
Global warming potential[kgCO2eq]	0.363096	0.246045	0.75395454	0.3551409	0.597500576
Ozone depletion	0.41158	0.305177	0.61307902	0.5858311	0.694822888

potential[kg CFC eq]					
Photochemical oxidation[kg C2H4 eq]	0.396707	0.251497	0.74850299	0.4491018	0.748502994
acaidification [kg SO2 eq]	0.351992	0.229127	0.77087287	0.3379981	0.581119545
Eutrophication kgPO4 e	0.264877	0.221292	0.77870758	0.2440725	0.430032543
Human toxicity (kg 1,4-DB)	0.206614	0.218773	0.80227857	0.1977214	0.353270856
aquatic ecotoxicity (kg 1,4-DB)	0.192283	0.21907	0.82738729	0.1726127	0.374334398
marine ecotoxicity (ton 1,4-DB)	0.212255	0.233771	0.80682379	0.1931762	0.377036032
terrestrial ecotoxicity (kg 1,4-DB)	0.235308	0.216984	0.78301582	0.2340975	0.387471747
Water Consumption (m3)	0.333325	0.266408	0.73359205	0.378285	0.330627042
Wastes (kg)	0.407376	0.19918	0.57279393	0.4866021	0.800820459
Green value	1.102614	0.832557	2.59121863	1.2480212	1.891266814

According to the green value found in Table 16, for the same calorie value, the largest burdens are related to the supply chain of zucchinis, while the lowest to pepper. The hierarchical order of supply chains according to the environmental burden based on nutritional value as functional unit is: Zucchini> Cherry tomato>tomato>melon>pepper. In study conducted by Cellura et al. (2012), Zucchini is also found to show the most environmentally harmful supply chain while the lowest burdens are related to tomato except for wastes and ozone depletion potential. Cellura et al. (2012) utilizes pie charts to show only one environmental factor which is Global energy requirement and bar chart to show waste rates. However, considering 1 kg of packaged vegetable as functional unit is also not relevant as all vegetables are neither of same kind nor of same weight or price or nutritional value etc.

Our next case study represents a clearer picture on the correlation between the functional unit and green value. These studies will also show the effect of benefit indicators on environmental sustainability.

Case 3

Another study conducted by Cerutti et al. (2013) investigated the environmental impacts of various apple cultivars supply chains in Northern Italy. The considered apple cultivars are: Golden delicious, Grigia di Torriana, Magnana and Runsé.

The objective of this study is to evaluate the environmental performance of commercial and ancient apple cultivars based on multifunctional unit. Two different functional units are considered here from original study: the earning of €1000 income by the grower and the production of 1 t of fruit. The supply chain stages considered here are: flow of resources, stock resources, soil preparation, harvesting, Orchard preparation, transportation to retail store. First, the environmental indicator data for functional unit of €1000 grower's income is shown in Table 17:

Table 17: Environmental impact of four apple cultivars (for functional unit= €1000 income equivalent fruit)

Indicator/€ 1000 income equivalent fruit	Golden	Grigia	Magnana	Runsé
Acidification potential (kg SO_2-eq)	1.55	1.413	1.427	1.481
Global warming potential(kg CO_2-eq)	327.76	305.208	293.904	291.078
Nutrient enrichment potential(kg NO_3-eq)	3.163	3.329	3.082	3.298
Ozone depletion potential (kg R11-eq)	4.60E-07	2.70E-07	2.50E-07	2.60E-07
Photochemical oxidant potential (high NOx) (kg ethene-eq)	0.081	0.068	0.068	0.069
Photochemical oxidant potential(low NOx) (kg	0.076	0.061	0.058	0.062

ethene-eq)

Changing of functional unit changes the value of indicators. Let us consider the functional unit as per 1 t fruit. The environmental impacts of the apple cultivars per ton of fruit are shown below in Table 18:

Table 18: Environmental impact of four apple cultivars (for functional unit= 1 t fruit)

Indicator/ 1 t fruit	Golden	Grigia	Magnana	Runsé
Acidification potential (kg SO2-eq)	0.775	0.954	0.971	0.945
Global warming potential(kg CO2-eq)	163.882	203.89	192.874	196.5484
eutrophication (kg NO3-eq)	1.581	2.304	2.284	2.304
Ozone depletion potential (kg R11-eq)	2.31E-07	1.67E-07	1.79E-07	1.65E-07
Photochemical oxidant potential (high NOx) (kg ethene-eq)	0.04	0.042	0.042	0.045
Photochemical oxidant potential (low NOx)(kg ethene-eq)	0.038	0.04	0.043	0.041

In Table 17 and Table 18, all the impact categories are environmental degrading indicator. In order to show the impact of environment benefit indicators on green value, the value of positive indicators have been taken from another study conducted by Donno et al. (2012) for these same apple cultivars in Northern Italy. The objective of the study (Donno et al., 2012) is to compare the nutritional value of ancient apple cultivars Grigia, Magnana, Runsé with their commercial counterpart Golden delicious. Nutritional value of food is undoubtedly environment benefit factors. Therefore, in present study, these nutritional values have been considered to observe the changes of green value of these four apple cultivars. To assess nutritional value of these fruits, Donno et al. (2012) consider Total Phenolic Component or TPC (mg_{GAE}/t fruit), anti-oxidant capacity (mmol Fe^{2+}eq/t fruit) and Vitamin C (mg/t fruit). The value of these benefit indicators have been shown for 1 ton fruit in Table 19.

Table 19: Environmental benefit indicator of the four apple cultivars (for functional unit= 1t fruit)

Indicator/ 1 t fruit	Golden	Grigia	Magnana	Runsé
TPC (mg_{GAE}/t fruit)	559579.4	1137103	786747.8	728216.2
Anti-oxidant capacity (mmol Fe^{2+}eq/t fruit)	63076.63	139715.7	88232.89	125472.9
Vitamin C (mg/t fruit)	25945.51	32558.9	86028.43	63620.94

Eqn (61) and eqn (73) have been applied on both Table 17 and Table 18. By varying the functional unit, changes happen in green values and their ordering. The value of the benefit indicators are also considered from Table 19 and by applying eqn (75) the green value for 1 t fruit has been calculated. All these green values have been reported in Table 20.

Table 20: Green values of four apple cultivars

Green value	Golden	Grigia	Magnana	Runsé
Green value(functional unit of € 1000 income equivalent fruit	1.379	1.147	1.083	1.114
Green value (functional unit of 1 t fruit)	1.342	1.622	1.661	1.639
Green value (for 1 t fruit including negative indicators)	0.834	0.618	0.664	0.697

Table 20 depicts the comparative analysis of green values of four apple cultivars in Northern Italy on the basis of functional unit and indicator type. When the functional unit is considered as €1000 grower's income equivalent fruit, Golden delicious is found to be the least green as it has the highest green value. Based on this functional unit, the three ancient cultivars Grigia di Torriana, Magnana and Runsé are found to have lower green value that means more environmentally sound. This result is similar to the conclusion found by original study. In this case, the hierarchical order for green values is: Golden delicious> Grigia > Runsé > Magnana. However, this outcome is totally opposite when the impact categories are compared by considering 1 t of fruit as functional unit. In this case Golden delicious is found to be the most green while the ancient cultivars are found to be less green. The hierarchical order of green value obtained here is Magnana> Runsé> Grigia>Golden delicious which is also similar to the original study. However, this deviation supports the argument presented by Cerutti et al. (2013) that the environmental impacts of fruit production is heavily dependent on the functional unit chosen. Although in both of these two cases, the original study (Cerutti et al., 2013) only concludes as which apple cultivar is more environmentally sound in which impact category. But they do not count any composite value to take a decision.

However, when the benefit indicators from Table 19 are considered for functional unit of 1 t fruit, it provides a completely reverse result. In this case, Golden delicious is found to be the least green while the ancient apple cultivars are found to be greener. The ranking of green value in this case Golden delicious> Runsé > Magnana > Grigia is also reported in Table 20. The purpose of the original study (Donno et al. 2012) is to show the benefit indicators contributed by ancient cultivars over their commercial counterpart golden delicious. Current study also shows the similar effect by considering positive indicators into calculating the Green value of these four apple cultivars.

From the above case studies, it is seen that the first case provides green values based on the life cycle inventories result while the rest two provides green values based on life cycle impact assessment result. Case 1 consider a single product but in different form and different locations. For this case, the result found from the current is identical with the conclusion found by original case study. In case 2, different crops are considered for same location. In this case the impact values are converted to similar equivalent calorie value to standardize the functional unit. By converting the functional unit in a specific standardized value, the result found here shows discrepancy with the original study. The last case clearly reveals the significance of functional unit for decision making for the same product. Changes in functional unit and including benefit indicators changes the decision of which supply chain is greener. Vector space theory applied to all the cases shows relevant green value result irrespective of the factors like functional unit or number and type (degrading /beneficial) of environmental factors or number and type of product categories. This method is also capable of meaningful representation of the physical system irrespective of changing the unit. And it is also found that meaningfulness is subject to particular functional unit. All these features reveal the compliance of vector space theory with the fundamental property of an index such as: Consistency, continuity, monotonicity and separability.

4.5. Conclusion

LCI is the most crucial part of LCA. In this chapter, a review has been presented on the evolution of various LCI methods, their calculation process and numerical examples. The advantages and disadvantages of various LCI methods and their potential scope are also presented. It is evident that various LCI methods are suitable for various purposes. As a potential scope of LCA, one novel frame work for decision making based on LCI has been proposed.

This framework act as an effective way to improve the sustainability of food supply chain is to perform an evaluation of their environmental performance. This also helps to determine how well a specific supply chain performs and which is the most competent one. To complete such an evaluation, a framework has been introduced here that can help determining an aggregated green value based on their Life cycle inventory/impact per functional unit. This method involves the collection of LCA data and application of vector space theory to determine the green value of individual supply chain.

Here, the positive and negative indicators are treated alike within the strict concepts of normed vector space, without the recourse of shifting variables or extraneous parameters. The ratio between physical indicators of the same factor is invariant after normalization, and the aggregated metrics are representative of the physical system. Taking zero as reference point allows a comparison among processes with similar factors and whose sustainability assessments are determined separately and independently.

This frame work broadens the scope of LCA. The study also signifies the influence of benefit indicators and functional unit on environmental performance of a product supply chain. The graphical representation of each indicator found from traditional LCA interpretation has been replaced by single aggregated value which facilitate unambiguous decision making.

CHAPTER 5: ENERGY MANAGEMENT STRATEGY FOR INDUSTRIES

5.1. Introduction

Energy acquires the biggest cost for any manufacturing system. One way to reduce this energy cost is to consume renewable fuel and achieving energy efficiency. However, for a industry working under variable electricity pricing, energy efficiency accompanied by an energy management strategy is highly necessary. WtE is found to be an attractive renewable source for energy. A small scale WtE is very suitable to be installed into an industry system. In this chapter a energy management strategy incorporating WtE and energy storage is proposed. The waste produced by the industry is used as renewable fuel for energy production. Consequently, it makes the industry energy efficient. In this work, an economic waste model is introduced which calculates the optimal capacity for WtE facility. The Fuzzy guiding rules for this system are decided from the industry requirement and electricity pricing period. The fuzzy inference system is implemented for designing the energy management strategy. A plastic container manufacturing industry is chosen for simulation. In order to justify the validity of the model, the cost analysis is also performed.

5.2. Energy Management Strategy for Industries

The proposed energy management system is shown in Fig. 6. A WtE system along with a waste storage and energy storage are installed into the industry.

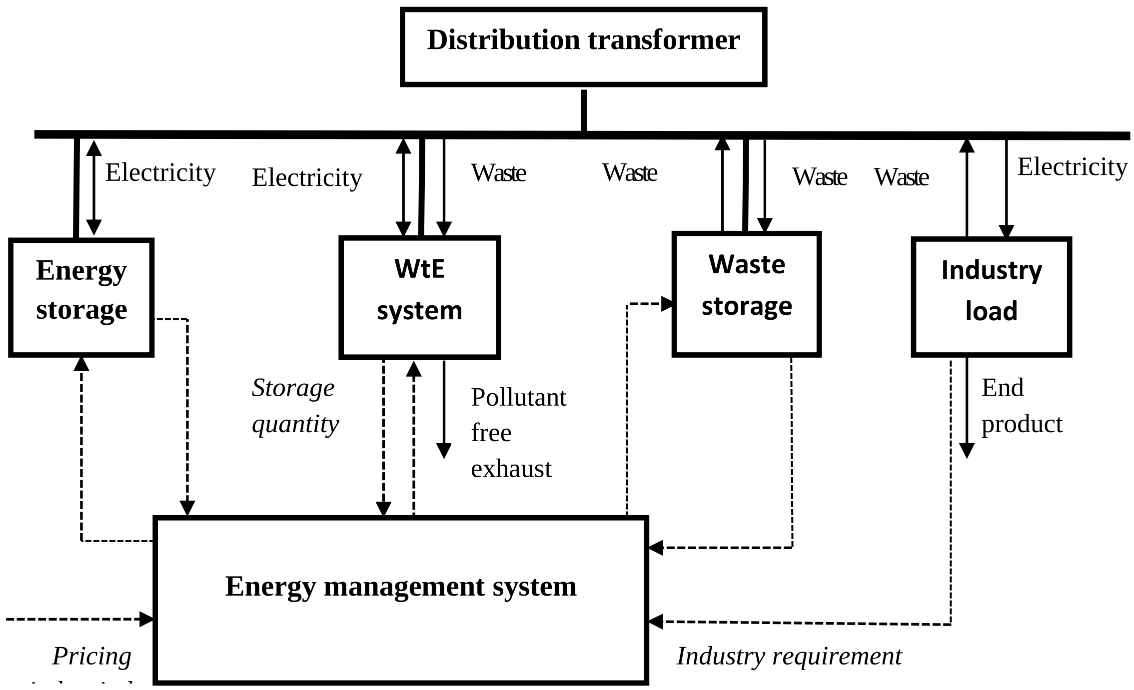


Fig.6. Energy management strategy model for industry

In Fig.6, a WtE for energy production, a waste storage and energy storage are installed in an industry. The industry produced waste is collected and stored in the waste storage. This waste is sent to WtE where electricity and pollutant free exhaust are produced. The generated energy is sent to energy storage. A fuzzy inference system (FIS) based energy management strategy will guide the energy discharge from energy storage.

In order to reduce the electric bill, the discharge quantity and discharge pattern from the energy storage are needed to be identified. The methodology is designed as the flow chart given in Fig. 7.

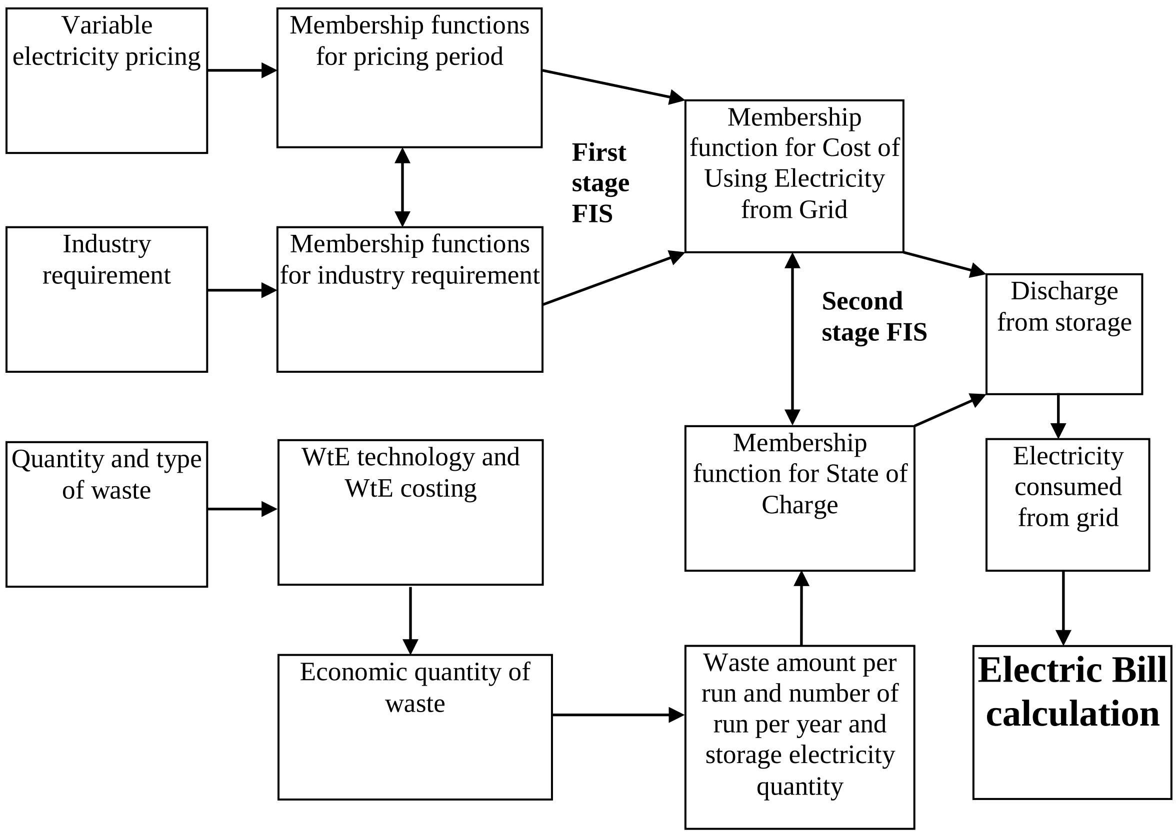


Fig. 7. Methodology of energy management strategy

The step by step methodologies are described below:

5.2.1. Category and Size of Waste

First, the daily waste production rate of or yearly waste production rate can are considered. To be commensurate with the waste quantity and type, the technology for WtE and capacity of energy are selected. This information is highly important because it determine the generator type, required consumable items, their quantity and required energy for operating WtE. Such as, waste gasification is more reasonable than waste combustion when per year waste quantity is less than 100,000 t (Ellyin and Themelis 2011). The energy production rate is also dependent on the waste's heating value or calorific value. After this step, the amount of waste to be treated by WtE is required to be determined.

5.2.2. Quantity of Waste to be Treated in WtE

Though an oversized system fulfills the full load demand but it is sometimes extravagantly prodigal. On the contrary, an undersized system is frugal, but it is not able to meet the load demand (Bhandari, Poudel et al. 2014). Caputo & Pelagagge (2001) conducted a study where the WtE plant is considered to handle 140 t per day though the waste production for that industry is only 52 t/day. Therefore, the capacity of WtE is ought to be relevant according to the amount of waste produced by the industry. These values are also important for assuming justifiable cost for the system. In order to aid these factors, an economic waste quantity model is presented here. The purpose of this model is to define the optimal WtE capacity which may fully consumes the economies of scale.

The total cost of WtE for a year depends on two costs: (i) Establishment cost; (ii) operating cost. The operating cost component of WtE is composed of two different type of costs. They are fixed cost and variable cost. The fixed cost does not depend on the quantity of waste and it is fixed for a run of WtE. Hence, when the WtE is operated, these costs must be incurred and they are not dependent on the quantity of waste being treated by it. The example of fixed cost are: maintenance cost, set up cost before and after operating WtE, labor cost, utility cost, cost for transportation of exhaust to landfill etc. For intance, if the WtE is operated, maintenance and set up (i.e.: waste movement from storage to WtE, lubricating, cleaning and so on) before and after the operation must be done and the cost associated with these do not depend on the amount of waste being treated. In contrast, the variable costs varies with the quantity of waste being treated in WtE. These kind of costs are not dependent of the number of operating runs of WtE; i.e.: tipping fee/unit waste for land fill, holding cost/unit waste, consumable cost/unit waste and the saving on electricity (considered as negative cost) etc.

Every industry produces an average amount of waste per day or per year. However, the most important question is to determine the amount of waste to be treated in WtE for each run which will minimize the total cost. Let us consider, the capacity of WtE is designed for dealing with a particular amount of waste in each run. Now the economies of scale is not fully consumed if the capacity is not fully utilized and an oversize WtE causes huge establishment cost. On the other hand for fully consuming this capacity, every single time waste are required to be carried out until gathering larger quantity. In this case, the holding cost becomes huge particularly if the waste is hazardous or waste carrying cost is expensive. Moreover, holding of waste results in two more costs: an opportunity cost for not producing electricity from waste and a cost of depreciation of WtE facility. In contrast, when the WtE facility is designed for small capacity, the capital or establishment cost becomes smaller. However, treatment of small amount of waste in each run leads to an increase in operating cost of WtE yet the holding cost is reduced. Thus, trade-off is required among these costs to define the optimal capacity of WtE.

The problem discussed above can be well compared with the scenario of Economic order quantity (EOQ) model for inventory. In EOQ model, the optimal order size which can reduce the total inventory cost is determined. The total inventory cost is composed of inventory holding cost and inventory ordering cost. If the economic waste quantity model is designed like EOQ model, it should be looked like Fig. 8. In the model shown in Fig.8, waste is held until its quantity reaches the optimal quantity Q_{eqw}. Hence, every time Q_{eqw} amount of waste is sent to WtE for energy production.

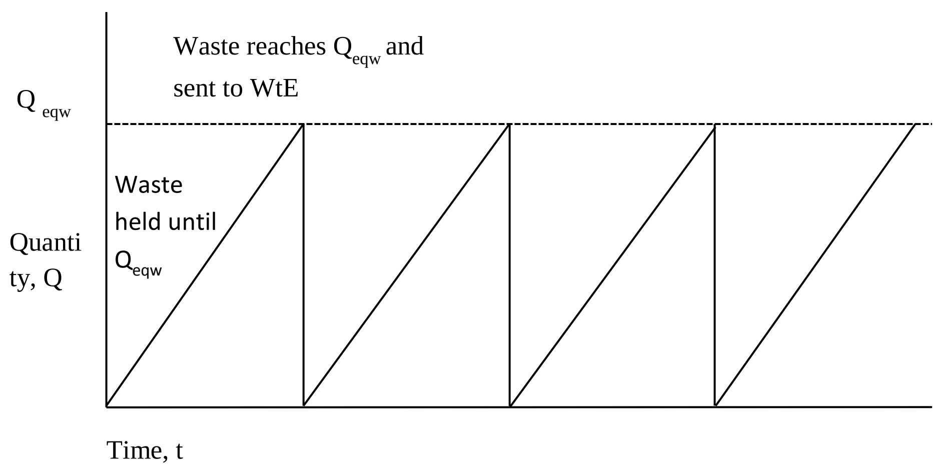


Fig. 8. Economic waste quantity model

The mathematical formulation for Economic waste quantity model is discussed below:

Let us consider the rate of waste holding is linear and instantaneous and exhaust is disposed each time the WtE is operated. So number of exhaust disposal is eual to number of WtE run.

The life of the WtE is considered for $\boldsymbol{n}$ years.

Average total waste produced per year= $\boldsymbol{w}$ t/year

Waste quantity for each run of WtE= $\boldsymbol{Q}$ t/run

$$\boldsymbol{w = y.Q} \tag{76}$$

Establishment cost is **S** $ and $\boldsymbol{P_1, P_2, P_3 \cdots P_n}$ equals the cash flows in year **1,2….n** and IRR is the internal rate of return.

$$\boldsymbol{S = \frac{P_1}{(1+IRR)} + \frac{P_2}{(1+IRR)^2} + \frac{P_3}{(1+IRR)^3} + \cdots + \frac{P_n}{(1+IRR)^n}} \tag{77}$$

Now if we consider the first year, the fixed setup cost for this period will be $\boldsymbol{\frac{P_1}{(1+IRR)}}$ $

Exhaust producing rate = $\boldsymbol{x}$/t

Electricity production rate = $\boldsymbol{e}$/t

Fixed cost:

Fixed Cost per run $\boldsymbol{C_0}$ $/run

Fixed cost for exhaust disposal $\boldsymbol{z}$ $/run

Variable cost

Per ton tipping fee for landfill= $\boldsymbol{t}$ $/t

Saving per unit energy= $\boldsymbol{i}$ $/t

Annual holding cost per unit=$\boldsymbol{C}$**c** $/t

Now,

Tipping fee for exhaust disposal in a year $\boldsymbol{t} \times \boldsymbol{x} \times \boldsymbol{w}$ \$/year

Total energy saving per year $\boldsymbol{i} \times \boldsymbol{w} \times \boldsymbol{e}$ \$/year

Average waste inventory level $=\frac{\boldsymbol{Q}}{\mathbf{2}}$ t

Annual holding cost $\boldsymbol{C_C} \times \frac{\boldsymbol{Q}}{\mathbf{2}}$ \$/year

If the total cost of running WtE per year is $\boldsymbol{T_c}$

$$\boldsymbol{T_c}=\frac{\boldsymbol{P1}}{(\mathbf{1}+\boldsymbol{IRR})}+\ \boldsymbol{t.x.w}+\boldsymbol{C_0}\times\frac{\boldsymbol{w}}{\boldsymbol{Q}}+\boldsymbol{z}\times\frac{\boldsymbol{w}}{\boldsymbol{Q}}+\boldsymbol{C_C}\times\frac{\boldsymbol{Q}}{\mathbf{2}}-\boldsymbol{i.w.e} \tag{78}$$

Differentiating $\boldsymbol{T_c}$ with respect to **Q**

$$\frac{\boldsymbol{dT_c}}{\boldsymbol{dQ}} = \mathbf{0}-\boldsymbol{C_0}\times\frac{\boldsymbol{w}}{\boldsymbol{Q^2}}-\boldsymbol{z}\times\frac{\boldsymbol{w}}{\boldsymbol{Q^2}}+\boldsymbol{C_C}/\mathbf{2} \tag{79}$$

Setting resulting function=0

$$\boldsymbol{C_0}\times\frac{\boldsymbol{w}}{\boldsymbol{Q^2}}+\boldsymbol{z}\times\frac{\boldsymbol{w}}{\boldsymbol{Q^2}}=\boldsymbol{C_C}/\mathbf{2} \tag{80}$$

The economic quantity of waste to be sent to WtE

$$\boldsymbol{Q_{eqw}}=\left[\frac{\mathbf{2}\boldsymbol{w}(\boldsymbol{C_0}+\boldsymbol{z})}{\boldsymbol{C_C}}\right]^{\frac{1}{2}} \tag{81}$$

Total minimum cost for year is

$$\boldsymbol{T_{opt}}=\frac{\boldsymbol{P1}}{(\boldsymbol{1+IRR})}+\ \boldsymbol{t.x.w}+\boldsymbol{C_0}\times\frac{\boldsymbol{w}}{\boldsymbol{Q_{eqw}}}+\boldsymbol{z}\times\frac{\boldsymbol{w}}{\boldsymbol{Q_{eqw}}}+\boldsymbol{C_C}\times\frac{\boldsymbol{Q_{eqw}}}{\boldsymbol{2}}-\boldsymbol{i.w.e} \qquad (82)$$

From eqn.(81) it is evident that the economic quantity of waste Q_{eqw} is a function of average waste production per year, fixed cost per run, transportation cost per run and holding cost per unit. This economic quantity does not depend on other variable costs. Other variable costs rely on the average waste amount produced per year and they must be incurred irrespective of the matter how much waste is sent to WtE.

After determining the optimal waste quantity, the next step is to find out how to compute the demand on energy discharge from the storage. For formulating this strategy the first two constraints are: electricity pricing and industry requirement.

5.2.3. Variable Electricity Pricing and Industry Requirement

The variable electricity pricing depends on demand period. In nationwide high demand period, the electricity price goes highest (peak hour) and vice versa. Let us consider a case of a sweater production industry. For this industry, the customer demand is the highest in winter season and the lowest in summer. In spring season, the customer demand stays somewhere in between as sometimes customers start to buy and gather for winter season. This industry is open for 6 days a week and Sunday is their holiday. Normally, electricity is charged the highest in summer and lowest in winter. In spring, the electricity charge is medium. The industry usually produces more at summer and spring time and store in the inventory. This production plan lower their inventory cost and avoid the risk of any lost sales in winter period. So, electricity requirement becomes high for them in summer and spring. For this case, the comparison among industry requirement and electricity pricing is shown in Fig. 9.

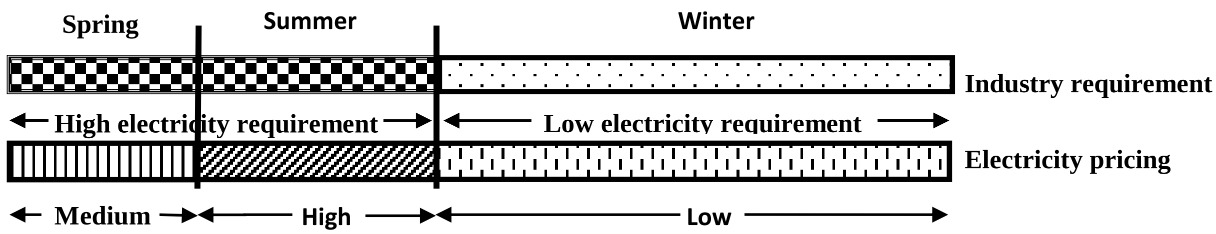


Fig. 9. Industry requirement vs. Variable electricity pricing

From Fig.9, three periods are identified. For these three periods, the cost of using electricity is different. For example, the period when industry requirement is low and electricity price is low the cost of using electricity from grid is the lowest. This is because; in this period both the price per unit electricity and consumed amount of electricity are the lowest. The period description and cost of using electricity in these periods are shown in Table 21.

Table 21: Period description and cost of using electricity

period	Description	Cost of using electricity from grid
Period 1	Time when industry requirement is high and electricity price is medium	medium
Period 2	Time when industry requirement is high and electricity price is high	highest
Period 3	Time when industry requirement is low and electricity price is low	lowest

Let us consider this sweater industry installs the proposed model described in Fig.6 as a backup electricity source for reducing their electricity bill in high pricing period. If cost of using electricity from grid is the highest, industry's demand for energy storage discharge is great and vice versa. So, the demand for discharge from energy storage is high at period 2. Period 2 is followed by period 1 where the demand for energy storage discharge is low. Period 3 is the lowest cost period for using electricity from grid so industry has no demand for energy discharge from storage. Considering all these requisites, another constraint comes into action which is amount of energy stored in the storage. Let us name it as State of charge (SOC).

5.2.4. State of Charge (SOC)

The energy storage capacity is established according to the electricity produced by the optimum quantity of waste. According to on the industry's demand for electricity in each period, the discharge from storage is determined. From Table 21, the Period 3 is found to be the lowest cost period. In this period WtE should be operated and storage should be charged. Period 3 follows period 1. Therefore, at the beginning of period 1 the storage charge is full. In period 1 the demand for energy storage discharge is low, so by end of this period storage charge is considered medium. Period 1 follows period 2 which is the highest demand for energy storage discharge period. Hence, the rest of the storage quantity is fully utilized in this period and storage becomes empty to be charged in next period. Cost of using electricity from grid and corresponding SOC are shown in Table 22:

Table 22: Cost of using electricity from grid and corresponding SOC

Period	Cost of using electricity from grid	SOC
Period 1	Medium	highest
Period 2	Highest	medium
Period 3	Lowest	lowest

5.2.5. Rule Preparation for Discharge From Storage

Based on the Cost of using electricity from grid and state of charge, the guiding rules are designed for discharge from storage. At Period 3, WtE is operated and storage is fully given charge. At the beginning of Period 1, storage remains full and cost of using electricity is medium, so discharge from storage is small. Alike, in Period 2, Cost of using electricity from grid is the highest and discharge is great or full. Hence the guiding rules can be written as:

- If Cost of Using electricity is the lowest and state of charge is lowest, Charge to full capacity.
- If Cost of Using electricity is medium and state of charge is the highest, discharge little.
- If Cost of Using electricity is highest and state of charge is medium, discharge to full capacity.

Hence, based on the above discussion, the principles for the proposed model are:

• Hold the waste until it reaches the optimal capacity of WtE

• During the high pricing period, reduce utilization of supplied power by the grid in order to reduce the electricity bill.

• During low pricing period, increase the utilization of supplied power from the grid

• When discharge from storage is less than required power, take the additional amount from the grid

• When discharge is greater than required energy, take the required amount and send the leftover back to storage or other portion where necessary(i.e-if it is the end of the period, send the extra energy to WtE for utilization or send it for revenue production)

• Ensure sufficient storage preservation at the end of any period followed by a peak period

• All energy stored in storage should be consumed by the system before the beginning of storage charging period for ensuring the availability of storage for charging.

• Charge the storage system during the off-peak period

5.2.6. Fuzzy inference system (FIS) based energy management strategy

Based on the above rules, FIS is adopted to regulate the energy management strategy. The inputs to this FIS are Industry requirement, electricity pricing and State of charge. And the final output is Discharge from storage. Fig. 10 describes the proposed FIS for energy management strategy.

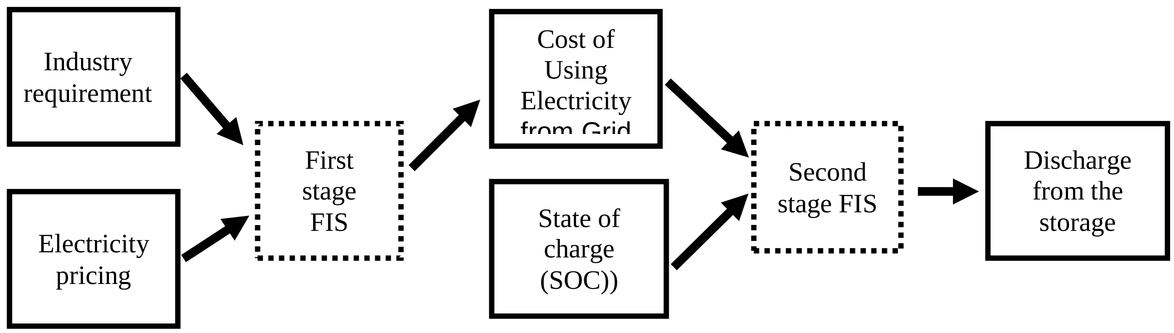


Fig. 10. Fuzzy inference system (FIS) based energy management strategy

In Fig. 10, Electricity Pricing and Industry requirement are the two inputs for the first stage FIS. Cost of Using Electricity from Grid (CUEG) is the output of this first stage FIS. This Cost of Using Electricity from Grid (CUEG) and state of charge (SOC) are the inputs for the second stage FIS. The output of this system is discharge from the storage which is the final output.

5.2.7. Electricity bill calculation

Electricity bill components are discussed below:

Fixed Customer Charge-The customer charge is generally the base monthly charge the customer pays regardless if they use any power or not. This base charge covers things like the cost of meter, billing and accounting.

Energy Charge-The energy rate is the rate paid for each kilowatt-hour of energy used by the customer. Flexible pricing allows electricity customers to choose being charged different rates for electricity during different times.

Distribution Charge – This charge recovers the cost of the lower voltage lines that carry electricity from the transformers to your meter. This is the calculated at a fixed rate per unit energy consumed.

Transmission Charge – This charge recovers the costs of owning and operating the high voltage lines that carry electricity to the substation transformers. This is the calculated at a fixed rate per unit energy consumed.

Tax-A fixed percentage of state tax is held on overall bill.

Let us assume fixed customer charge is Fc, electricity consumption at peak, shoulder and off peak are E_{peak}, $E_{shoulder}$, $E_{off\ peak}$ respectively and energy charges are Ec_{peak}, $Ec_{shoulder}$, $Ec_{off\ peak}$ respectively. Distribution and Transmission charges per unit are Dc_{unit} and Tc_{unit} respectively. So, total electricity consumption is

$$E_{total}= E_{peak}+E_{shoulder} +E_{off\ peak}$$

Total Electricity bill= Fixed Customer Charge(Fc)+ Energy Charge(Ec)+ Distribution Charge(Dc)+ Transmission Charge(Tc)+ Tax

Electricity bill= Fc+ (E_{peak}xEc_{peak}+ $E_{shoulder}$x$Ec_{shoulder}$+ $E_{off\ peak}$x $Ec_{off\ peak}$)+ (Dc_{unit}* E_{total})+(Tc_{unit}* E_{total})+ Tax

Taking discharge from energy storage reduce the electricity consumption from grid. Reducing the electricity consumption from grid, reduces the energy charge, Distribution charge, transmission charge and tax. Therefore, it saves a significant amount on overall electric bill

5.3. Case Study

A plastic container manufacturing industry located in Dhaka, Bangladesh has been considered to apply this proposed energy management strategy. The industry is open for 6 days a week and Tues day is their off day. The industry has three seven hours shifts with 1 hour gap in between. The electricity demand in shift periods is around 462 kWh on average. As in gap, it needs a small amount of electricity around 27 kWh. The industry’s average waste production rate is 192.3 t per year. Their production waste consists of various kinds of plastic bottle, containers and packaging plastic. The industry usually crushed and disposed their waste every day by third party transportation support. The industry produces around 450 kg waste plastics per day and per day disposal costs $76.86. The tipping fee for waste landfilling is $6.25/t. The industry is operating under variable electricity pricing where the peak period costs $0.20/kWh, shoulder period cost $0.15/kWh and off peak period cost $0.08/kWh. Depending on the waste quantity and waste type, a small scale WtE plant consisting of bubbling fluidized bed gasifier and ORC turbine is considered. The industry currently pays around $6349.567 for a 31 day month electricity bill.

So, the currently electricity usage pattern in a Wednesday for the industry is shown in Fig. 11. From Fig. 11, it can be understood that the major contribution into the electric bill comes from the period called 9 am-11 am (peak), 18 pm-21 pm(peak), 11 am-16 pm(shoulder) and 21 pm-24 pm(shoulder).

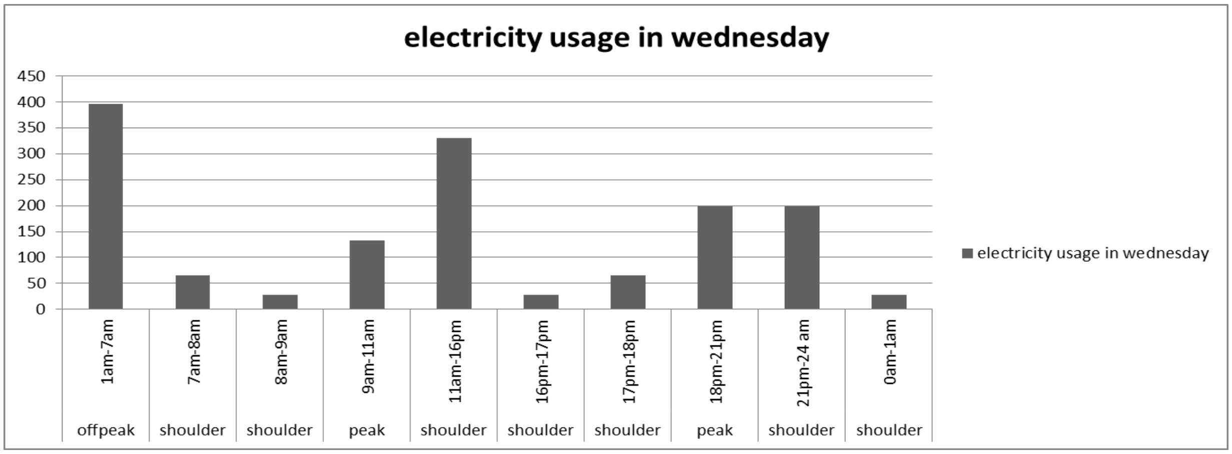


Fig. 11 Industry electricity consumption on a day

Let us consider the proposed model to be installed in above industry. Due to the similarity in waste type and quantity, the plant capital cost is estimated from literature (Arena, Di Gregorio et al. 2011; Arena, Di Gregorio et al. 2015).

One plastic container on average is 0.021 kg

Production per month 30,00,000

Waste bottle for out of specification is 20%

So, per month waste is 6,00,000 piece

Waste in weight=12600 kg=14 t

Let, packaging plastic material waste is 15% of waste container

Total waste per month=14+.15*14=16.1t

So total waste per year=16.1*12=193.2t per year

Estimated plant capital cost k$=2121.28 k$ (Arena, Di Gregorio et al. 2011)

Plant life is estimated for 20 years

Waste type: mixed plastic

Lower heating value: 22.09 MJ/kg (Arena, Di Gregorio et al. 2011)

Economic quantity of waste calculation

For economic quantity of waste amount we need holding cost, fixed cost per run and transportation cost

Holding cost per ton per year is assumed as the summation of:

- Per year depreciation per ton
- Opportunity cost of Per ton electrical energy
- Insurance cost
- Maintenance cost

Per year at 5% depreciation per ton = 551.5/ton/year.

If the weighted average of the variable electricity prices are taken to compute average cost per unit electricity,

Average price per unit electricity= 0.14$/kwh

So, Opportunity cost per ton electrical energy=$266.6/ton/year.

Insurance cost per year= $70/t/y

Maintenance cost=$11/t/year(0.1% capital cost)

Total holding cost/t= per year depreciation+ Opportunity cost per ton electrical energy + insurance cost+ maintenance cost

= 551.5+266.6+70+11=$900

Fixed cost per run= each time set up of the plant before and after the operation+ labor cost per run

Each time set up= handling of waste, cleaning, set up and startup of machine

Each time set up of the plant before and after the operation = $1.25/run

Each run require 3 labor.

Each labor cost=$ 1.87

Total labor cost= $5.6

Total fixed cost per run=$6.85

Transportation cost= $51.2

Economic quantity of waste by using eqn. (6) =5 t

Plastic conversion rate = 1860 kwh/ton(Arena, Di Gregorio et al. 2011)

Exhaust production= 0.44 ton/ton waste (Arena, Di Gregorio et al. 2011)

Total exhaust production per run= 0.55 ton

Total electricity production per run= 9300 kwh

Total number of days industry open=313(365 a year with 52 days off)

Number of run per year= 38.5 times ~ 39 times

Length of cycle= 8 days

So the WtE running dates on the month of January are 1,9,17,25

Now, the industry has three seven hours shifts with 1 hour gap in between. It has big electricity demand in shift periods. As in gap, the industry just performs their maintenance, set up and changeover activities, it need a small amount of electricity. The timing details of shift time, gap between shifts and Off day are shown in Table 23.

Table 23: Industry shifts, gaps and off day

Period	Description
Shift time	(9h~4h),(5h~24h) & (1h~8h)
Gap between shift	(4h~5h),(24h~1h) & (8h~9h)
Off day	Tues day(whole)

Their electricity usage pattern changes with their requirement in shift period. In contrast, the price of electricity is a function of time. Under the flexible electricity pricing period- the peak, shoulder and off peak period have been described here. Table 24 shows the electricity pricing period and corresponding duration.

Table 24: Electricity pricing period

Pricing period	Description
Peak Period	9h~11h and 18h~21h from Sunday to Thursday
Shoulder Period	7h~9h, 11h~18h and 21h~1h from Sunday to Thursday
Off Peak Period	1h~7h from Sunday to Thursday and all of the weekend(Friday and Saturday)

Now, if the periods are segmented based on the Industry requirement and Variable electricity pricing comparison for industry at the opening day, weekends and all day offs , we can figure out the guiding rules for our first two input variables. Periods based on comparison between industry requirement and electricity pricing in an industry open day are given in Fig. 12:

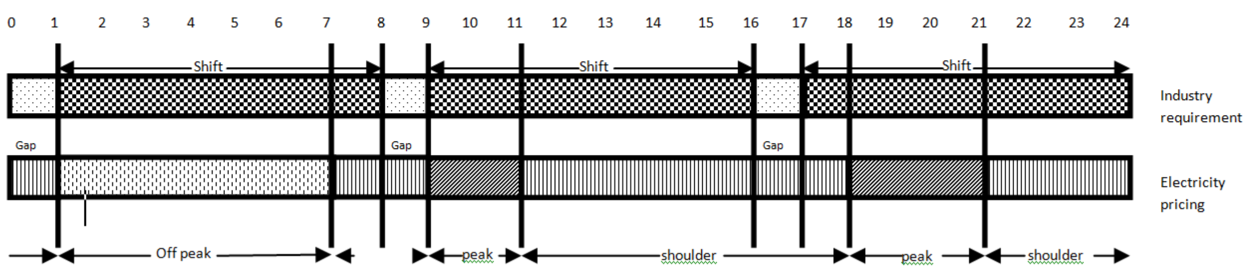


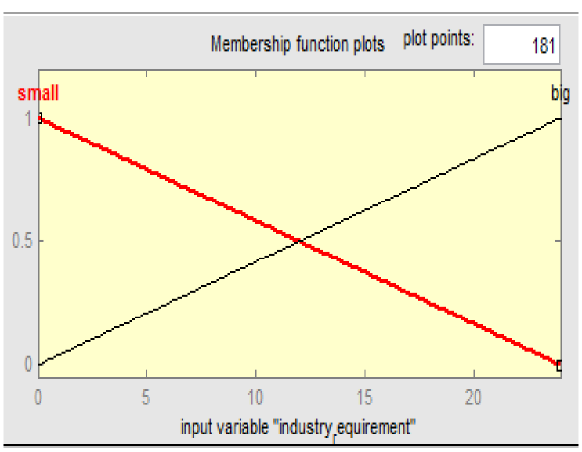
Fig. 12 Periods based on comparison between industry requirement and electricity pricing in an industry open day

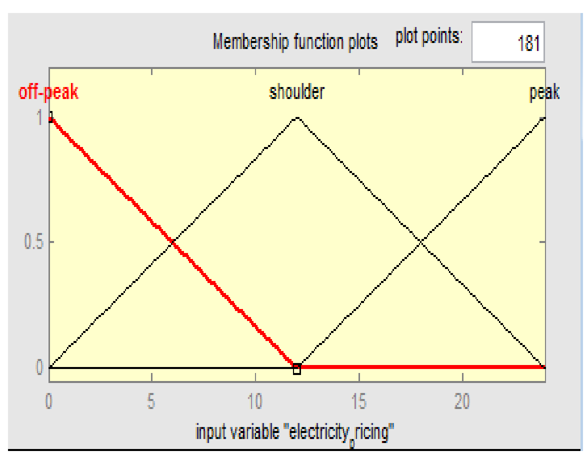
Total five periods can fully describe the above figure.They are given in Table 25.

Table 25: Period and rule description for first stage FIS

Period	Rule Description	Cost of using electricity from grid(CUEG)
Period 1	If industry requirement is big and electricity pricing is off peak	lowest
Period 2	If industry requirement is big and electricity pricing is shoulder	middle
Period 3	If industry requirement is small and electricity pricing is shoulder	low
Period 4	If industry requirement is big and electricity pricing is peak	highest
Period 5	If industry requirement is small and electricity pricing is off peak	lowest

Now based on the above table,the first stage FIS is applied for two input variables '*Industry requirement'* and pricing period and output '*CUEG*'. The membership function plots for the input and output variables of the first stage FIS system is shown in Fig. 13 .





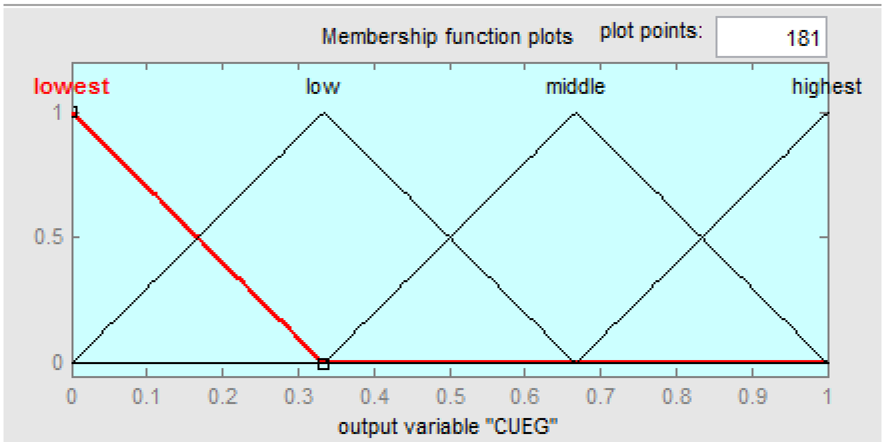


Fig. 13 Membership function plots for the input and output variables of the first stage FIS system

These five periods for CUEG accompanied by the State of charge (SOC) would result into the final guiding rules for second stage FIS as shown in Table 25. In this case, the discharge from storage given in Table 26 as follows:

Table 26: Rule description and discharge from storage for second stage FIS

Rule description	Discharge from storage
If CUEG is lowest & SOC is high	Discharge great(DG)
If CUEG is lowest & SOC is medium	Discharge medium (DM)
If CUEG is lowest & SOC is low	Charge great (CG)
If CUEG is low & SOC is high	Discharge small (DS)
If CUEG is low & SOC is medium	Discharge small (DS)
If CUEG is low & SOC is low	Discharge small (DS)
If CUEG is middle & SOC is low	Discharge medium (DM)
If CUEG is middle & SOC is medium	Discharge medium (DM)
If CUEG is middle & SOC is high	Discharge medium (DM)
If CUEG is highest & SOC is low	Discharge great(DG)
If CUEG is highest & SOC is medium	Discharge great(DG)
If CUEG is highest & SOC is high	Discharge great(DG)

The membership functions for the inputs and output of second stage FIS are given in Fig. 14 below:

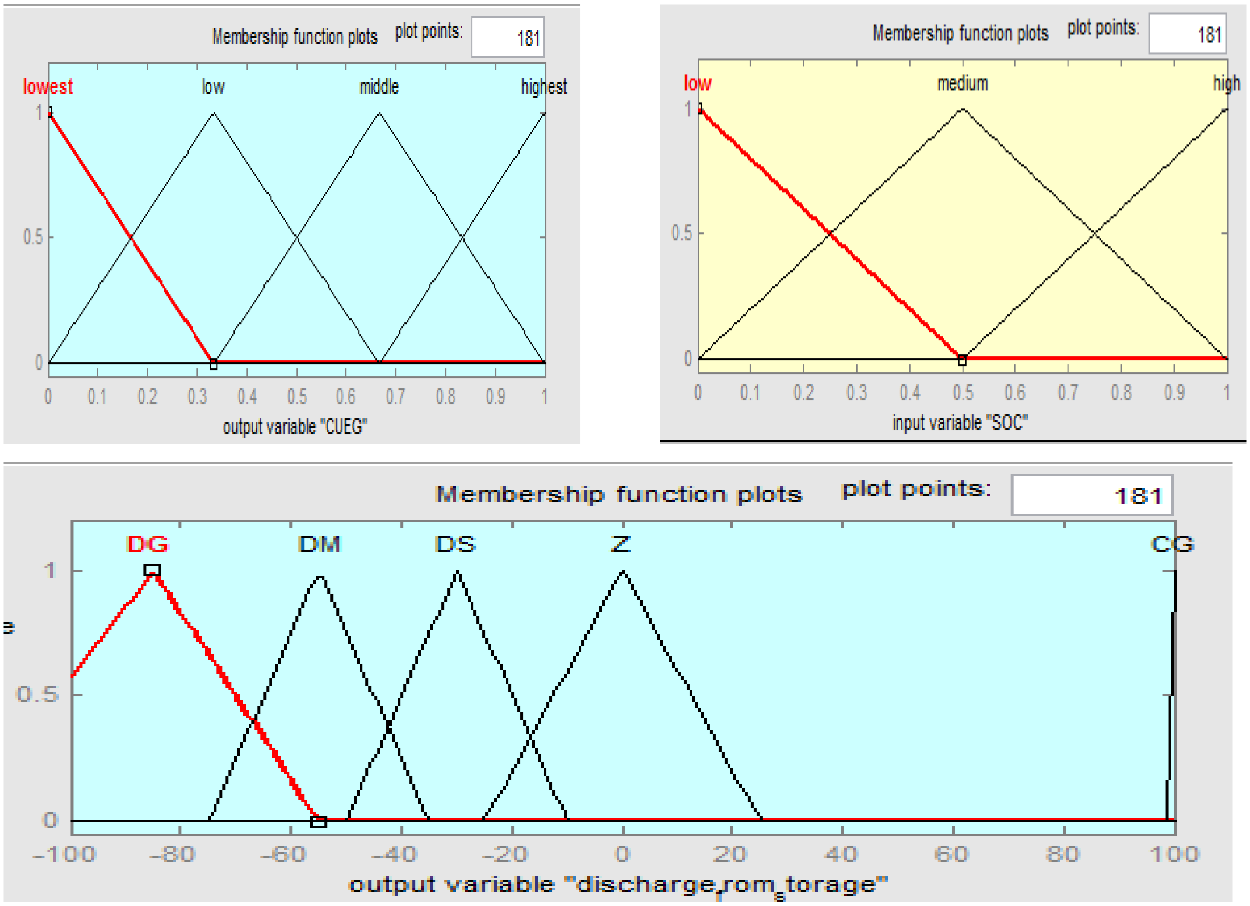


Fig. 14 Membership functions for the inputs and output of second stage FIS

The result is simulated for the month of January, 2015. From simulation, it is seen that, the proposed model is saving around $5922.617 on electric bill in first year. Though it saves a great amount on electricity bill under variable pricing but it incurs a higher establishment cost. However, if the overall energy and waste management is considered, it saves huge amount each year. The cost analysis is shown in the next section.

5.4. Cost Analysis

Here the detail cost component of Total Capital cost is shown in Table 27. The cost component is estimated from Arena et al. (2015) assuming a plant size of 192.3 t plastic waste/ year. All cost component in Table 27 is given in k$ unit.

Table 27: Capital cost component of the proposed model

Cost terms (Plant size:192.3 t/year)	Costs(k$)

Civil works	7
Feeding section	67
Gasifier	300
Auxiliaries (fans, burner, etc.)	10
Ash extraction system and storage	44.8
Syngas/air heat exchanger	28
Cyclone dust collector	16.8
Burner and combustor	112
Auxiliaries	33.6
Diathermic oil boiler	67.5
ORC complete system	670
Air heater	28
Sorbent storage and feeding system	22.4
Bag filter	44.8
Chimney	10
Piping and insulation	10
Instrumentation	20
Syngas and flue gas analysis equipment	112
Power lines and connection to the network	22.5
PLC and data management system	56
Electro-instrumental and pneumatic installation	56
Service fluid lines and auxiliaries	56
Safety devices	22
storage	112
Installation cost(10% of total cost)	192.84
Total capital cost	**2121.28**

The major components of proposed plant Operating costs are explained in previous section. The detail component of Operating cost for an estimated plant size of 192.3 t plastic waste per year is shown in Table 28. All cost components in Table 28 is calculated on $/year unit.

Table 28: Estimated Operating cost

Design assumption	Cost per year($/year)	Unit cost
Maintenance cost	2125.2	$11/t
Power consumption	2324.26	$12.1/t
Labor cost	218	$5.6/run
SRF pre treatment	3846	20/t
Chemical and additives	3846	20/t
Tipping fee for exhaust	135	6.25/t
Transportation cost	2997.54	76.86/run
Insurance and security	13524	70/t (0.7% of capital cost)
Total cost	**29016**	

For conducting cost analysis the current cost of waste management is also collected from the company which is shown in Table 10. All cost components in Table 29 is calculated on $/year unit.

Table 29: Waste disposal cost before

Design assumption	Cost per year ($/year)	Unit cost
Overhead cost(waste crushing, processing, utility)	5473.8	$17.5/day
transportation	24060	76.86/run, total 313 days
fee for waste disposal	1202	6.25/t
Labor cost	1752.8	5.6/day
Total cost	**32488.6**	

Therefore, the first year cash flow F_k is:

F_k = *saving on electricity+ cost of waste management before-cost of waste management after*

=$71127+$32488.6-$29016= $74600.

In computing net present value (NPV), return on investment and break even period (BEP) interest rate is assumed as 0.03 and the cash flow is assumed with 15% increase every year. Plant life is assumed for 20 years. The cost parameters and their calculated values have been shown in Table 30.

Table 30: Cost parameters and calculated values

Parameter	value
Capital cost	$2121280
Cost before installing WtE and storage model	$32488.6
Cost after installing WtE and storage model	$29016
Savings on electricity	$71127
Interest rate	0.03
Plant estimated life	20 years
NPV	$2890417
ROI (%)	-95,- 91,- 85,- 79,- 72, -64, -55, -44, -32, -17,1.5,17,38,63,92,125,163,206,256,314
BEP	10 years

5.5. Conclusion

In this thesis, a Fuzzy logic based energy management system with small scale WtE and energy storage is proposed for an industry. Industry's production waste is utilized as a renewable fuel for this system. The strategy for this system is to produce and store electricity in low pricing period and supply it in the high pricing period. To test this model data has been collected from a plastic container manufacturing industry and the electricity billsaving is found as $71127 in first year . To justify the higher establishment cost the overall cost analysis for waste and energy management is shown. Due to the similarity in waste type and quantity, the plant capital cost is estimated from an Italian industry. The estimated total capital cost is $2121280 and BEP is 10 years.

This energy management strategy is applicable for process industries under variable electricity pricing. Though this is an energy management policy, it can be an attractive solution for combined waste and energy management.

In this work, the costs of WtE plant are assumed from an Italian industry due to the similarity in waste nature and quantity. The study is applied on a plastic manufacturing industry in Bangladesh. If the Bangladeshi market prices of the equipment were considered, the capital cost would be less and the cost analysis result would be more feasible

This work will be applied on some more energy intensive industries to test and compare the results. The final output variable will always be the same. The input variables can change depending on industries electricity requirement and electricity pricing period.

CHAPTER 6: GREEN SUPPLY CHAIN

6.1. Introduction

Bangladesh is an agricultural country and rice is the main crop accounting for 76% of total cultivation area (Ahiduzzaman, 2007). Rice plant produces a significant amount of residues (Straw, Husk etc.) which can be used for energy conversion. These residues are distinguished into field residue and process residue. Field residues are left at the field after harvesting such as rice straw. On the other hand, process residues can be collected from rice mill which are removed from the main product (Milled rice) via milling operations such as husk, bran. Percentages of fractions (main product and residues) of rice are shown in Table 31 (Hassan et al., 2011):

Table 31: Amount of fractions of rice

Crop	Fraction	Amount of fractions (%)
	Straw	50
	Grain	25
Rice	Milled rice	17
	Husk	6
	Bran	2

Rice straw management is an important part of rice production. Currently, farmers utilize straw in two ways: burning straw for increasing field yield and using straw for feeding animals. Usually lower part of long straw and 100% bad quality straw is burnt. Usually 30% straw is burnt. However, this open burning generates large amount of gaseous and particulate emissions including carbon dioxide (CO_2), carbon monoxide (Turco et al., 2016), un-burnt carbon, nitrogen oxides (NO_x) and sulphur dioxide (SO_2) (Gadde et al., 2009). Burning provides an average net annual benefit over not burning because removal of excessive straw is costly and burning increases the field yield for successive crop. According to Haider (2013) if the farmers were subsidized this gain by external source or if any alternate usage of straw were found, this burning would be stopped.

Another major residue of rice production is rice husk which is found after the milling operation of paddy in the rice mill. Around 70% of the rice husk is used as the fuel for parboiling in the rice mill (Ahiduzzaman, 2007). 22% of husk is surplus and is used for other purposes like briquetting, poultry bed etc. The surplus rice husk and rice husk ashes is dumped into nearby land which also causes environmental pollution. A study conducted by Shafie et al. (2012) shows that 10 ton rice husk can produce 1.5 MWh electricity. Therefore, if the surplus husks produced at Bangladeshi mills are collected by power plant at a minimum price, then the husk can be potentially utilized for energy conversion and the mill owners become more motivated about improved parboiling technology and better rice husk management practice.

From the above discussion it is evident that, rice is one of the major sources of biomass available in Bangladesh. The current practice on the rice residue management is environmentally harmful and also causes a lot of rice residue to be dumped which actually have alternate beneficial use. In this work a supply chain network has been designed for rice straw and rice husk co firing in a coal power plant situated in Barapukuria, Rajshahi.

6.2. Methodology

The step-by-step methodology is described below:

6.2.1. Identify the Biomass Source

As the coal power plant is situated in the Rajshahi division, so in this work the districts located in Rajshahi divisions are chosen for rice straw and rice husk collection. Rajshahi is comprised of 16 districts. The commercial rice processing units play an important role in the rice Supply chain (Hisano and Mohacsi, 2003). According to the "Rice Mill Owners Association of Bangladesh" five districts under Rajshahi division is comprised of rice mill clusters and each cluster is composed of approximately 500 rice mills located in close proximity to each other (Islam and Mondal, 2013).The amount of total produced paddy (Bangladesh Bureau of statistics, 2014-2015), estimated residues amount and which districts include rice mill cluster zone (Islam and Mondal, 2013) are given in Table 32:

Table 32: Rice production amount for 16 districts in Rajshahi division with their plant

availability

Districts	Total rice (husked)	Total paddy	Rice mill cluster zone
Bogra (BG)	13,79,523	84,02,549	YES
Joypurhat (JP)	5,48,116.5	33,38,528	
Pabna (PB)	9,88,876.6	60,23,158	YES
Sirajgonj (SI)	4,47,452.2	27,25,391	
Rajshahi (RJ)	5,20,789.4	31,72,081	
Noagaon (NO)	11,26,421	68,60,925	YES
Natore (NT)	8,27,782.1	50,41,946	
Nawabgonj (NG)	5,83,781.4	35,55,759	YES
Dinajpur (DJ)	16,26,461	99,06,628	YES
Thakurgaon (TH)	6,35,876.1	38,73,063	
Panchagar (PN)	4,90,512.5	29,87,667	
Rangpur (RN)	10,66,522	64,96,086	
Gaibandha (GB)	8,66,823.4	52,79,742	
Kurigram (KR)	7,00,716.7	42,68,002	
Nilphamari (NL)	6,56,716.2	39,99,998	
Lalmonirhat (LL)	4,67,582.4	28,48,002	

6.2.2. Determining the Stages of the Supply Chain

It is evident that two types of rice residue- rice straw and rice husk will be collected from two locations field and mill respectively and then they will be sent to the only coal power plant situated in Barapukuria, Rajshahi. Therefore there are three stages of this supply chain consisting of 16 districts, 5 mills and 1 plant.

6.2.3. Determining the Available BioMass Amount

It is already seen from section that 50% of the Paddy is composed of rice straw. Around 30% of the bad quality straw is usually burnt or dumped and the rest is used for various purposes like cattle feeding, land fertilizer and cooking fuel.

On the other hand, the rest 50% of the paddy is obtained as rice grain which is sent to the mills. After milling conversion 6 % of paddy is found as rice husk. That means 12% of the grain is found as rice husk. In this husk, 70% is used for parboiling and 30% is left for other purposes. Let us consider to take 10 % from these left over.

6.2.4. Determining Transportation Cost

The transportation cost depends on the material density and distance travelled. Rice straw is a low bulk density material hence it would result in a much larger number of vehicle movements (Delivand et al., 2011). The bulk density of straw is 75 kg/m^3 (Kargbo et al., 2010) and husk is around 110 kg/m^3 (Mansaray and Ghaly, 1997). Depending on the vehicle capacity and available amount of biomass, number of trips required is determined. All the distances among the 16 rice field sources and 5 mills are determined. Distance among all 16 rice fields and 5 rice mills with the coal power plant are also computed. All of these data are utilized to calculate total transportation cost. Transportation cost for husk is considered as 0.5 usd/t/km (Lam et al., 2013). Therefore, according to the density ratio the transportation cost for straw is considered as 0.8 usd/t/km. In Table 33 the distance between each district and plant location is given:

Table 33: Distance between source districts and the plant location

Districts	Distance (km)
Bogra (BG)	141.26
Joypurhat (JP)	96.45
Pabna (PB)	262.99
Sirajgonj (SI)	209.99
Rajshahi (RJ)	204.87
Noagaon (NO)	137.5
Natore (NT)	209.85
Nawabgonj (NG)	337.16
Dinajpur (DJ)	0
Thakurgaon (TH)	57.52
Panchagar (PN)	95.7
Rangpur (RN)	86.89
Gaibandha (GB)	130.76
Kurigram (KR)	140.05

Nilphamari (NL)	59.86
Lalmonirhat (LL)	128.03

In Table 34 the distance between 16 districts to 5 mill locations are given:

Table 34: Distance between 16 districts to 5 mill locations

Districts	Bogra Mill	Pabna Mill	Noagaon Mill	Nawabgonj	Dinajpur Mill
Bogra (BG)	0	121.7	50.75	196.41	141.26
Joypurhat (JP)	58.44	180.1	45.47	256.04	96.45
Pabna (PB)	121.7	0	130.94	210.64	262.99
Sirajgonj (SI)	69.25	83.48	118.13	135.49	209.99
Rajshahi (RJ)	107.03	101.26	57.11	251.03	204.87
Noagaon (NO)	50.75	130.94	0	245.28	137.5
Natore (NT)	68.22	63.52	77.39	213.28	209.85
Nawabgonj (NG)	196.41	210.64	245.28	0	337.16
Dinajpur (DJ)	141.26	262.99	137.5	337.16	0
Thakurgaon (TH)	196.75	318.48	192.99	392.65	57.52
Panchagar (PN)	219.46	340.75	231.17	415.36	95.7
Rangpur (RN)	107.27	228.85	151.33	303.02	86.89
Gaibandha (GB)	71.38	193.11	115.59	267.28	130.76
Kurigram (KR)	152.59	274.32	196.8	348.49	140.05
Nilphamari	164.67	286.4	154.66	360.57	59.86

(NL)					
Lalmonirhat (LL)	140.57	262.39	184.78	336.47	128.03

In Table 35 the distance between 5 mill locations to the plant are given:

Table 35: Distance between 5 mill locations to the plant

Mill	Distance
Bogra Mill (Mill_BG)	141.26
Pabna Mill (Mill_PB)	262.99
Noagaon Mill (Mill_NO)	137.5
Nawabgonj Mill (Mill_NT)	337.16
Dinajpur Mill (Mill_DJ)	0

6.2.5. Total cost for rice residue transportation

The total cost of rice residue transportation is the summation of transportation cost and price of rice residue. By talking with the mill owner of Bangladesh it is found that, the price of rice straw is $ 0.1 per ton and the price of rice husk is $0.2 per ton.

6.2.6 Ratio during Co-firing

During co firing, 10 ton rice husk can provide 1.5 MWH electricity (Shafie et al., 2012) and the ratio of electricity production among rice straw and rice husk is 0.09:0.15. Co-firing is a great alternative solution for reducing CO_2 emissions from conventional fossil fuel power plants (Basu et al., 2011). Co firing of biomass in coal power plant is successful up to 20% of biomass mix and each ton of biomass co fired directly reduces fossil fuel CO_2 emissions by over 1 ton. (Demirbaş, 2003).

6.2.7. Supply chain network synthesis

Finally the maximal superstructure and all the combinatorial feasible individual networks between the involved materials and streams with the supply chain stages are generated. This step is performed internally by the P-graph algorithms MSG and SSG in P-Graph studio version 4.0.5.0.

6.3. Result and Discussion

The maximal structure of the biomass supply network is constructed by using P-graph approach in P-Graph Studio software version 4.0.2.1 and it is shown in Fig. 15.

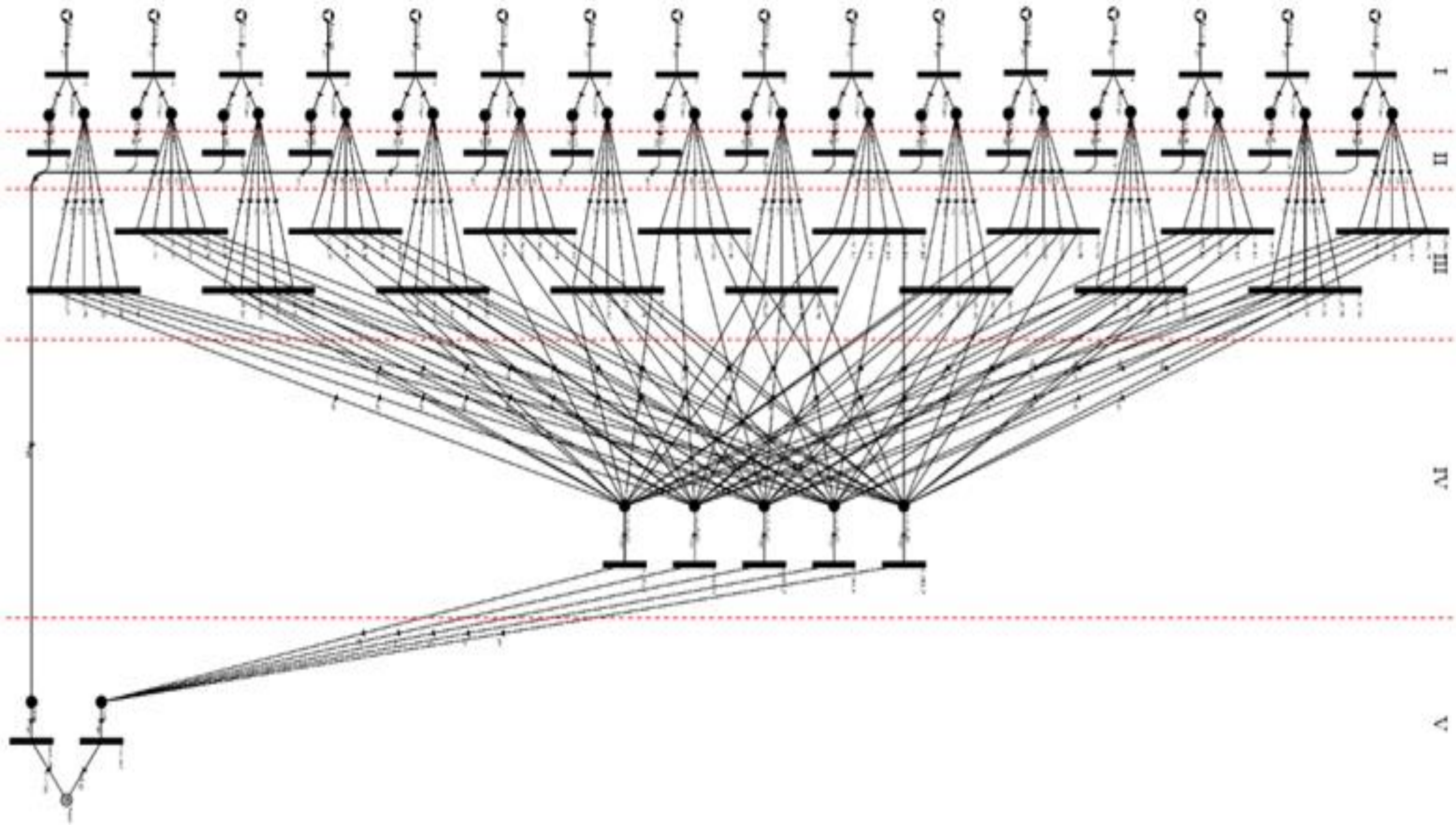


Fig.15 Maximal structure of the biomass supply network

The descriptions for each layer of the maximal structure are listed as follow:

• **Layer I:** This layer refer to the biomass sources in each district in Bangladesh. The amount of available biomass (i.e. rice husk and paddy straw) is defined in this layer. It is reported that 1 ton of harvested paddy will produce 0.5 ton of paddy straw and 0.06 ton of rice husk (reference). However, only 10 % of the generated rice husk and 30 % of the generated paddy straw are utilized in the co-firing power plant as the remaining biomass are used as animal feed, fertilizer and etc. On top of that, the material cost required to be collected for this biomass are defined in this layer as well. The material cost of each material are tabulated in Table 36

Table 36: Material cost of biomass

Material	Cost
Rice husk ($/ton)	0.2
Paddy Straw ($/ton)	0.1
Electricity ($/MWh)	61

• **Layer II:** The "operating units" in this layer refer to the transportation of paddy straw from each biomass source to the co-firing plant. The transportation cost for each distribution path is defined in this layer. It is assumed that the generic transportation cost required to deliver rice husk and paddy straw are $ 0.5/ ton and $ 0.8/ ton respectively.

• **Layer III and IV:** Layer III refers to the transportation of rice husk from each biomass source to the five existing rice mill in Bangladesh. 10 % of the generated rice husk will be delivered to the co-firing power plant in layer IV.

• **Layer V:** The power generation is defined in this layer. Generally, rice husk contains a higher heating value compared to paddy straw (reference). It is reported that the power conversion ratio for rice husk and paddy straw are 0.15 MWh/ton and 0.093 MWh/ton respectively (reference).

The annual power generation from the coal power plant located in Dinajpur, is about 1,000,000 MW (reference). In this work, it is aimed to replace 20 % of the coal-power (i.e. 200,000 MW) with biomass energy. After applying ABB algorithm built in P-Graph Studio software, the optimal structure of the energy supply chain is obtained which is tabulated in Table 37.

Table 37: Optimal structure for biomass network

Source	Rice husk [rice mill] (ton)	Paddy Straw (ton)	Energy (MW)
BG	50,415.3 [BG]	0	7562.29
JP	20,031.2 [DJ]	0	3004.68
PB	0	0	0
SI	0	0	0
RJ	0	0	0
NO	41,165.6 [DJ]	0	6174.84
NT	0	0	0
NG	0	0	0
DJ	59,439.8 [DJ]	1,485,990	147,113
TH	23,238.4 [DJ]	100,725	12,853.19
PN	17,926 [DJ]	0	2688.90
RN	38,976.5 [DJ]	0	5846.47
GB	31,678.5 [DJ]	0	4751.77
KR	25,608 [DJ]	0	3841.20
NL	24,000 [DJ]	0	3600.00
LL	17,088 [DJ]	0	2563.20
Total	349,567.3	1,586,715	200,000

The annual net expenses on these energy supply chain is $ 9,009,560. The high transportation cost is expected as the biomass are basically low-bulk-density materials. In term of environmental performance, by assuming the carbon emission rate through the biomass distribution as 90 g CO_2/km/ton (Lam, et al., 2013), the annual carbon emission from the transportation is about 1670 ton CO_2. On the other hand, the substation of biomass energy for fossil coal will indeed credit to the environment. As reported, carbon emission rate for the coal power generation is 967 gCO_2/kWh (Qin, et al., 2006). As a whole, 19.8 % of the carbon emission (191,730 ton CO_2) from the power plant is reduced.

6.4. Conclusion

In this work a supply network has been designed for co-firing of rice straw and rice husk in Rajshahi coal power plant. P graph approach is used to design this network. Though a high transportation cost is found for this network, a substantial reduction in carbon emission enable this network to become more favorable. It is worth to mention that the carbon emitted from biomass combustion are biogenic carbons, thus, it will not increase the carbon amount in the environment (Zaimes & Khanna, 2015). Therefore, the carbon footprint from biomass combustion is considered as 0.

This P-graph approach makes a easier method to represent supply network. Though the optimal solution is only explained in this thesis but near optimal solutions are also found in hierarchical order.

CHAPTER 7: CONCLUSION

This thesis demonstrates the project of establishing a green framework for manufacturing system via improvement under product, process and system level that leads the manufacturing towards green. Green manufacturing is a robust area and there are various scopes for improvement. This work is a small compilation of three piece meal work involving product, process and system level improvement for achieving green manufacturing. Under product level improvement, various methods of LCI are discussed with their evolution, examples and uses. A novel application of LCI has also been presented here for MCDM among various supply chain. Under process level improvement, a Fuzzy logic based energy management system with small scale WtE and energy storage is proposed for an industry. This system is especially useful under variable electricity pricing. For system level improvement, a green supply chain network has been designed for co-firing of rice residue in coal fire plant in Bangladesh.

7.1. Product Level Improvement

In this work, a review has been presented which depicts how the evolution of LCI increases, how to use it and it's applicability in the area of green manufacturing. Matrix method is superior to the PFD method particularly for the most simplified systems. Pure IO LCI can be most suitable for first proxy. However, when PFD is compared with the integrated hybrid method analysis, the latter provides system completeness in LCI results. With information on the monetary value only for cut-off flows and with improved availability of environmentally extended IO data, integrated hybrid method method becomes the best choice though the method is quite expensive. Therefore, with time and money available, integrated hybrid method is the best option. On the other hand, the tiered hybrid method analysis has the appeal of easy extension on existing PFD and IO LCI systems in filling the gaps. However, the connection between the two inventory subsystems is made externally which may cause double counting. In contrast, the IO-based hybrid method analysis shows higher resolution for the IO-based system and does not have problems of overlap. For a faster rough green manufacturing decision i.e. DfE, IOA is suitable while for long term decision like new green product design, process analysis or tiered hybrid method is appropriate.

On the contrary, with time and money available, the choice for any green attempt should clearly be integrated hybrid method.

One application of LCI is shown via presenting a new method of MCDM decision making using vector space theory. The application of this method has been shown via three case studies which have been found in literature.

7.1.1. Contribution of This Work

The contribution of this work is given below:

- A consolidated review on the evolution of various LCI methods has been presented.
- The step-by step methodology of applying each LCI method is shown which helps to identify the required data, application process, and suitability of each method.
- Advantage and disadvantages of LCI methods with suitable application is shown.
- A green index is proposed to assess the environmental sustainability of food supply chain.
- The contribution of functional unit in assessing the environmental sustainability is shown

7.1.2. Limitation of This Work

Some limitations of this work are given below:

- In this work, the LCI part of LCA is discussed but other stages of LCA are also important element to be discussed further.
- Detail on allocation method in LCI and uncertainty of LCI is not included in this work
- In the green value computation, weight assumption of each environmental impact is avoided.

7.2. Process Level Improvement

In this work a small scale WtE along with energy storage are proposed to be installed into the industry. Fuzzy logic is used to prepare the guiding rules of energy storage discharge to be sent to the industry. Here, Industry's production waste is utilized to produce energy at low pricing period and use this energy at high pricing period. To test this model data has been collected from a plastic container manufacturing industry and the saving on electricity bill is shown. To justify the higher establishment cost the overall cost analysis for waste and energy management is also shown.

7.2.1. Contribution of This Work

The contribution of this work is given below:

- An economic waste quantity model is found similar to circular economic theory is proposed.
- The proposed energy management strategy saves around $5922.617 on electric bill in first year.
- With 0.03% interest rate the breakeven point for onsite small scale WtE is found as 10 years.
- Though this is an energy management model, the model act for waste management as well.

7.2.2. Limitation of This Work

The limitation of this work is given below:

- The development and implementation of Economic waste quantity model ignored the "reduce" principle of the circular economy theory.
    - The sensitivity analysis has been avoided.
    - For simplicity, heterogeneity among waste is not considered.

7.3. System Level Improvement

In this work a green supply chain network is designed for co firing of rice residue in coal fire plant in Rajshahi, Bangladesh. Here, p-graph approach is adopted instead of conventional integer programming approach. This work is capable to remove the technical and supply chain related problem for biomass supply network. Transportation cost is optimized here along with carbon emission.

7.3.1. Contribution of This Work

- As a whole, 19.8 % of the carbon emission (191,730 ton CO_2) from the power plant is reduced.

- The optimal annual net expenses on these energy supply chain is found as $ 9,009,560.

7.3.2. Limitation of This Work

Even though important aspect has been covered along this paper, there is still several extension works to be done:

- Sensitivity analysis is yet to do for this work.

- Research on volume reduction of biomass should be conducted in order to reduce the transportation cost

- Steps should be taken to include more types of underutilized biomass which contain high potential in biomass-combustion.

7.4. Future research scope

Some future scope of this research work can be:

- Preventive energy management strategy to reduce energy consumption is important.

- Preventive waste management to reduce waste at source location in industrial plant can be beneficial.

- Some research can be done to reduce life cycle impact on products use and end-of-use phase

- Research is required for An optimal location selection to set up a biomass co firing plant in Bangladesh.

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