PALM BIOMASS

SUPPLY MANAGEMENT:

A PREDICTIVE ANALYSIS TOOL

Completed by

TANG JIANG PING, BEng

With the supervision of

LAM HON LOONG, PhD

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Department of Chemical and Environmental Engineering

University of Nottingham, Malaysia Campus

ABSTRACT

The flourishing of oil palm industry has always been regarded as a double-edged sword. While it has significantly contributed to the economic growth, it is, nonetheless, disputably unsustainable as it is a land-intensive industry and causing disposal problems by leaving behind massive waste. To strengthening the industry's competitive advantage and offsetting its drawbacks, this thesis presents a forward-looking framework – Biomass Supply Value Chain (BSVC)– to put emphasis on the value creation for the biomass industry. It aims to enhance the current biomass supply chain by harnessing the emerging technological advancement of artificial intelligence (AI), as well as by incorporating game theory to examine the strategic arrangement of the industry players. The proposed framework is capable of optimising the procurement process in the supply chain management: first, by identifying biomass properties for optimum biomass utilisation through the developed Biomass Characteristic Index (BCI); second, by applying AI into supply chain-related tasks for aiding better decision-making and problem-solving; and third, by adopting game theory in analysing strategic options, and providing appropriate strategies to minimise uncertainty and risk in procurement process. The "value" as suggested in the BSVC

does not merely refer to a narrow economic sense, but is an all-encompassing value concerning non-monetary utility values, including sustainability, environmental preservation and the appreciation of the biomass industry.

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Conference

1) 17th Conference on Process Integration, Modelling and Optimisation for Energy Saving and Pollution Reduction, 23-27 August 2014, Prague, Czech Republic.

   Oral presentation in Integration of renewables: fuels session.
   Title: Biomass characteristics index: a numerical approach in palm bio-energy estimation.

2) 18th Conference Process Integration, Modelling and Optimisation for Energy Saving and Pollution Reduction23- 27 August 2015 Kuching, Sarawak, Malaysia.

   Oral presentation in Operational Research, Supply Chain and Technology Management session.
   Title: Game theory approach in Malaysia palm biomass industry analysis.

   Poster presentation in Integration of Renewables, Biomass and Energy Conversion Technologies session.
   Title: Incorporation of calorific value into palm Biomass Characteristics Index.

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LIST OF ABBREVIATIONS AND ACRONYMS

AHP	Analytic hierarchy process
AI	Artificial intelligence
BCI	Biomass characteristics index
BELCA	Biomass element life cycle analysis
BSVC	Biomass supply value chain
ECN	Energy research Centre of the Netherlands
EFB	Empty fruit bunches
FAS	Free air space
FFB	Fresh fruit bunches
GDP	Gross domestic product
GNI	Gross national income
ha	Hectares

IEA	International Energy Agency
IRENA	International Renewable Energy Agency
kW	Kilowatt
m.c.w.b	Moisture content of wet basis
MPOB	Malaysia Palm Oil Board
PKS	Palm kernel shell
t	Metric tonnes
wt./wt.	Weight to weight
y	Year

1 CHAPTER 1 INTRODUCTION

The past decades have witnessed significant technological inventions and advancements in agriculture sector; alongside agricultural development, the waste from agriculture have even been turned into renewable energy and ultimately contributing to sustainable development. Biomass has now become a reliable and sustainable alternative energy source. In Malaysia, the oil palm industry is the main agricultural sector that generates abundant biomass as renewable sources. Being the world's second largest producer of palm oil after Indonesia, the oil palm plantations in Malaysia spanning a total of 5.74 million hectares of land, producing approximately 15.91 tonnes of fresh fruit bunches (FFB) per hectare per year (MPOB, 2017). Thus, the availability and continuity of the raw biomass material is unquestionable. There are several types of biomass, comprising empty fruit bunches (EFB), palm kernel shell (PKS), leaf frond, replanting palm trunk and so forth, that could be used to generate renewable energy. The most common and highly utilised biomass is EFB.

However, there are several factors that affect the efficiency of EFB utilisation. One of them being the technical barrier that hinges on its quality and quantity control. Both quality and quantity of this biomass are heavily contingent upon weather and season – these natural phenomena are predictable yet inevitable. For example, the biomass properties such as moisture content is influenced by season; during wet season, the moisture content of the bunches would increase, and hence longer time would be needed, and additional costs would incur for post-processing. Meanwhile, the availability of the palm biomass is also depended on the palm fruits harvest yield (Figure 1-1) – low harvest yield might fail to fulfil market demand, otherwise might lead to over-supply.

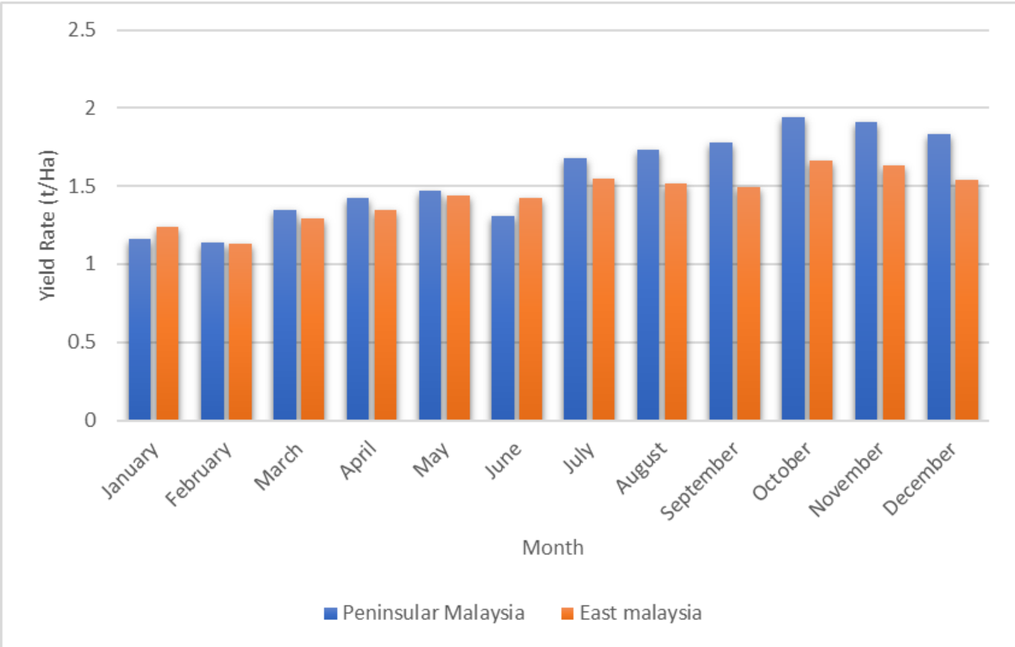

Figure 1-1: FFB yield in year 2017

Therefore, two of the key issues that intended to be highlighted and tackled in the present thesis are:

i. Technical problem: to propose pre-process identification techniques for biomass to overcome problems due to natural environmental factors
ii. Management problem: to suggest appropriate and profitable strategy to aid the decision making in biomass supply chain management.

1.1 Problem statement

a) The lack of incentive to encourage mill owners to commit to the biomass quality. In order to maximise the profit, they tend to minimise the operation cost by leaving the biomass out. Even when the biomass is processed, the product is no guarantee of quality and hence might be unmatched with the current market demand.
b) There is an absence or non-development of a comprehensive system that integrate the real-time and community data comprising location of biomass resources, process plant and actual market demand. This leads to disparity between supply and demand, failing to make full use of the waste and generate greater value for the biomass industry as a whole.

c) The lack of safety net system to counter measure critical risk factors to minimise biomass owner's losses and process deficiency. Risks including natural disaster and volatile market price need to be addressed. The most significant risks involved including the inevitable natural disaster and the extremely volatile market price.

1.2 Objectives of research

Malaysian palm biomass industry is currently tackling several issues; it is overwhelmed with big data, facing intense competitive rivalry within the industry, and constantly grappling with environment issues. Hence, a smart management system for biomass supply chain is needed to cope with these challenges and to improve the process efficiency. Therefore, the objectives of this research are:

a) To manage the factors affecting the efficiency of biomass utilisation.
b) To develop an intelligent decision-making system to aid biomass industry entrepreneur in maximising return through increasing the utilisation of biomass.

1.3 Scopes of research

a) Database construction

Real-world data consisting of all stages in biomass industry workflow ranging from weather, yield, supply, logistic, price to market demand will be collected to build a premise for the first trial run of the BSVC system. The system will then able to perform intelligent self-learning through AI algorithms. Moreover, the selected outputs related to industry players' experience and common practice will also be fed into the database for future reference.

b) Integrated framework construction

This thesis ambitiously proposes an integrated supply value chain system through combining different frameworks and models that is specifically designed to meet unique needs of each part of the system. Chapter 3 proposes BCI for palm bio-energy estimation, adding convenience to sourcing and procurement for suitable biomass in generating bio-energy. Chapter 4 presents an AI algorithm to perform data-driven price prediction, enabling commodity prices to be forecasted. Chapter 5 introduces game theory approach to analyse decision-making process within competitive situation involving multiple industry players with conflicting objectives. Each chapter dedicates a considerable amount of space to the discussion of the respective model and framework and of how they complement each other in developing the integrated BSVC.

c) Real-world grounded analysis

This thesis adopts a grounded approach to closely associate with the actualities in the real-world. The data collected, used and generated are constantly compared to the real-world's in order to verify the feasibility of the models presented. This is especially crucial for the realization and implementation of the proposed system to contribute to the development of biomass sector as a whole.

1.4 Research methodology and planning

a) Database construction

Various databases need to be constructed to provide different parameter inputs for the system for decision-making and process optimisation. These can be done through collecting statistical data and inputs from actual situation, government departments and mills, plantations or plants owners.

b) Levels of analysis

i. Biomass physical classification

Multiple biomass materials are classified based on its physical appearance and condition.

ii. Supply price prediction

Artificial neural network is used to predict biomass price in a specific period of time.

iii. Competitive scenario simulation

Game theory technique is applied into the supply chain to manage competition among industry players, supplies constraint, and emerging risks (man-made or natural) for generating Win-Win situation.

For the details of the methodology, it will be elaborated separately in Chapters 3, 4 and 5.

1.5 Thesis outline

Being one of the world's biggest palm oil producer and exporter, Malaysian's biomass industry is gaining its momentum. The significant biomass volume growth, which driven by the plantation expansion and FFB yield improvement, is projected to increase to 85 – 110 million dry tonnes by 2020 (Agensi Inovasi Malaysia, 2011). However, the potential of oil palm biomass is yet to be fully unleashed. Issues ranging from biomass quality management to lack of integration and standardisation in the entire flow of supply chain have hindered Malaysian biomass industry to propel to new heights.

This thesis presents an integrated one-stop system to providing the stakeholders in biomass industry an efficient model in making the right decision. Chapter 3 explores the biomass characteristic for palm bio-energy estimation through a numerical framework. BCI is developed to specifically study the physical appearance and properties of various biomass, wherein their bulk density and moisture content are calculated and classified to provide a more accurate forecast for optimum biomass utilisation. By doing so, the relationship between BCI, bulk density and moisture content can be unpacked to generate a new regression equation. To further improve the overall biomass operational management effectiveness, the estimated biomass value is then added into computer aided programming, which is the AI system.

Chapter 4 proceeds to propose the incorporation of AI methodologies into Malaysian biomass supply chain management. AI, or previously known as machine learning, is literally intelligence exhibited by machines. It uses computers to simulate human intelligence, capable of learning, acquiring and classifying information, as well as reasoning to gain insights into data. To date, AI's application in supply chain management, particularly in biomass industry, is still limited. This thesis suggests that by applying AI in the biomass industry workflow – ranging from the stage of supply and procurement management, logistic network and demand forecasting, the efficiency and excellence of biomass industry can be significantly improved.

Chapter 5 focuses primarily on the sustainable oil palm biomass procurement through the lens of game theory. The suggested approach allows biomass plant owners to gain advantage in the purchasing inputs by providing an optimal non-cooperative strategy and simultaneously minimising uncertainty in the decision-making process. Game theory is adopted to shed light on the industry players' objective and interest, and more crucially their psyche within a competitive business environment (Bhattacharya, 2013). In this way, appropriate and feasible strategy can be identified effectively without consuming much time and resources. Unlike conventional optimisation method that optimising the entire process, game theory approach is a targeted optimisation process that primarily emphasizes on key area and without incurring additional cost.

2 CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

Artificial intelligence (AI) has been widely recognized as a useful tool for decades. In 2016, it has even cemented its place in the technology mainstream, wherein technology companies such as IBM, Google and Amazon are jumping on the bandwagon in a race for AI by launching new AI-enabled products. In the field of supply chain management, AI is considered as important yet disruptive technologies with respect to supply chain strategy (SCM World, 2017).

A few literatures have been explored AI application in supply chain management. Min (2010) reviewed records of the success of AI implementation in different areas of supply-chain management to identify the areas that can gain the most advantages from AI. He pointed out that AI systems are particularly useful in addressing strategic issues and tackling various facets of supply chain problems. He drew a conclusion that supply chain management in today's world has increasingly evolved into knowledge management that requires the understanding of complicated and interrelated decision-making process, hence the importance of the creation of an intelligent decision-aid tool. Liu (2015)'s research highlighted on the emerging AI known as neural network, which emerged from the modern biology research achievements of human brain tissue, targeting at stimulate human brain structure and behaviour. He particularly emphasized the capability of neural network in terms of self-learning, and hence contributing to the optimisation of the supply chain management that consisted of multi-level system.

2.2 Artificial Intelligence Algorithm

In the early 90s, the advantage of neural network in self-learning has been applied in the logistic field for autonomous vehicle navigation. Pomerleau (2012) utilised such capacity to manoeuvre a land vehicle along a single lane on a highway and the result was promising. Despite the application of neural network in auto-piloting was limited to a certain road condition and traffic environment during that time, it nonetheless underlined its potential in mimicking human's cognition.

Another area that has proven the applicability of neural network in supply chain is the lot-sizing and setup process to develop hierarchical supply chain planning. For example, it is capable determining the capacity needed for setups, estimating optimal lot-size for supply chain processes, linking inventory and even making scheduling decisions and production planning decisions at both lower and higher level (Gaafar and Choueiki, 2000; Rohde, 2004). Their studies have shown that neural network is able to integrate interconnected and interdependent supply chain processes more effective that the traditional operation research techniques.

In recent years, AI has been specifically applied to the biomass industry by researchers. Nonetheless, given that biomass is a relatively low-cost commodity compared to other agriculture products, related studies merely focused on the issues of biomass yield, time constraint and demand fulfilment. Moreover, most of the biomass supply chain quantitative model construction are targeted on the facet of transportation, distribution network, harvesting technique, facility location, process optimisation, resource planning and inventory control (Behzadi et al., 2017). AI application in the aspect of decision-making in biomass supply chain management is scarce.

In fact, to further integrate AI algorithms into biomass supply chain management, there are three competitive priorities – namely cost, efficiency and supply reliability – needed to be highlighted in the analysis. Effective supply chain management requires these priorities to be linked with business strategy to lead the direction of functional strategies in terms of meeting customers' expectation and remained competitive within the biomass market (Torjai et al., 2015). From this perspective, a predictive model that is capable of planning, monitoring and controlling (Pinho et al., 2017) is essential to provide tactical decision for the biomass business strategic design to ensure its competitiveness in both service and products.

There are few researches of decision-making on pricing-related issue have shed light on this matter. For instance, Huang and Hu (2018) studied on the pricing strategy and decision-making by biofuel producers and farmers, which were assumed to be profit-driven. This study, however, has yet to take into consideration of the competition amongst farmers or biofuel producers, and hence no strategy was involved. This thesis argues that competition is inevitable in real-world business; competitors' response is critical to the business itself in terms of strategic deployment. This is where the players may transform disadvantages into advantages to ensure their service and product competitiveness in biomass business.

Table 2-1 is a categorised list of AI's implementations in the industry and shows that the most commonly utilised algorithm within the sector is artificial neural network and the application is mainly targeted on biomass material properties prediction. Amongst all, there is a sole research (paper 9 in Table 2-1) focusing on biomass price prediction through comparing the most cost-effective raw material for electricity generation.

Table 2-1: List of recent biomass artificial intelligence research

No	**Year**	**Algorithm**	**Prediction Model**	**Reference**
1	2017	Artificial Neural Network	biomass material components	(Castro et al., 2017)
2	2017	Fuzzy Logic, Artificial Neural Network	biomass moisture content	(Rico-Contreras et al., 2017)
3	2017	Artificial Neural Network	biomass heating value	(Ozveren, 2017)
4	2016	Artificial Neural Network	biomass heating value	(Uzun et al., 2017)
5	2016	Fuzzy Logic, Artificial Neural Network	soil moisture content for irrigation schedule	(Tsang and Jim, 2016)
6	2016	Artificial Neural Network, Fuzzy Logic	biomass heating value	(Akkaya, 2016)
7	2016	Artificial Neural Network	biomass quantity	(Vahedi, 2016)
8	2015	Artificial Neural Network, Genetic Algorithm	optimisation process	(Das et al., 2015)
9	2014	M5P	electricity price from biomass	(Azofra et al., 2014)
10	2014	Artificial Neural Network	gasification performance	(Mikulandrić et al., 2014)
11	2008	Artificial Neural Network	biomass yield	(Günay et al., 2008)

In general, the implementation of the prediction model has shown high accuracy and precision.

It has contributed to a generalised model to be widely apply in the biomass industry. However, the application is still limited to specific task-oriented project and has yet to be integrated into a comprehensive biomass framework specifically of supply chain management for further development.

2.3 Biomass Supply Value Chain

Value chain framework is a business analysis tool to consider and identify the manner in which value is added in the different phases of transforming inputs to outputs from conception to its end use and beyond (Porter, 2008). Through analysing each involved activity along the chain, value adding action is achieved either through cost reduction or increase differentiation. In the end of chain process, business firm is expected to gain additional final profits and benefits. Drawing from this inspiration, a value chain framework (Rudi et al., 2017) that targets on biomass supply chain is proposed. The proposed framework is BSVC (Figure 2-1) which aims to create additional value on each process involved in the biomass supply chain. The ultimate goal of the anticipated framework is to further promote and improve the overall performance of the industry. In fact, given that biomass is a value-added commodity, biomass inputs are not merely a part of ‘supply chain’ but more to ‘value chain’ that involves value-creation process.

By dividing the whole biomass supply chain into discrete module, value chain analysis can be targeted on each process more efficiently. Some of the modules may cover a few sub-modules and different modules may interact with each another despite such interaction might not necessary in a sequential order.

On the initial phase of sourcing for raw biomass, the classification of the biomass characteristics (Tang et al., 2014) enables the right material to be fed in can contribute to cost saving and simultaneously increase the process efficiency. Once the desired biomass is being identified, the material can be transported to a suitable storage facility without delay. The logistics network or supply stream can be optimised to reduce transportation cost and storage handling charges (Hong et al., 2016).

These processes take place in parallel with the procurement action. Biomass procurement activity focuses on the best purchasing strategy to outsmart the other competitors in the same region. By analysing and choosing the appropriate strategy, the logistics arrangements for biomass to be transported from collection point to storage facility can be more efficient and time-saving (Tang et al., 2017).

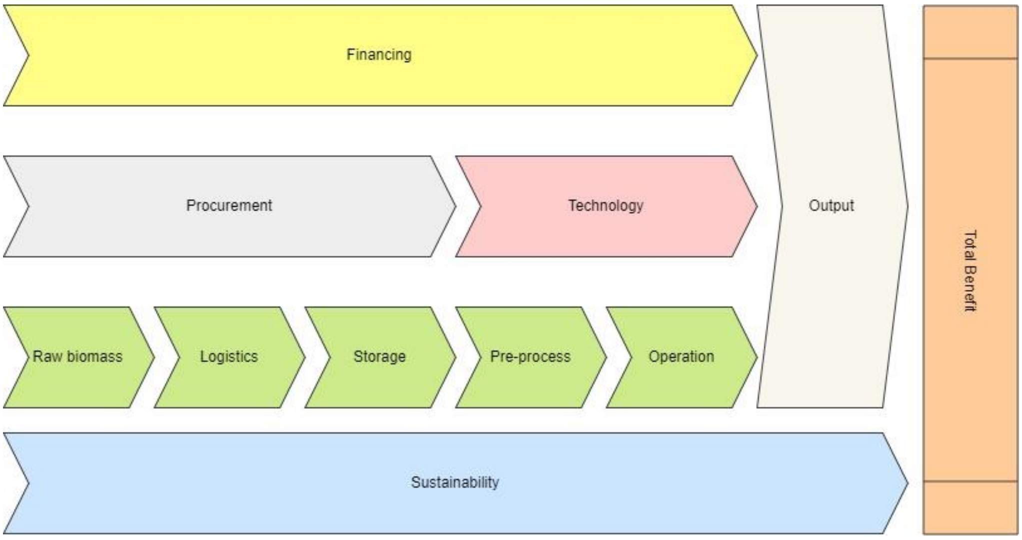

Figure 2-1: Biomass Supply Value Chain (BSVC)

Before biomass enters the plant for further operation process, the material will need to go through quality check and filtering (Lim and Lam, 2016). Then, the filtered biomass will be processed as a desired feedstock as required by the plant specification. Other process such as drying, sizing and packaging will be taken place at this stage as well. The complexity of the process depends on the types of technology being adopted.

After standard feedstock being fed into the plant process, it will go through the conversion process to produce the desired outputs. Therefore, the variety of the outputs determines the choices of which technology is being used in the plant. At this stage, diversification of products (Abdulrazik et al., 2017) is pivotal for multiplying profits for the biomass industry. The final success, nonetheless, is relied on a well-planned marketing strategy to address the market demand.

In terms of the plant process technology, the optimised technology needs to be identified to minimise waste and increase output (Ng and Lam, 2014). Some of the existing technologies such as combustion, pyrolysis, CHP and so forth can be revisited or even a combined process can be proposed to obtain higher efficiency model. For instance, a hybrid process model can be implemented to combine the advantages of different technologies to achieve the highest productivity.

Process optimisation is closely associated with the establishment of innovative technology or process modification, and this requires additional funding and investment. Here, both business planning model and financial service come into play. The prospect of the project, risk management (Yatim et al., 2017) and estimated production, market acceptance, investment payback period and other considerations need to be analysed in advance. This is crucial to ensure that minimal investment cost can yield high return in a short period of time.

Last but not least, the proposed BSVC is incomplete without taking into consideration of the sustainability issue of the greater context (How and Lam, 2017). The value chain is not merely adding up additional economic value in the end but is essentially about generating value in the sustainability aspect. Environmental protection and sustainability has become a priority interest in many industries nowadays, and it is even of great significance for the biomass industry. Biomass industry itself is inherently derivative of a value-added waste-to-energy process. Besides making profit from the products, the whole chain expects to be low emission and low waste to achieve sustainability goal.

The present thesis intends to develop an intelligent framework for palm biomass to align with BSVC approach. The main objective is to improve the biomass procurement module (Figure 2-2).

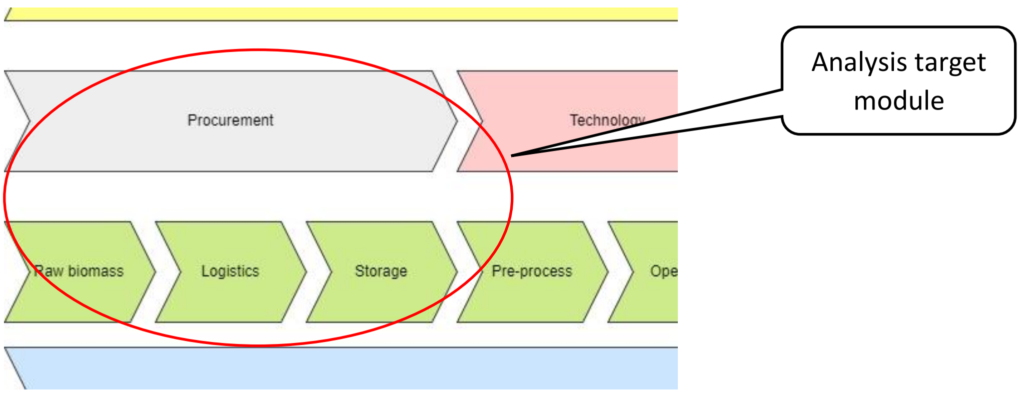

Figure 2-2: Analysis target module

In Chapter 3, BCI is introduced to identify the physical structure and potential quality of the biomass. Based on this information, procurement team can fine-tune their strategy payoff in response to competitor’s action. The application game theory in

Chapter 5, can potentially offer the best possible strategy for the upstream supply chain. Next, the biomass cost price can be predicted via artificial neural network model by taking into account the external environment factors. If the predicted price is unacceptable at that particular time-frame, BCI is able to refer another suitable biomass. New biomass characteristics will again be fed into the game theory strategy formulation, and new analysis will be done. Adjusted strategy profile is re-defined again to meet with the new requirement. The detailed literature review of BCI and game theory will be elaborated in respective chapters. Therefore, the whole framework (Figure 2-3) is a dynamic analysis system wherein one's output is another one's input. This thesis suggests that a dynamic, adaptive and resilient system can be the solution to tackle and manage the challenges from the ever-changing biomass industry.

In summary, the ultimate goal of BSVC is to create both measurable and unmeasurable, tangible and intangible "values" for the biomass industry in specific, and the society as a whole. Apart from the monetary profit that matters, the proposed framework also put considerable emphasis on the long-term benefit to the environment and society well-being. Sustainable framework is the future of biomass industry; it is moreover the life-supporting system for the society.

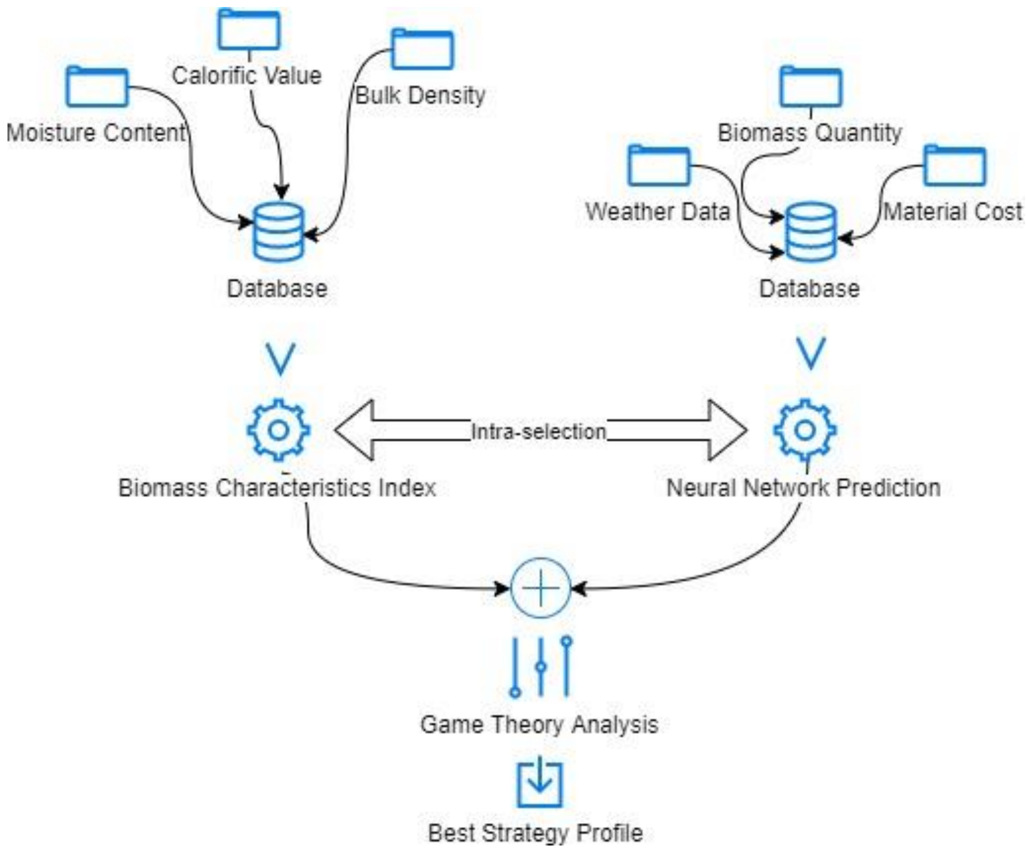

Figure 2-3: Process flow of smart system

3 CHAPTER 3 BIOMASS CHARACTERISTICS INDEX: A NUMERICAL APPROACH IN PALM BIO-ENERGY ESTIMATION

3.1 Introduction

Biomass is widely used as an alternate fuel source for power generation. Biomass is transformed to reusable matter from waste especially agricultural residues. Thermal processes such as gasification, pyrolysis, combustion may be used to convert biomass into specific form (e.g. pellet, bulk, and granule) for energy generation purpose via combine heat and power, co-firing and so forth. After the development of two decades, biofuel has evolved from the first to the third generation. First generation biofuel is obtained directly from traditional food feedstock such as sugarcane and corn or direct burning of solid biomass. As less processing technology is involved, the quantity of first generation biofuel is limited and is not a cost-effective solution for the environment. Thus, second generation biofuel is proposed, with a wide range of feedstocks available through forestry and agricultural residues, energy crops, food waste, industrial and municipal wastes. Due to different conditions of the raw materials in terms of moisture content and size, post processing (shredding, densifying, pulverizing and handling) and conversion technologies (gasification, pyrolysis, combustion) are needed before these raw materials can be used as fuel sources. The advancement of the processing technology has increased the amount of fuel for power generation plant as compared to the first generation biofuel. For example, gasification of biomass converts the maximum available energy content to increase the efficiency of power generation (Fodor and Klemeš, 2012). In addition, the utilisation of the above-mentioned residues has positive effect on the environment, considering the amount of waste that directly enters the soil can be significantly reduced. The third generation biofuel is known as advanced biofuel (IEA, 2012), which is originated from algae biomass and non-food feedstock. It is important to note that the third generation biofuel is facing challenges from technical, economical and geographical issues. Notwithstanding, the development of biofuel shows little progress in tropical developing countries such as Southeast Asia countries, and is predominantly limited to first generation biofuel production. Despite the abundance of forest and agriculture residues, there is a lack of mature technologies to further develop new biofuel. Compared to European countries wherein their natural resources are relatively scarce and facing severe weather threats – who have been sprinting to boost biofuel development; biofuel development in Southeast Asian countries on the other hand, remains stagnant at an early stage. The varied and rich profusion of bio residues that are readily available have yet to be fully utilised for biofuel projects but are directly burnt as fuel without prior process (Goh and Lee, 2010).

3.2 Literature Review

In Malaysia, huge amount of biomass wastes is available from the palm oil mill. Among those residues, the most reusable matters are EFB and PKS (Ng et al., 2012). The factor that determines the usefulness of these biomass is their calorific value. Higher calorific value indicates that it is more efficient as an energy source (Everard et al., 2012). Another aspect of the biomass that should be taken into account is their physical characteristics, which consisted of the moisture content and bulk density (Figure 3-1).

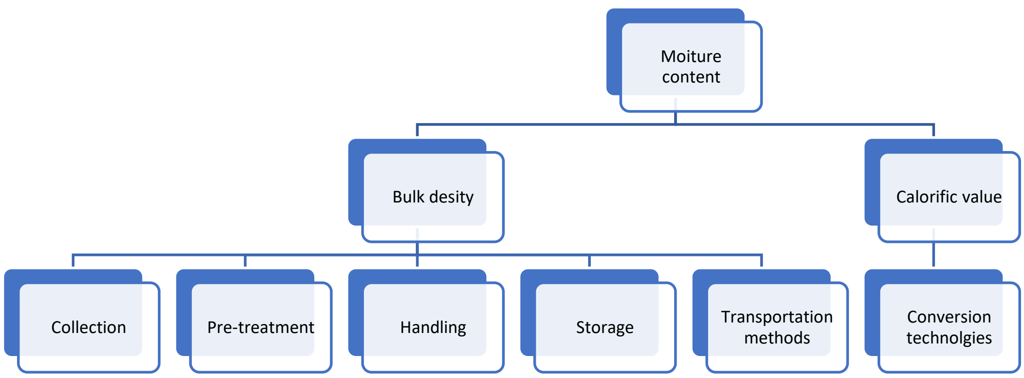

Figure 3-1: Biomass characteristics relationships mapping

Both of these properties are interrelated and are linked to the structure and physical appearance of biomass. While moisture content is the quantity of water that contains in the biomass material, bulk density is defined as the ratio of biomass mass over its volume. These characteristics affect the operational aspects of a biomass supply chain (Annevelink et al., 2017) such as its collection, handling, storage and logistics. There are several points needed to be noted. First, raw biomass is associated with high moisture content, low bulk density and lower calorific value. Low bulk density leads to the difficulties in material handling, storage, transportation (Wu et al., 2011). For instance, biomass of large particle size biomass such oil palm trunk requires pre-treatment of sizing or drying, special handling during collection, suitable storage facility and optimised transportation route to the process facility. This thus increase the total cost incurred of the biomass supply chain. Second, higher moisture content decreases the calorific value of biomass (Chiew et al., 2011), hence different conversion technologies will be selected for cost saving purpose in the supply chain (Elbersen et al., 2017). Moreover, when the bulk density of oil palm EFB is low, the moisture content will then be high. This makes EFB more difficult to be compacted and increases its total volume; thus causing difficulties in storage and transportation (Miccio et al., 2011). Besides, bulk density changes with types, size and shape of the biomass itself. As shown from Figure 3-2 and 3-3, the appearance and shape of raw EFB is completely different from the shredded bunches. Therefore, bulk density of the dry raw EFB is lower than that of the shredded EFB as its smaller particle size of occupies lesser space with same weight of mass (Basu and Basu, 2013).

Figure 3-2: Raw EFB

Figure 3-3: Shredded fiber from EFB

Apart from moisture content, air volume also influences the bulk density. Free air space (FAS) is measured for solid organic waste during composting process. The distribution of air in the waste will affects its performance of composting (Druilhe et al., 2013). FAS represents the ratio of air volume over global volume (air, water, solid). A pycnometer will be used for FAS measurement. At higher bulk density, the air voids will be displaced as the solid becomes more compacts. This shows a linear relationship between FAS and bulk density for manure compost (Agnew et al., 2003). There are numerous studies relate air porosity to bulk density (Ruggieri et al., 2009) and the relationships are established for different biomass types. Therefore, it is possible that biomass have air voids trap inside the material itself especially for fibrous biomass like EFB. The space in between the particle of biomass material is a perfect spot for air voids.

The analysis of moisture content and bulk density have been reported in different studies, depending on the application areas (refer to Table 3-1), either for the pre-treatment process or final product (pellet for most cases). Note however that the focus of those research works in Table 3-1 were mainly targeted on the performance of final product rather than the raw biomass itself. There is no analysis on both properties regarding raw biomass appearance before the pre-treatment stage. The appearance of raw biomass has essential information that determines the handling, transportation and storage issues (Lam et al., 2013). This information can be feed into biomass supply chain for the purpose of resource planning and optimisation (Lam et al., 2011). A well-designed supply chain plays an important role to achieve the efficiency in cost and energy utilisation (Klemeš et al., 2013).

Secondly, acquisition of bulk density and moisture content are obtained through empirical methods such as the British Standard ("Solid Biofuels — Determination of Bulk Density", 2009). Results from those methods may vary from sample to sample and the consistency is affected by handling procedures. There is no standard or reference value of bulk density and moisture content for biomass such as EFB. Most of the relevant researches merely focus on either one of the characteristics such as bulk density, moisture content or component breakdown of biomass. There is a lack of comprehensive and all-rounded analysis that integrating the physical properties of the biomass to generate.

For example, Chevanan et al. (2010)'s research, focuses on the characterization of bulk density of switchgrass, wheat straw and corn stover, and then proposes separate relationships model for each respective biomass.

Table 3-1: Bulk density and moisture content research overview on biomass

Application area	**Measured characteristics**	**References**	**Scope of research**
Bio-Fuel	Bulk density	(Antonio Bizzo et al. 2014)	The generation of residual biomass during the production of bio-ethanol from sugarcane, its characterization and its use in energy production
Bulk Density Determination	Wet bulk density, dry bulk density	(P. S. W. Lam et al. 2008)	Bulk density of wet and dry wheat straw and switchgrass particles
CHP Plant	Moisture content, calorific value	(Chiew, Iwata, and Shimada 2011)	System analysis for effective use of palm oil waste as energy resources
Briquette	Moisture content, bulk density, calorific value	(Y. Liu et al. 2014)	Study of briquetted biomass co-firing mode in power plants
Classification	Moisture content, bulk density, ash content, particle dimension and size distribution	(Shankar Tumuluru et al. 2011)	A review on biomass classification and composition, co-firing issues and pre-treatment methods
Combustion	Bulk density, moisture content	(Elmay et al. 2013)	Energy recovery of date palm residues in a domestic pellet boiler
Compaction	Moisture content, bulk density, particle density	(Mani, Tabil, and Sokhansanj 2004b)	Evaluation of compaction equations applied to wheat straw, barley straw, corn stover and switchgrass
Compaction	Bulk density, particle size	(Chevanan et al. 2010)	Bulk density and compaction behavior of knife mill chopped switchgrass, wheat straw, and corn stover
Densification	Moisture content, bulk density, durability, percent fines, calorific value	(Tumuluru et al. 2011)	A review of biomass densification systems to develop uniform feedstock commodities for bioenergy application
Densification	Moisture content, particle size, bulk density	(Kaliyan and Morey 2010)	Densification characteristics of corn cobs

Continue from Table 3-1

Application area	Measured characteristics	References	Scope of research
Fly Ash Properties	Bulk density	(Jaworek et al. 2013)	Properties of biomass vs. coal fly ashes deposited in electrostatic precipitator
Grinding Performance	Moisture content, bulk density, particle density	(Mani, Tabil, and Sokhansanj 2004a)	Grinding performance and physical properties of wheat and barley straws, corn stover and switchgrass
Pelletizing	Particle density, bulk density, moisture, crushing resistance, compression resistance	Zamorano et al., 2011	A comparative study of quality properties of pelletized agricultural and forestry lopping residues
Pelletizing	Bulk density	Liu et al., 2013	The properties of pellets from mixing bamboo and rice straw
Pelletizing	Moisture content, bulk density, true density, durability	(Theerarattananoon et al. 2011)	Physical properties of pellets made from sorghum stalk, corn stover, wheat straw, and big bluestem
Pelletizing	Moisture, bulk density	(Samuelsson et al. 2009)	Effect of biomaterial characteristics on pelletizing properties and biofuel pellet quality
Pelletizing	Bulk density, particle density, durability, moisture sorption rate and moisture sorption isotherm	(Fasina 2008)	Physical properties of peanut hull pellets
Physical Characterization	Bulk density, particle density	(M. R. Wu, Schott, and Lodewijks 2011)	Physical properties of wood pellets, wood chips and torrefied pellets
Pyrolysis	Moisture content	(Abdullah, Sulaiman, and Gerhauser 2011)	Characterization of oil palm empty fruit bunches for fuel application
Physical Characterization	Bulk density, apparent density, true density and moisture	(Cardoso et al. 2013)	Physical characterization (density, particle size and shape distributions) of sweet sorghum bagasse, tobacco residue, soy hull and fiber sorghum bagasse particles

Continue from Table 3-1

Application area	Measured characteristics	References	Scope of research
Pelletizing	Compressive force, particle size and moisture content	(Mani, Tabil, and Sokhansanj 2006)	Effects of compressive force, particle size and moisture content on mechanical properties of biomass pellets from grasses
Torrefaction	Moisture content, gross calorific value, weight, volatile matter, fixed carbon, bulk density	(Patel, Gami, and Bhimani 2011)	Improved fuel characteristics of cotton stalk, prosopis and sugarcane bagasse through torrefaction
Torrefaction	Moisture content	(Sadaka and Negi 2009)	Improvements of biomass physical and thermochemical characteristics via torrefaction process
Torrefaction	Moisture content, ash	(Sabil et al. 2013)	Effects of torrefaction on the physiochemical properties of oil palm EFB, mesocarp fiber and kernel shell

However, there is no consolidated model of characterization for various biomass proposed.

In this thesis, BCI is proposed to correlate the physical appearance of biomass to its properties - bulk density and moisture content. Numerical method is used to perform BCI calculation. The methodology is discussed in detail in the following section.

3.3 Methodology

Numerical method is chosen to analyse the biomass physical properties. It is an efficient method that saves time in understanding the relationships between moisture content and bulk density of different biomass, as compared to analytical method. Regression analysis is performed on the BCI curve. Prediction can be obtained easily once the BCI curve has been established. The work flow diagram of BCI is represented in Figure 3-4 while the detailed calculation and the BCI curve establishment is presented in the next section.

3.3.1 Relationships between bulk density and moisture content

Raw biomass materials are exposed to the open-air environment, its moisture content is inherently higher. Wet biomass has a larger volume especially of fibrous biomass like EFB. The more pore space in the biomass will lower the value of biomass bulk density. Sims (2002) provided an intuitive formula that related bulk density and moisture content of a biomass (Equation 3-1).

$$\text{Bulk Density}\left(\frac{\text{kg}}{\text{m}^3}\right) = \frac{13600}{(100-\%\text{m.c.w.b})} \tag{3-1}$$

Constant value of 13,600 is only applicable for wood chips in Sims (2002)'s research. A more generalized equation with a constant parameter of k applies for different types of biomass.

$$\text{Bulk Density}\left(\frac{\text{kg}}{\text{m}^3}\right) = \frac{\text{k}}{(100-\%\text{m.c.w.b})} \tag{3-2}$$

Note that the constant k is a reference index for various appearance of biomass and is proposed as BCI.

3.3.2 BCI calculation

A systematic numerical approach proposes:

a) Database construction

   To obtain a series of BCI, a complete biomass database is a prerequisite. Various forms of biomass with different bulk densities and moisture contents are needed to be obtained prior to establishment of the biomass database that covers on every biomass available in the market of different appearance and shape.

b) BCI calculation

   From the above database, BCI can be calculated from bulk density and moisture content using Equation 3-3.

$$\text{BCI} = \text{Bulk Density} \times (100 - \%\text{m.c.w.b.}) \tag{3-3}$$

c) Relationships among BCI, bulk density and moisture content

After a full set of BCI is obtained, a graph is plotted to show the relationships between BCI and bulk density. From the graph, linear regression is best fitted on the plots. A new regression equation is obtained through the fit.

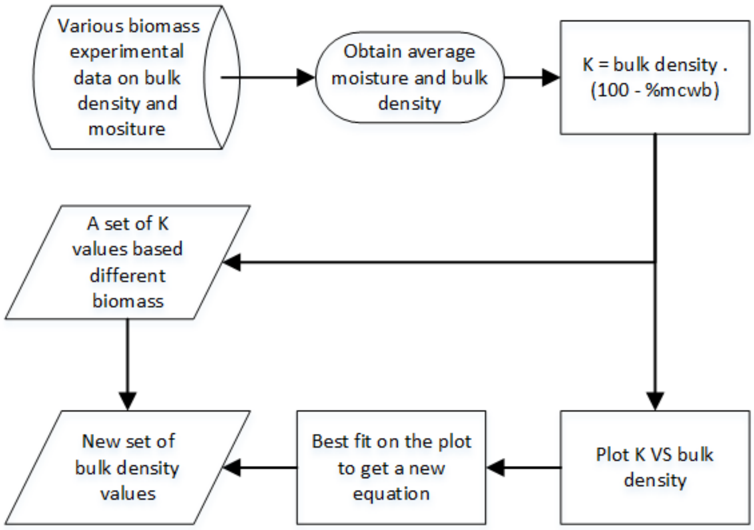

Figure 3-4: Flow chart of BCI calculation

3.4 Case study

A case study is demonstrated on a set of biomass with different appearance and shapes. The database comprises most of the commonly found biomass in the market.

Table 3-2 shows the bulk density and moisture content for all the commonly found biomass. Average value of bulk density and moisture content are calculated for BCI in Equation 3-3.

A linear relationship is shown by plotting the BCI values and the average bulk densities in a graph. Figure 3-5 shows the linear regression fit on the plotted data. The best fit linear regression equation is derived as shown in Equation 3-3 with R-squared value of 0.8675.

$$y = 90977x - 6115.10 \tag{3-3}$$

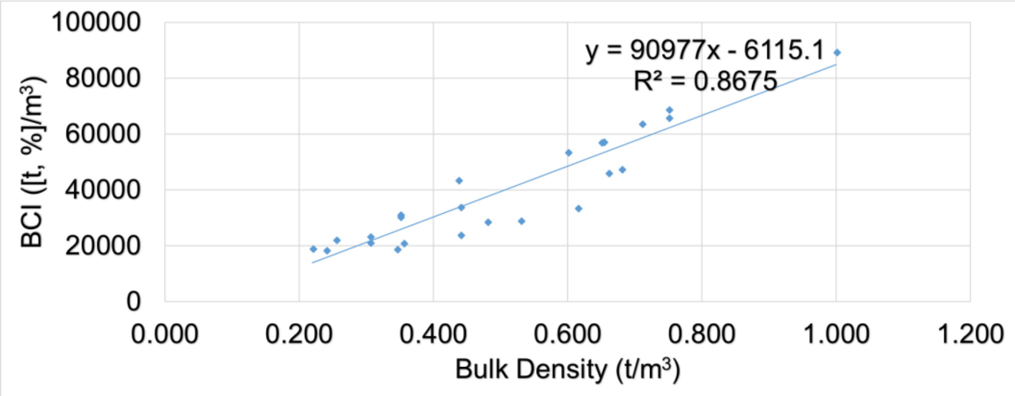

Figure 3-5: BCI vs bulk density

Table 3-2: Biomass characteristics

Biomass Types	Moisture (Min)	Moisture (Max)	Average Moisture	Bulk Density (t/m^3, Min)	Bulk Density (t/m^3, Max)	Average Bulk Density (t/m^3)	BCI
Air dry wood chips	20.00 %	25.00 %	22.50 %	0.190	0.290	0.240	18,600
Green wood chips	40.00 %	50.00 %	45.00 %	0.280	0.410	0.345	18,975
Kiln dry wood chips	10.00 %	15.00 %	12.50 %	0.190	0.250	0.220	19,250
Empty Fruit Bunch	15.00 %	65.00 %	40.00 %	0.160	0.550	0.355	21,300
Kiln dry wood chunks	10.00 %	15.00 %	12.50 %	0.200	0.310	0.255	22,313
Air dry wood chunks	20.00 %	25.00 %	22.50 %	0.240	0.370	0.305	23,638
Green wood chunks	40.00 %	50.00 %	45.00 %	0.350	0.530	0.440	24,200
Mesocarp Oily Fiber	30.00 %	N/A	30.00 %	N/A	N/A	0.305	21,350
Kiln dry sawdust	10.00 %	15.00 %	12.50 %	0.240	0.370	0.350	30,625
Fresh Fruit Bunch	40.00 %	N/A	40.00 %	N/A	N/A	0.480	28,800
Green sawdust	40.00 %	50.00 %	45.00 %	0.420	0.640	0.530	29,150
Straw bales	7.00 %	14.00 %	10.50 %	0.200	0.500	0.350	31,325
Green roundwood	40.00 %	50.00 %	45.00 %	0.510	0.720	0.615	33,825
Air dry roundwood	20.00 %	25.00 %	22.50 %	0.350	0.530	0.440	34,100
Ash	0.00 %	N/A	0.00 %	N/A	N/A	0.437	43,700
Sterilized Fruit	30.00 %	N/A	30.00 %	N/A	N/A	0.660	46,200
Fruitlets	30.00 %	N/A	30.00 %	N/A	N/A	0.680	47,600
Wood pellets	7.00 %	14.00 %	10.50 %	0.500	0.700	0.600	53,700

Continued from Table 3-2

Biomass Types	Moisture (Min)	Moisture (Max)	Average Moisture	Bulk Density (Tonne/m^3, Min)	Bulk Density (Tonne/m^3, Max)	Average Bulk Density (Tonne/m^3)	BCI
Press expelled cake	12.00 %	N/A	12.00 %	N/A	N/A	0.650	57,200
Palm Nuts	12.00 %	N/A	12.00 %	N/A	N/A	0.653	57,464
Cracked mixture	12.00 %	N/A	12.00 %	N/A	N/A	0.653	57,464
Dry EFB Cut Fiber	10.00 %	N/A	10.00 %	N/A	N/A	0.710	63,900
Shell	12.00 %	N/A	12.00 %	N/A	N/A	0.750	66,000
Coal	6.00 %	10.00 %	8.00 %	0.700	0.800	0.750	69,000
Wood briquettes	7.00 %	14.00 %	10.50 %	0.900	1.100	1.000	89,500

3.5 Analysis

The validity of calculated BCI values can be verified through comparison with the actual field data. As shown from Table 3-3, the error differences are relatively small for selected biomass. The highest differences are observed for EFB and FFB, which are 52.07 % and 33.79 % respectively. This is mainly due to the nature of these biomass that have a broad range of moisture content (Omar et al., 2011).

Table 3-4 shows that the calculated BCI value for EFB varies from 5,600 to 46,750, due to different moisture contents. However, for the whole spectrum of biomass material, the average value of moisture content and bulk density are used. The BCI curve fit linearly and without any serious distortion as the R^2 value is determined as 0.8675 (see Figure 3-4).

Table 3-3: Comparison of collected and BCI forecast bulk density

Oil Palm Biomass	Collected data (t/m³)	Forecast from BCI (t/m³)	Difference (t/m³)	Difference
Empty Fruit Bunch	0.628	0.301	0.327	52.07 %
Mesocarp Oily Fiber	0.257	0.302	0.045	17.51 %
Fresh Fruit Bunch	0.580	0.384	0.196	33.79 %
Ash	0.550	0.548	0.002	0.36 %
Sterilized Fruit	0.640	0.575	0.065	10.16 %
Fruitlets	0.640	0.590	0.050	7.81 %
Press expelled cake	0.550	0.696	0.146	26.55 %
Palm Nuts	0.653	0.699	0.046	7.04 %
Cracked mixture	0.535	0.699	0.164	30.65 %
Shell	0.650	0.793	0.143	22.00 %

Table 3-4: Calculated BCI for empty fruit bunch (EFB)

Moisture Content	Bulk Density (t/m³)	BCI
65.00 %	0.160	5,600
15.00 %	0.550	46,750

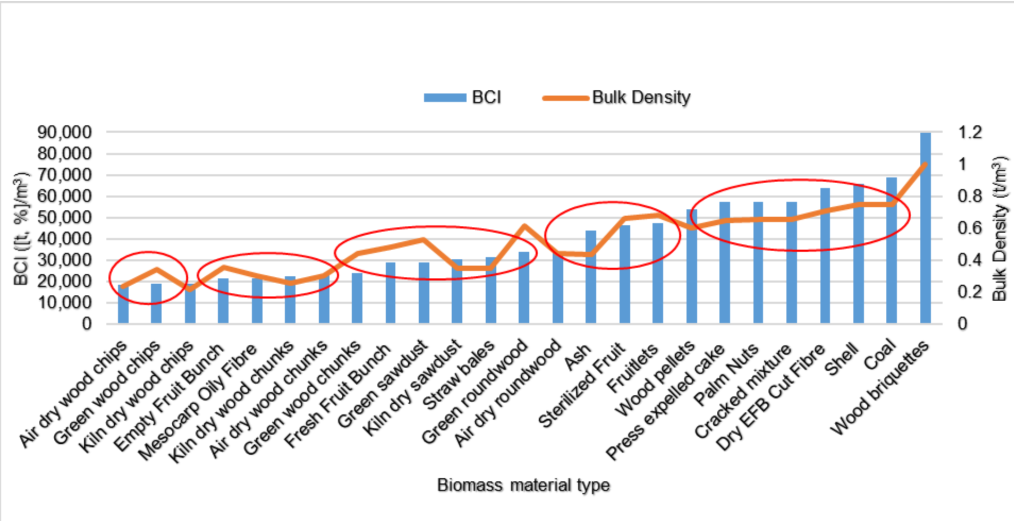

Figure 3-6: Clustering on similar biomass shapes

BCI is capable of performing a cluster forecast on multiple biomass materials. Classification of biomass type can potentially be used on industrial application (Lam et al., 2013). Figure 3-5 demonstrates that BCI and bulk density values are lined up on a bar chart to reflect its dependency. It can be observed from the clustering in red circle on the different biomass, as well as the bulk density values. Referring to Figure 3-3-5, all chips materials have a similar range of BCI, from 18,600 to 19,250. Different type of chunks also has closer range of BCI value. This proposes that biomass with similar shape have a relatively similar bulk density values as reflected on BCI value, and thus the group of biomass can be identified by simply referring to the clustered BCI value. In other words, BCI can forecast the types and physical appearance of biomass based on a narrow BCI range. From there, bulk density and moisture content are predictable.

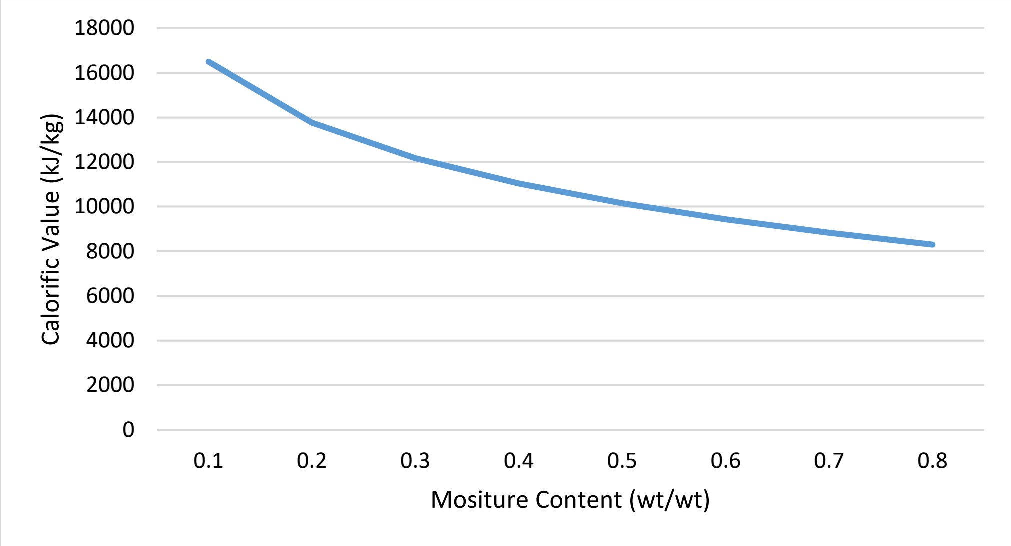

Figure 3-7: Calorific Values (kJ/kg) versus Moisture Content (% wt./wt.) for palm empty fruit bunches (Aziz et al. 2011)

As demonstrated above, specific BCI value is able to provide the information of bulk density (Figure 3-5) and moisture content of the biomass. In addition, calorific value can also be determined through the relationships with moisture content. Aziz et al. (2011) reported that the relationships between heat value and moisture content are not necessary in linear form especially for empty fruit bunches. The results in Table 3-5 is cross checked with experimental and online biomass database.

Table 3-5: Calorific value comparison for EFB

Moisture Content	Aziz et al. (2011) **research**	**BOM calorimeter**	**ECN Phyllis 2** ("Phyllis2, Database for Biomass and Waste," 2017)
5.00 %	17.17 MJ/kg	18.20 MJ/kg	15.86 MJ/kg
60.00 %	9.13 MJ/kg	6.86 MJ/kg	6.68 MJ/kg

Tables 3-5 verifies that Figure 3-6 is reliable on predicting calorific value of EFB by referring to its moisture content. Therefore, BCI can be enhanced to cover the information of calorific value. Incorporation of calorific value, moisture content and bulk density into BCI value creates a robust tool in biomass supply chain for physical properties estimation.

3.6 Demonstration of application case study

3.6.1 BCI alternative sourcing

In conventional biomass process design, the value of bulk density and moisture content for a given biomass material are needed in the system efficiency calculation. In this case study, it can be predetermined by referring to the specific BCI. Similar appearance and shape of the material will yield a specific range of BCI value. For instance, a co-firing plant (Figure 3-7) is planning to source green wood chunks as an alternate fuel as it is widely available for this particular period. Before purchasing this feedstock, the energy density can be estimated in the process. By referring to green wood chunks BCI (24,200), bulk density is estimated to be 350 kg/m^3 (using the linear regression equation from Figure 3-4) with average moisture content of 45 %. Typical heat value for 45 % moisture content green wood chunks is 10 MJ/kg (refer to Figure 3-8). Therefore, the estimated energy density is 3,500 MJ/m^3. From the estimated energy value, the management can then decide whether the purchase of this material is economical or not, in terms of storage cost and efficiency for the plant. Without going through the hassle of experimentation on the samples for bulk density and moisture content, the design objective can be achieved.

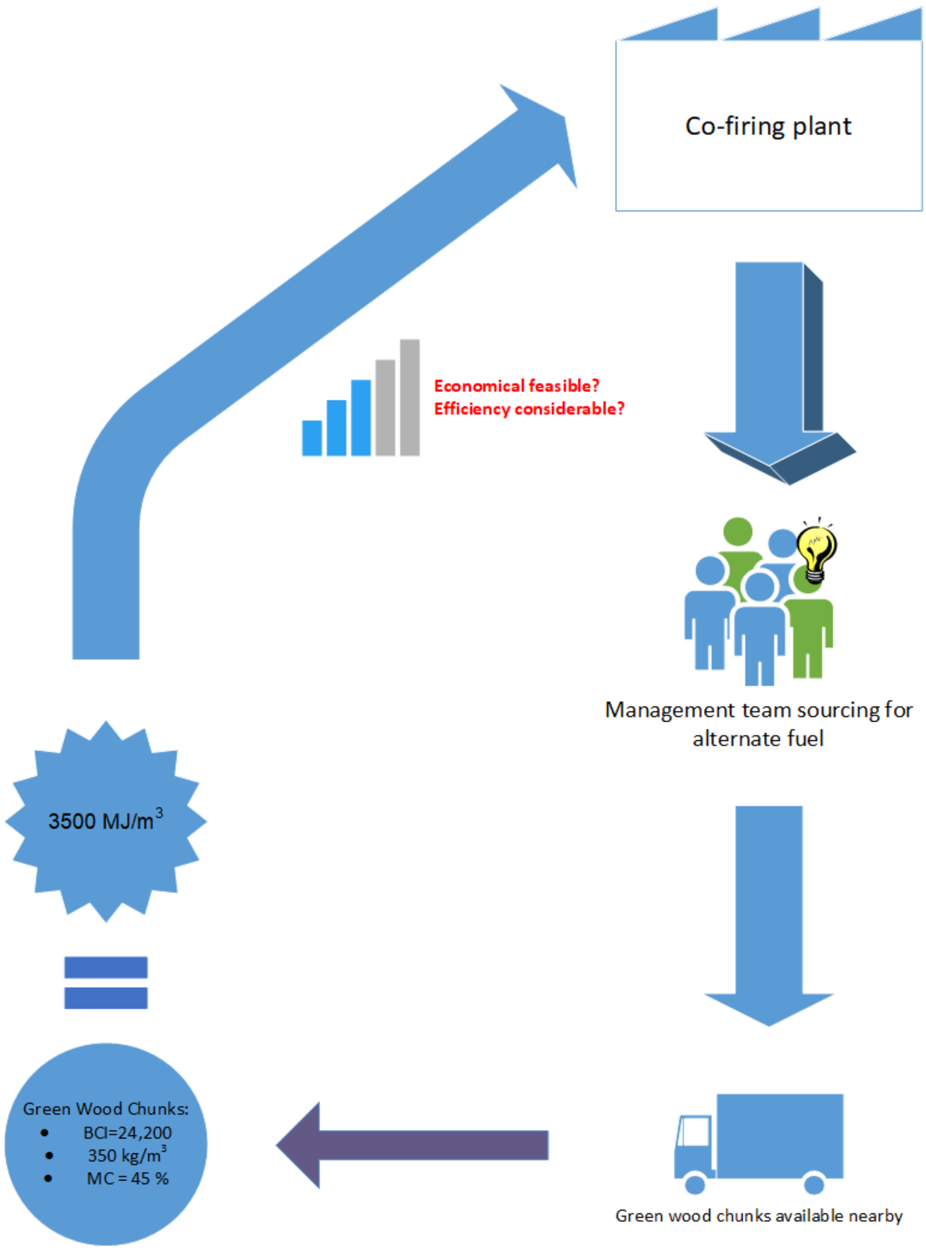

Figure 3-8: Flow diagram of alternative sourcing using BCI

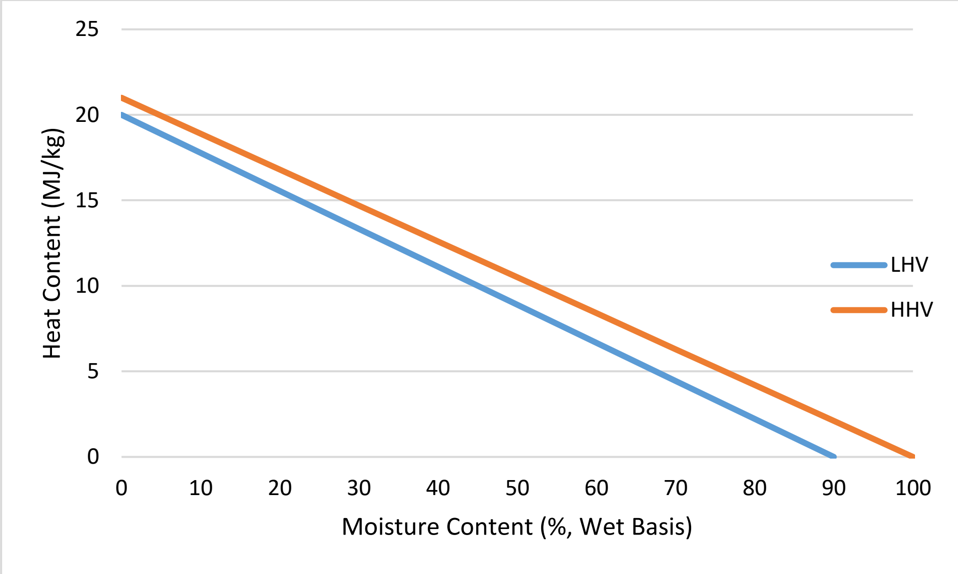

Figure 3-9: Typical biomass higher heating value and lower heating value versus moisture content (Ciolkosz, 2010)

3.6.2 Biomass materials filtering using BCI

In terms of biomass management planning, bulk density or moisture content of the biomass need to be identified in advance for the ease of transportation and to maximise the output in the power plant. This is because different level of bulk density or moisture content of biomass requires different types of treatment and cost. For instance, wet and large volume biomass occupy more space and thus causing higher transportation cost. Also, high moisture content biomass has a lower calorific value (Figure 3-9) and thus decreasing the output efficiency of the plant.

By referring to the BCI, the desired value of bulk density or moisture content can be obtained conveniently. For example, when a biomass power generation plant (Figure 3-9) experiences low feedstock problem with their existing fuel - straw bales and the management wishes to source an alternative feedstock as fuel source for replacement, the BCI will come useful. The BCI of straw bales is given as 31,325 in Table 3-2. The latter also shows that the green sawdust, kiln dry sawdust, air dry roundwood and green roundwood are possible substitute which fall under BCI value of 30,000. Obviously, kiln dry sawdust is the most suitable replacement as its bulk density (350 kg/m^3) and moisture content (12.50 %) are closer to those of straw bales (350 kg/m^3, 10.50 %). Alternatively, air dry roundwood will be the next suitable substitute (440 kg/m^3, 22.50 %) if straw bales are not available. In terms of management, the procurement of the suitable material can be done in an accurate manner without further delays.

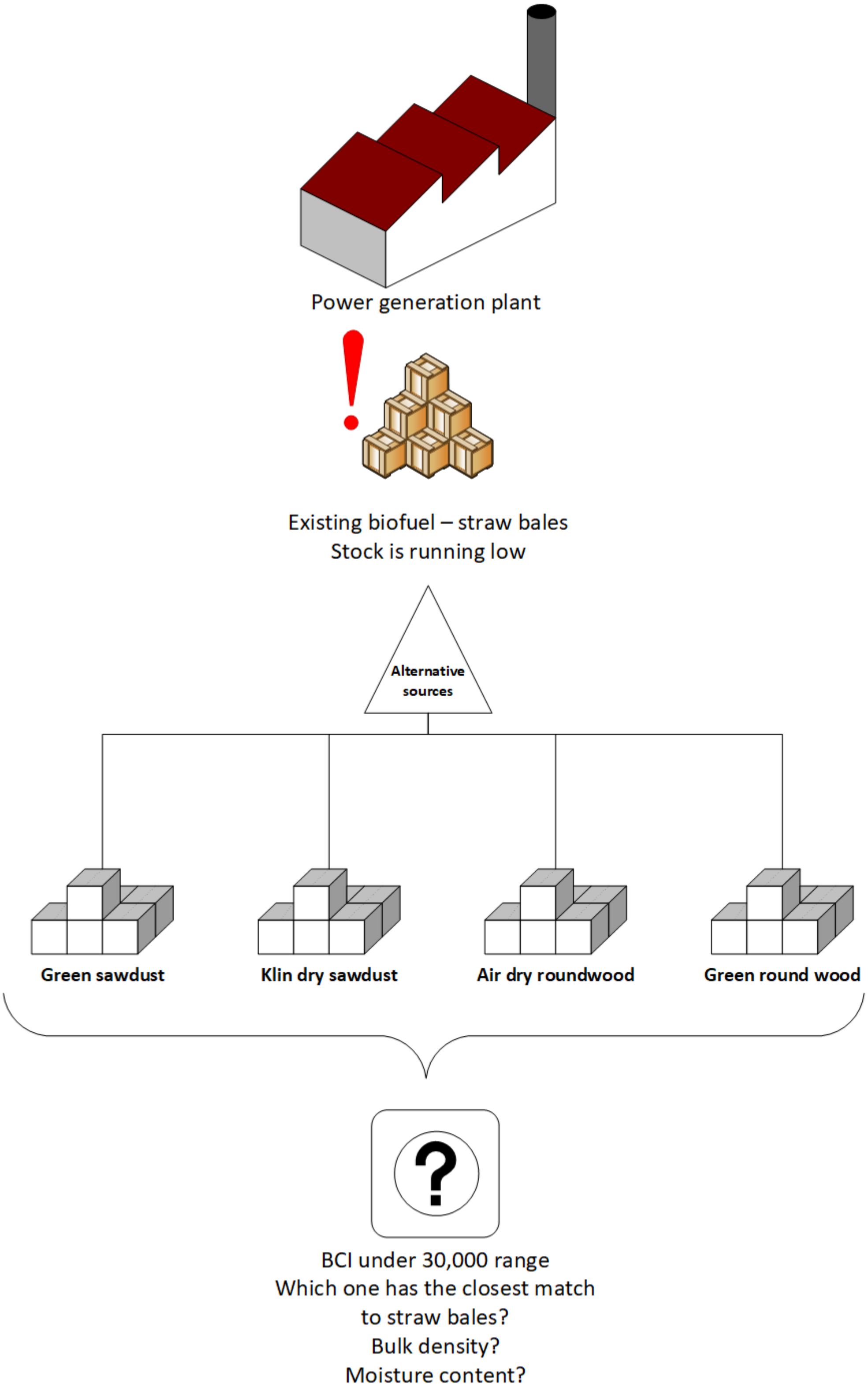

Figure 3-10: Biomass material filtering illustration

3.7 Conclusion

This chapter has proposed a preliminary framework for BCI in forecasting the physical properties of various biomass. A numerical framework of BCI is developed to represent the appearance and shapes of different biomass materials. By referring to the correct BCI of biomass material, the forecast of bulk density and moisture contents can be obtained effectively without running any time-consuming experiments. These values are critical to the amount of biomass fuel being transferred and the generated output power from the plant. Thus, it improves the overall biomass management process design and development. An efficient design means more output, less waste.

4 CHAPTER 4 PREDICTION MODEL FOR PALM KERNEL SHELL PRICE

4.1 Introduction

In BSVC, the simplest assessment of the goal is the profit generated at the end of the chain. In this context, the profit is basically defined by the selling price of the output or product. Therefore, the development of a reliable price prediction mechanism will be a crucial module for the intelligent procurement system. PKS is chosen as the analysis target given that it has the highest heating value among palm biomass (Wahid et al., 2017). Besides, the shell is also used as an alternative fuel source for both local and export market. Therefore, it is a valuable commodity to the palm biomass industry (Wu et al., 2017).

4.2 Background

This chapter conducts a case study focusing on Johor state of peninsular Malaysia. Johor has the largest planted oil palm area in peninsular Malaysia with a land bank totalling 745,630 hectares (MPOB, 2017) (13 % of total planted area in whole Malaysia) . The topography of Johor state is a flat terrain (Figure 4-1) compared to others state in peninsular Malaysia. Such terrain is suitable for case study analysis as palm biomass materials are more accessible. Transportation difficulties are greatly reduced due to flatter terrain and direct route to the mill. Therefore, handling cost is reduced. For analysis purpose, route condition is not taken into cost calculation considering that its landscape is in fact transportation friendly.

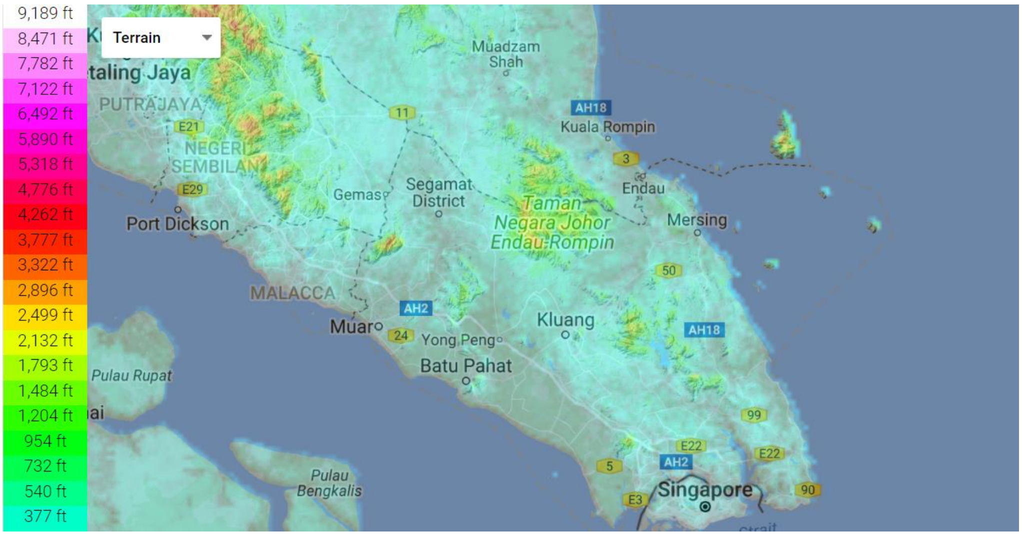

Figure 4-1: Johor state topography

4.3 Input database construction

Many of the AI prediction models are using direct related component of the subject to create formula. However, the price of PKS price is not fixed but fluctuating from time to time. Hence, more parameters should be considered in creating formula. Although most of the parameters might not be directly related, it is nonetheless critical enough to influence the outcomes. Given that the adopted parameters are cross-disciplinary data; preliminary data filtration (Figure 4-2) is necessary to ensure the most accurate data is being fed into prediction model.

Market price has been chosen as the output subject because pricing plays a substantial role in biomass procurement activity.

There are few factors to be taken into consideration for the predictive model simulation.

a) Weather

The climate in Malaysia is typically hot and humid throughout the year which is affected by two monsoon seasons. The relatively higher rainfall during monsoon season would influence the quality of palm biomass especially the EFB due to its fibrous nature (as reported in Chapter 3) which can absorb a huge amount of moisture. Biomass with high moisture contents is less useful as the calorific value is low, yet at the meantime it is charged with higher handling and transportation cost. Moreover, high moisture content biomass requires additional pre-processing procedure such as drying before turning into usable input for biomass plant. Therefore, another cost incurred.

b) Outdoor temperature

The yearly average temperature in Malaysia is above 30 °C. This temperature is suitable for drying the biomass naturally (Röser et al., 2011). In this way, the biomass moisture contents can be reduced prior to pre-processing stage.

c) Rainfall

The moisture contents of biomass material would increase during rainy season as the biomass is stored in open air environment. As mentioned above, the moisture content is an indicator of the biomass quality; high moisture content would deal a blow to the selling price and market acceptance of the biomass. In contrast, low moisture biomass has high calorific value and requires less pre-processing, and therefore expected to fetch higher price. It is worth mentioning that higher profit margin is the goal of procurement process.

d) Yield

Available palm biomass quantity can be estimated through the amount of FFB; the available biomass quantity is proportional to the quantity of FFB. EFB and PKS are the by-products of palm oil milling process.

e) Fuel price

The fluctuation of diesel fuel price plays a key role in determining the transportation cost of biomass. What is more, the longer the distance, the higher the cost. This analysis assumes that the biomass collection points are all within 100 km radius (most of the collection points are palm oil mills as the palm biomass is a direct waste output from it). This is to standardise the transportation cost, ignoring the route condition and collection point location as these two factors are not the major focus in this analysis.

f) Currency

Malaysia exchange rate to US dollars would affect the selling price of palm biomass. Currently, PKS is exported to Japan as an alternative fuel. The rate does not merely influence the selling price range, but also affects the market demand of biomass materials.

g) Handling and transportation

Palm biomass is the waste output of milling process. There are three common palm biomass: mesocarp fibre, EFB and PKS. The collection point of these materials is the mill itself, which is more accessible compared to other estate location. Due to its nature of waste, the biomass is not properly stored. The waste is usually left on the open-air ground, which is susceptible to rainfall. This will greatly affect the quality of the biomass and increase the difficulties of handling (Sansaniwal et al., 2017) and cost of transportation (Gracia et al., 2014).

h) PKS's price

The subject of the analysis is the selling price of the PKS. The shell is primarily exported as an alternative fuel. In comparison to the EFB, which is not sold as a commodity, the price of PKS is rather fixed.

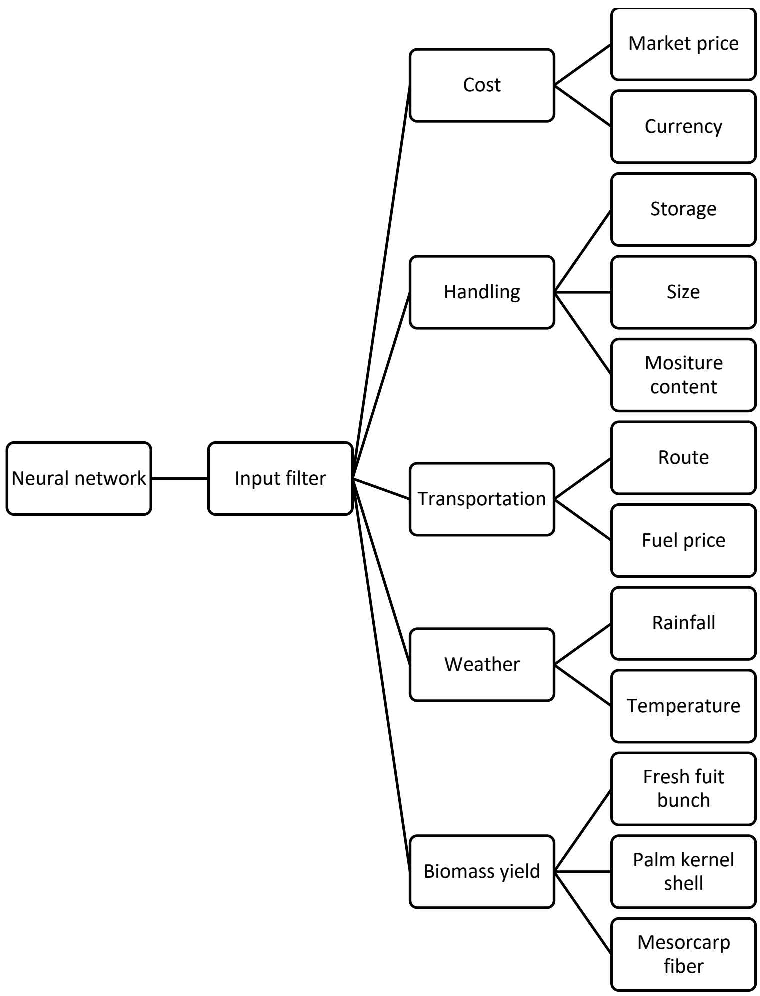

Figure 4-2: Input database selection flow

4.4 Methodology

4.4.1 Quasi-Newton

Quasi-Newton method is an optimisation method to find zeroes or local minima or maxima of a given function. In neural network, this method is used as a training algorithm to update weight of each neuron to minimise the loss function of the network. Quasi-Newton is an alternate version of Newton's method, but it has faster computation and cheaper computational cost.

The steps are:

a) Calculate

$$x^{(k)} = x^{(k-1)} + t\Delta x \tag{4-1}$$

where

$$\Delta x = -H_{k-1}^{-1} \nabla f(x^{(k-1)}) \tag{4-2}$$

b) Update H_k

Using Broyden-Fletcher-Goldfarb-Shanno (BFGS) update (Broyden, 1970)

$$H_k = H_{k-1} + \frac{yy^T}{y^T s} - \frac{H_{k-1} s s^T H_{k-1}}{s^T H_{k-1} s} \tag{4-3}$$

where

$$s = x^{(k)} - x^{(k-1)} \tag{4-4}$$

$$y = \nabla f\left(x^{(k)}\right) - \nabla f\left(x^{(k-1)}\right) \tag{4-5}$$

Inverse update

$$H_k^{-1} = \left(I - \frac{sy^T}{y^T s}\right) H_{k-1}^{-1} \left(I - \frac{ys^T}{y^T s}\right) + \frac{ss^T}{y^T s} \tag{4-6}$$

The calculation above will be running through multiple iteration until loss function target is satisfied.

4.5 Artificial Neural Network

Artificial neural network is an AI computational method that attempts to mimic the way of human brain in processing information. An artificial neural network is made of input, output and neuron with multiple layers. The basic unit of a network is a single neuron (Figure 4-3).

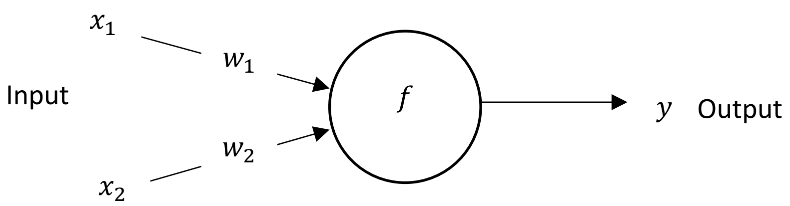

Figure 4-3: Example of single neuron in neural network

The output y takes the inputs x_1 and x_2 with associated weight w_1 and w_2 which fire through an activation function f.

$$y = f(x_1 w_1 + x_2 w_2) \tag{4-7}$$

Activation function is to generate non-linear signal to the output which is used for training purpose. There are few common activation functions that are used by artificial neural network.

a) Sigmoid

$$f(x) = \frac{1}{1+e^{-x}} \tag{4-8}$$

b) Hyperbolic tangent

$$\tanh(x) = \frac{2}{1+e^{-2x}} - 1 \tag{4-9}$$

c) Linear

$$f(x) = ax + b \tag{4-10}$$

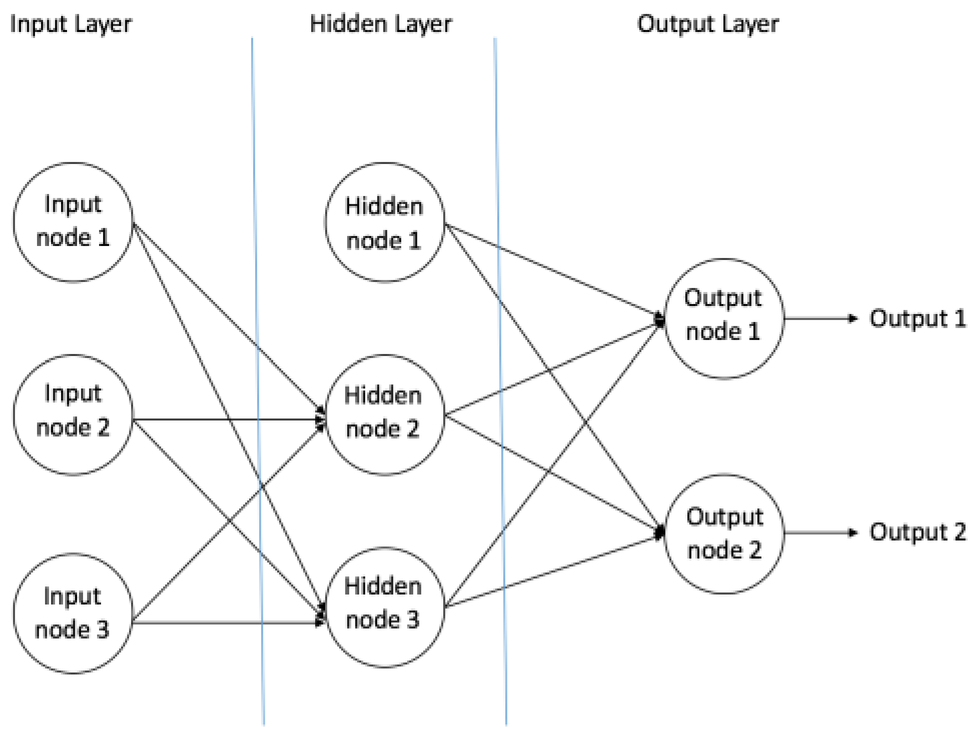

Figure 4-4: Example of neural network with layers

The computational of artificial neural network run through many iterations until the stopping condition is met and desired loss function is achieved. Then an independent testing dataset is used to verify the performance of the network.

4.6 Neural Network Modelling

4.6.1 Input database

In biomass procurement process, pricing is the key consideration. This project utilises artificial network analysis to generate an approximation model for price prediction, different data collection needs to be gathered according to specific factors based on previous section discussion.

Table 4-1: Input database description

Item	Factor	Unit	Remarks	Source
1	Outdoor temperature	°C	N/A	(World Weather Online, 2017)
2	Rainfall	mm	N/A	(World Weather Online, 2017)
3	Processed fresh fruit bunch	MT	Metric tonnes	(MPOB, 2017)
4	Exchange rate		With respect to USD	Bank Negara Malaysia
5	Transportation cost	RM	Based on diesel fuel	Malaysia Ministry of Domestic Trade, Co-operatives and Consumerism
6	Palm kernel shell market price	RM	Refer to successful transaction	BIO CONCEPT SOLUTION

Table 4-2: Importance of data points

Data points (months)	Input-Output correlation
24	0.605
30	0.667
42	0.789
54	0.901

Parameter 1, 2 and 3 in Table 4-1 are monthly data of Johor state. They are collected from year 2013 to the first half year of 2017 (54 months). The more data points (Table 4-2), the higher accuracy of the price prediction. This is proven by the correlation between amount of data points and input-output relationships.

The analysis is focused on a localised area. The purpose of this is to emphasize the factor's subtle influence at local level compared to national level.

4.6.2 Data pre-processing

Before the inputs are fed into the artificial neural network analysis, useful information can be derived from the raw data.

a) Parameter 3 (Table 4-1) is the quantity of FFB being processed at the mill. The figure is shown in '000 metric tonnes. The quantity of PKS is proportional (Palm Oil Biomass, 2016) to EFB (estimate around 5.5 %) since both derive from the same material. This is more manageable for the calculation.

b) Parameter 4 (Table 4-1) is the raw data of USD to RM daily exchange rate from Bank Negara Malaysia. To get the monthly average rate:

$$\mathrm{Rate}_{\mathrm{month}} = \frac{\sum_{\mathrm{i}}^{\mathrm{n}} \mathrm{r_i}}{\mathrm{n}} \tag{4-11}$$

r is the daily exchange rate.

n is the number of days in a month that has actual transactions.

c) Parameter 5 (Table 4-1) is the adjusted transportation cost based on 100 km radius. According to the information deom local transporters, one litre of diesel fuel (Table 4-3) may travel up to 2 km for a truck with 30 t full of load.

$$\mathrm{Cost_T} = \frac{100}{2} \times \mathrm{Price_{Diesel}} \tag{4-12}$$

Table 4-3: Monthly average diesel price

No	Year	Month	Price (RM/litre)
1	2013	January	1.80
2		February	1.80
3		March	1.80
4		April	1.80
5		May	1.80
6		June	2.00
7		July	2.00
8		August	2.00
9		September	2.00
10		October	2.00
11		November	2.00
12		December	2.00
13	2014	January	2.00
14		February	2.00
15		March	2.00
16		April	2.00
17		May	2.00
18		June	2.00
19		July	2.00
20		August	2.00
21		September	2.00
22		October	2.20
23		November	2.20
24		December	2.23
25	2015	January	1.93
26		February	1.70
27		March	1.95
28		April	1.95
29		May	1.95
30		June	2.05
31		July	2.05
32		August	1.95
33		September	1.80
34		October	1.90
35		November	1.90
36		December	1.90

Continue from Table 4-3

No	Year	Month	Price (RM/litre)
37	2016	January	1.60
38		February	1.35
39		March	1.35
40		April	1.55
41		May	1.55
42		June	1.55
43		July	1.60
44		August	1.70
45		September	1.70
46		October	1.75
47		November	1.90
48		December	1.85
49	2017	January	2.05
50		February	2.15
51		March	2.20
52		April	2.14
53		May	2.04
54		June	1.93

4.6.3 System initialisation

Artificial neural network is simulated on Neural Designer by importing the required training database, inputs and target will then able to be identified (Appendix A). There are four inputs for the neural network, comprising rainfall, FFB quantity, adjusted transport cost and exchange rate with USD while the output or the target is PKS price.

Table 4-4: Inputs database

Month	Temp (°C)	Rainfall (mm)	Qty ('000 mt)	Transport (RM)	FX	Shell (RM)
1	29	155.78	1,176.93	90.00	3.04	190
2	29	204.16	926.11	90.00	3.10	190
3	30	162.19	974.59	90.00	3.11	195
4	31	140.62	1,084.12	90.00	3.05	195
5	31	80.19	1,138.93	90.00	3.02	195
6	31	33.49	1,267.79	100.00	3.15	198
7	30	47.82	1,431.79	100.00	3.20	195
8	31	74.96	1,401.66	100.00	3.29	193
9	32	78.36	1,576.56	100.00	3.26	191
10	32	114.49	1,564.50	100.00	3.18	183
11	32	217.74	1,425.53	100.00	3.21	175
12	30	222.95	1,278.65	100.00	3.25	175
13	29	104.10	1,151.09	100.00	3.31	168
14	31	23.59	920.93	100.00	3.31	175
15	32	92.83	1,109.40	100.00	3.29	175
16	33	161.09	1,126.43	100.00	3.26	175
17	33	113.09	1,242.47	100.00	3.23	175
18	32	55.03	1,280.75	100.00	3.22	175
19	32	44.08	1,401.80	100.00	3.19	175
20	32	84.56	1,674.59	100.00	3.18	170
21	32	63.91	1,477.43	100.00	3.22	170
22	33	72.04	1,433.38	110.00	3.27	172
23	32	183.06	1,295.64	110.00	3.35	175
24	31	264.98	991.18	111.50	3.49	180
25	30	172.82	862.66	96.50	3.59	197
26	31	83.78	924.72	85.00	3.60	215
27	32	245.93	1,235.29	97.50	3.69	220
28	33	230.10	1,443.07	97.50	3.64	218
29	34	107.61	1,478.95	97.50	3.61	208
30	33	67.83	1,445.79	102.50	3.74	195
31	33	63.61	1,422.53	102.50	3.81	195
32	33	49.43	1,568.32	97.50	4.07	195
33	33	40.86	1,443.86	90.00	4.32	190
34	34	117.39	1,425.13	95.00	4.27	195
35	33	267.36	1,205.33	95.00	4.31	215
36	32	230.07	982.49	95.00	4.29	230
37	32	234.56	815.11	80.00	4.35	238
38	31	154.15	842.45	67.50	4.19	245
39	32	213.62	937.55	67.50	4.08	245
40	34	170.30	1,006.30	77.50	3.91	240

Continued from Table 4-4

Month	Temp (°C)	Rainfall (mm)	Qty (‘000 mt)	Transport (RM)	FX	Shell (RM)
39	32	213.62	937.55	67.50	4.08	245
40	34	170.30	1,006.30	77.50	3.91	240
41	34	121.62	1,069.12	77.50	4.05	238
42	33	37.71	1,183.76	77.50	4.09	243
43	33	72.56	1,177.16	80.00	4.02	243
44	34	40.87	1,319.54	85.00	4.03	243
45	34	39.77	1,404.32	85.00	4.11	243
46	34	94.37	1,398.26	87.50	4.18	240
47	32	243.20	1,395.81	95.00	4.34	238
48	31	163.40	1,296.36	92.50	4.47	240
49	31	216.80	1,080.86	102.50	4.46	242
50	31	180.30	1,108.63	107.50	4.45	242
51	32	202.60	1,084.64	110.00	4.44	237
52	33	224.60	1,110.22	107.00	4.41	237
53	34	91.60	1,164.96	102.00	4.32	237
54	34	54.60	1,070.77	96.50	4.28	240

The database (Table 4-4) is divided to three segments to separate the large data into training set (60 %), model selection set (20 %) and testing set (20 %).

4.6.4 Learning process

There are few constraints that need to be assigned to the system before running the simulation. All of the data inputs are normalised by using minimum-maximum method. The activation function of the neuron is hyperbolic tangent function. Quasi-Newton method is used as the training algorithm to map the inputs to output.

Four different models are evaluated to determine the most suitable prediction model for the case study. The model is differentiated by number of hidden layer. The number of neuron in each hidden layer determines the system selection method. It is an incremental trial and error method which stops at maximum 10 orders. This limit is to prevent overfitting of the model. However, the order limit can be adjusted to more than 10 if there were more input parameters for future work.

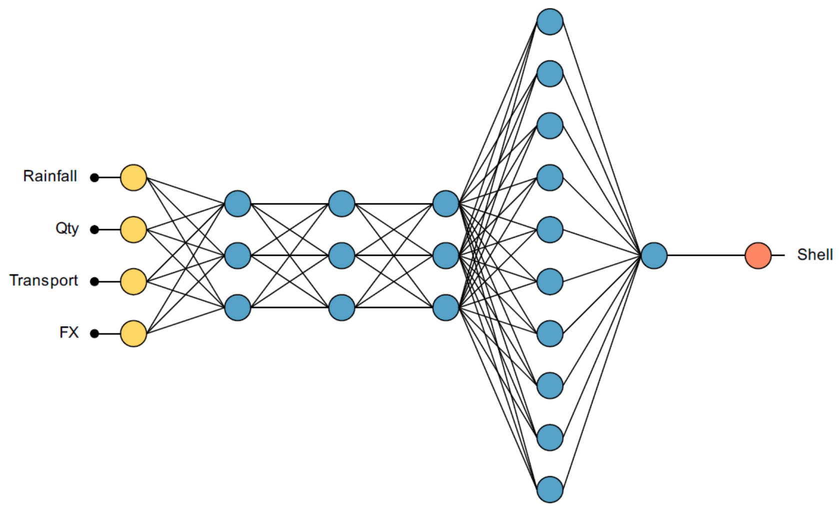

Figure 4-5: Four hidden layers neural network

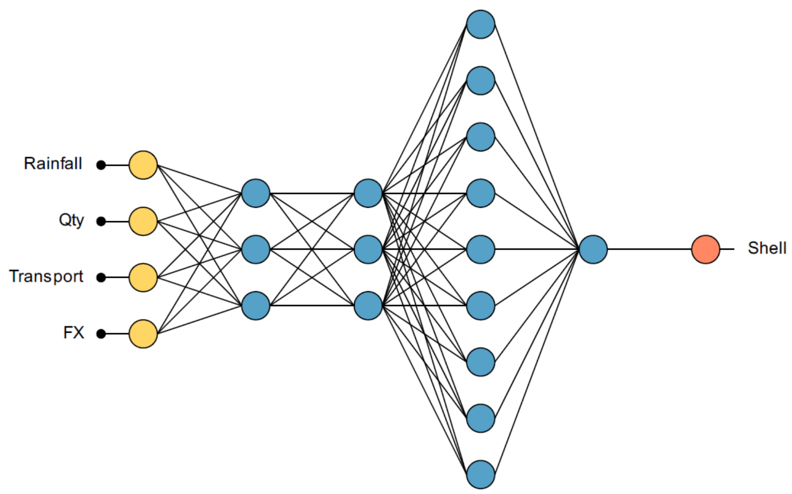

Figure 4-6: Three hidden layers neural network

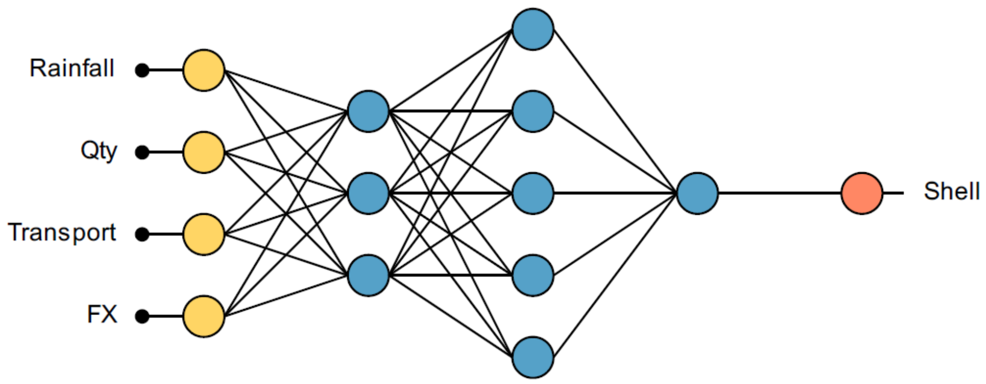

Figure 4-7: Two hidden layers neural network

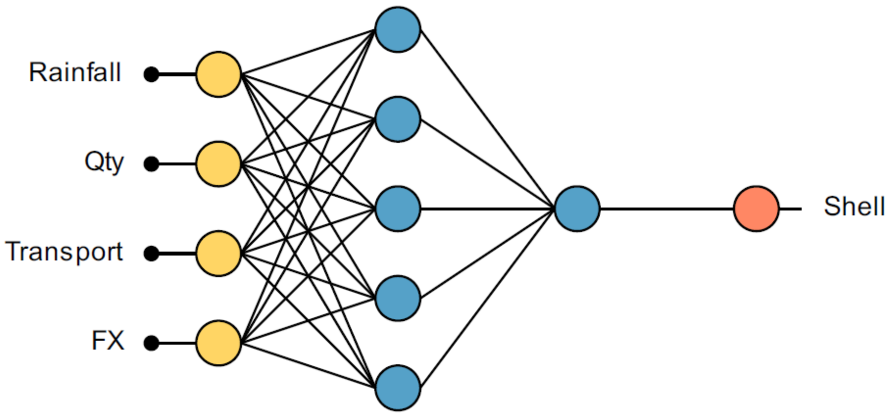

Figure 4-8: One hidden layer neural network

Table 4-5: Learning model performance

Configuration	4 hidden layers	3 hidden layers	2 hidden layers	1 hidden layer
Neurons	3:3:3:10	3:3:9	3:5	5
Loss	0.106	0.0787	0.102	0.108
Parameters norm	79.9	77.8	100	104
Selection loss	12.5	0.529	0.249	0.132

The number of neurons for each configuration is determined by the system model selection function. The selection target loss for each configuration is the minimum value that the neural network system can generate. Value less than 0 means there is no over fitting of the model. However, four hidden layers configuration has a selection loss of 12.5, indicating that the neurons number of 3:3:3:10 is an over fitting model for the case study. In neural network, more layers do not necessarily result in a better prediction model. There are a few parameters can be considered.

Parameters norm indicates the complexity of the model. The model is more stable if the norm figure is lower. The stability of the model can provide a more consistent prediction result. Here, three hidden layers configuration is outdoing the other three models, recording a value of 77.8. Finally, the loss index is the performance and quality measurements of the neural networks. Loss is the sum of errors of the model. Each configuration will minimise the loss, the lower the better. Overall, three hidden layers configuration is the best prediction model among all as it recorded a loss index of 0.0787.

4.7 Prediction model verification

To verify the model prediction performance, four models are tested using linear regression method on the predicted output and actual output. The test is run on an independent testing data set which is set before the system initialisation.

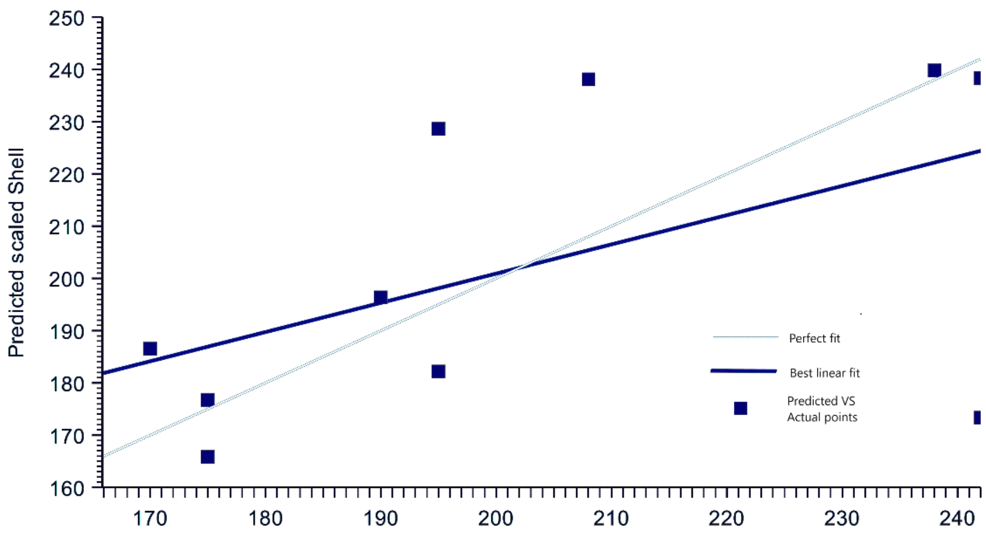

Figure 4-9: Four hidden layers verification result

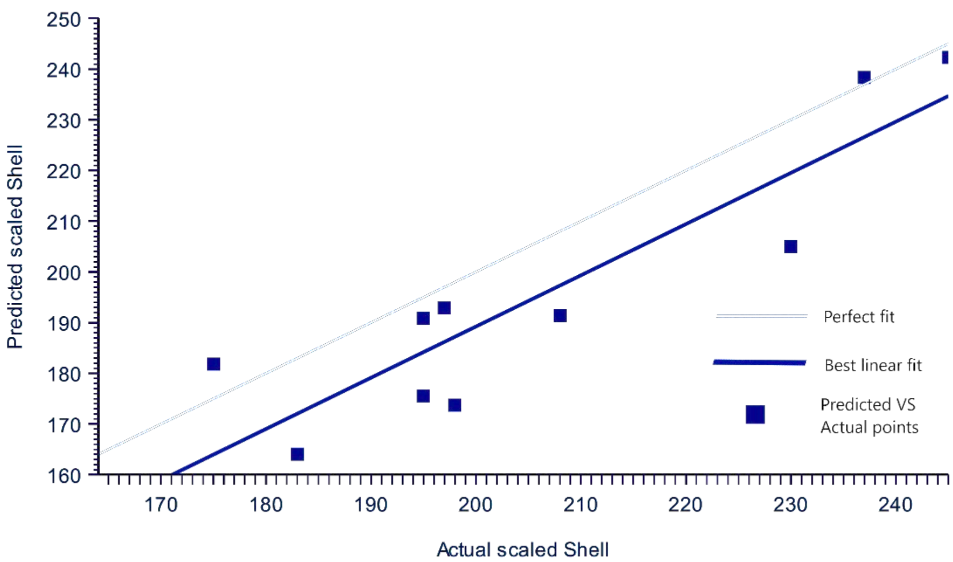

Figure 4-10:Three hidden layers verification result

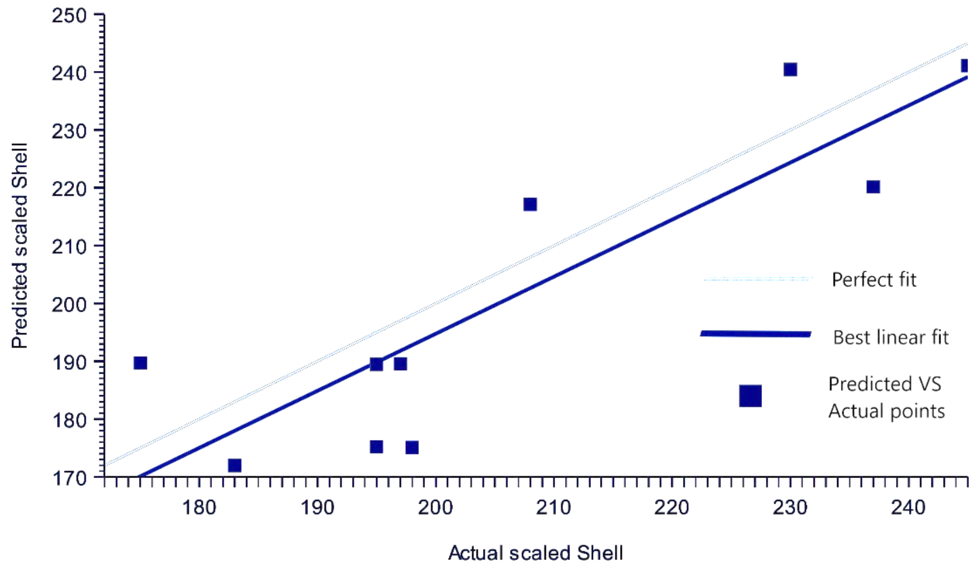

Figure 4-11: Two hidden layers verification result

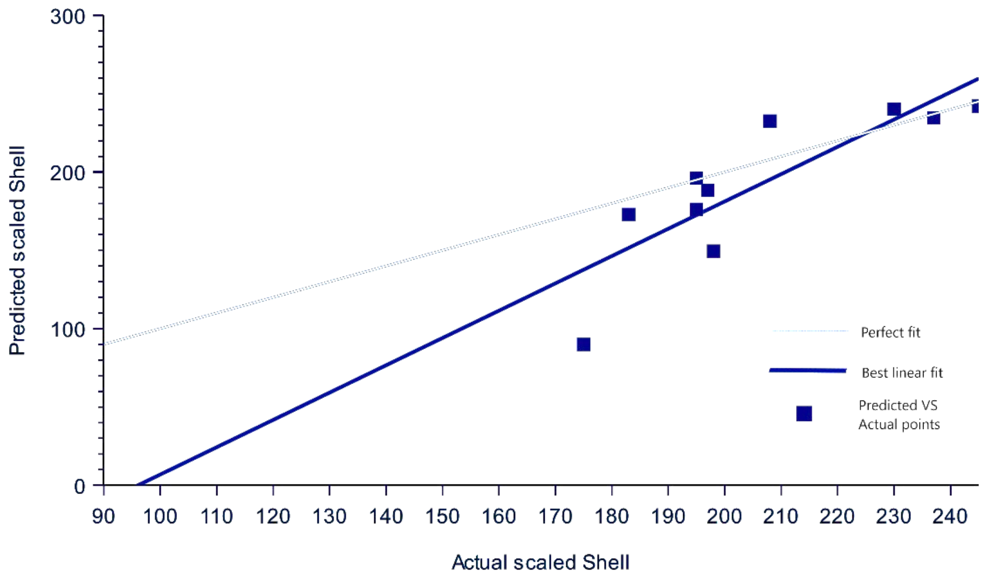

Figure 4-12: One hidden layer verification result

The predicted values are plotted versus the actual ones as purple squares. The blue coloured line indicates the best linear fit on the purple data points. The grey line indicates a perfect fit of the prediction model output after the neural network was trained.

Table 4-6: Prediction model verification result

Configuration	4 hidden layers (Figure 4-9)	3 hidden layers (Figure 4-10)	2 hidden layers (Figure 4-11)	1 hidden layer (Figure 4-12)
Intercept	89.1	-12.8	-2.6	-167
Slope	0.559	1.01	0.987	1.74
Correlation	0.526	0.901	0.87	0.843

This analysis leads to three parameters for each output variable. If the analysis had a perfect fit (outputs exactly equal to targets), the slope would be 1, and the y-intercept would be 0. If the correlation coefficient (R^2) was equal to 1, then there would be a perfect correlation between the outputs from the neural network and the targets in the testing dataset. Therefore, the blue line will overlap on the grey line. From Table 4-6 above, three hidden layers model yields the best predictive model (Appendix B) among all, in which records R^2 value of 0.901.

4.8 Discussion

The price of PKS can be forecasted by utilising the prediction model. From the inputs of rainfall, available quantity, fuel price and exchange rate, a realistic future price is predicted. The predicted price can be used as a guideline for the biomass procurement team on their strategic planning. They can decide whether or not to stock in advance or to stock more in quantity (if they were doing export business) or to source for alternative biomass (if they were using it for local consumption) which is cheaper and has similar performance by referring to the predicted price. If they decided to look for another biomass source, BCI properties introduced in previous Chapter 3 can be referred. In the end, the outcome of the price will be an input for the payoff consideration of game theory in Chapter 5.

The prediction model is a dynamic process where it can constantly update its learning process. When there are more input data points from historical data, the accuracy of output data will be enhanced. Thus, the predicted price is closer to the real-world. Biomass industry procurement player will be greatly benefitted from this outcome.

Apart from the predicted price of PKS, other palm biomass also can be applied into the model, on the premise that there is sufficient training data. The next potential palm biomass prediction will be EFB and mesocarp fiber. The model can be extended beyond price to predict the biomass yield or biomass properties. These can be combined into multiple target outputs. However, these require more complete and complex input parameters to cover all the required aspects such as carbon emissions, storage facility locations, capacity of the biomass plant and others.

4.9 Conclusion

This chapter has demonstrated that the three hidden layers neural networks – which takes rainfall, FFB quantity, transportation cost and foreign exchange rate as inputs – can potentially serve as an effective predictive model for PKS price. Although neural network modelling is not an entirely new method in making data-driven prediction; this approach is, nevertheless, a bold attempt to use non-technical features as parameters. The proposed prediction model has mapped different sets of unrelated elements, ranging from weather, yield, cost, price to currency, to develop a model to forecast commodity price scientifically. While most of the AI prediction models use related data sets to construct algorithm; prediction for the price of PKS requires multivariate sets of data, considering the fluctuations of its price from time to time. Through constructing an overarching database comprised of cross-disciplinary data, the designed algorithms have successfully contributed to the future price prediction from the input data. Crucially, the predicted price can be further taken as input criteria for the payoff scoring which will be discussed in the next chapter.

5 CHAPTER 5 GAME THEORY APPROACH IN MALAYSIA PALM BIOMASS INDUSTRY ANALYSIS

5.1 Introduction

Oil palm industry is a significant economic backbone of Malaysia – it is currently the fourth largest contributor to the national economy, accounting for approximately 8 % of the country's GNI per capita and 6 % of Malaysia's GDP (Abdul-Manan et al., 2014). As at December 2017, there are 5.74 million hectares of oil palm planted area in Malaysia, occupying nearly three quarters of the country's agricultural land, which is 14 % of the total land area of the country (MPOB, 2017). The entire area has produced 17.32 million tonnes crude palm oil in 2016 and accounted for 39 % of world palm oil production (MPOB, 2017). Being such a large agricultural sector in Malaysia, oil palm industry has simultaneously generated vast amount of surplus palm biomass waste, which constituted approximately 85.5 % of biomass in the country, with an average of 53 million tonnes each year and is even projected to rise to 100 million dry tonnes by the year of 2020 (Umar et al., 2014). Generally, the solid biomass wastes come directly from oil palm plantations in the form of harvested trunks and pruned fronds, and also from the palm oil extraction mills, such as EFB, mesocarp fiber and PKS. These biomass wastes are in turn being used either in plantations or mills. For instance, the fronds, trunks and EFB are often left in the plantations for mulching purposes or to be decomposed naturally as nutrient replacement, whilst mesocarp fiber and PKS are utilised in palm oil mill as in-house fuel for generating steam and energy. Given its abundant availability, oil palm biomass is particularly regarded as a valuable alternative for energy regeneration in Malaysia. There are a plethora of researches on the relevant field, such as the optimisation of biomass, in order to convert it into a variety of value-added products (Sabri, 2015).

This thesis, notwithstanding, aims to veer in a new direction for the oil palm biomass industry to focus on the sustainable oil palm biomass procurement as a premise for further optimisation process. It should be first recognized that despite of its vast availability nationwide, procurement of palm oil biomass at regional level is nonetheless a challenge for those external biomass processing plants. Stiff supply competition is inevitable especially for whom do not own plantations. They do not merely strive for local biomass supply for their own plants and business, but also facing competition from external buyers from different states who come to procure the biomass. Irregular biomass supply, which is contingent upon oil palm harvest cycle and yield, can further aggravate competition amongst the industry players (Umar et al., 2014). Additionally, the quality of biomass that is largely affected by surroundings moisture might considerably impact the subsequent process and cost before it can be utilised in the plant. BELCA (Lim and Lam, 2016) and BCI (Tang et al., 2014) methods can provide an insights of biomass material characteristics before it is ready for the plant. All these aspects ought to be taken into consideration in measuring and identifying the best strategy to ensure sustainable palm biomass procurement.

5.2 Problem statement

Strengthening technology, process optimisation, supply chain optimisation and product market diversification are typically the main emphasis within oil palm biomass industry. From the perspective of biomass plant entrepreneurs in particular, these facets are deemed to be closely affiliated with the profitability. Intensifying technologies and equipment can undoubtedly improve the efficiency of new biomass processing technology to produce reliable and higher value products, yet it would at the same time incur higher cost on the production cycle (Klemeš et al., 2013). While process optimisation also aims to increase efficiency, its focus is primarily on enhancing existing process without adding to the cost and thus maximising profit. Instead of merely focusing on increasing efficiency of processing biomass, it is equally crucial to shed light on sourcing strategy for effective procurement within such a competitive environment. Ultimately, strategic procurement would be a complement to the optimisation steps stated above and further enhance the overall efficiency.

5.3 Literature review

Game theory has recently resurged as a relevant tool in the analysis of supply chains, especially with multiple agents, wherein the conflicting competition and cooperation might possibly occur in a supply chain. In a situation in which the decisions of numerous agents affecting each other's payoff, game theory precisely deals with interactive optimisation problems (Cachon and Netessine, 2004).

Game theory was originally developed as a mathematical approach by John von Neumann and Oskar Morgenstern in the 1940s (Poundstone, 1992). It was later adopted and applied in social science and empirical research fields of study, particularly to deal with human interactions where there are several parties involved. Thereafter, game theory also known as the interactive decision theory as it examines strategic choices between interacting individuals (McCain, 2010). The most established example of game theory is the 'Prisoner's Dilemma', which was formalized by Merrill Flood and Melvin Dresher in 1950, and was named by Albert W. Tucker (Poundstone 1992). It is an exemplary conflict situation showing that the most rational decision does not necessarily lead to the best possible outcome. Despite its rather simple framework, the ‘Prisoner’s Dilemma’ has set a fundamental for analysing the interactions of multiple agents and crucially, to further generating strategy alternatives for maximising one’s payoff.

In the light of supply chain management – that is embedded in the corporate process and comprised of the transformation from raw materials to final products, game theory approach can serve as an effective analysis tool to shed light on the challenges in regards to time, cost, risk (Papapanagiotou and Vlachos, 2016) and opponents’ threat (Leng and Parlar, 2005). Conventionally, supply chain optimisation emphasises on the performance and improvement the supply chain structure and operation by looking into alternate sourcing, supply route management, collection hub positioning, and effective handling method, wherein cost is the key performance metric (Zhang et al., 2014). This chapter intends to expand the discussion by specifically focusing on the competition amongst industry players in the supply chain.

Table 5-1: Comparison of biomass supply chain analysis approach

Feedstock	Analysis approach	Reference
Multiple biomass	Database setup	(Black et al., 2016)
Multiple biomass	Stochastic programming	(Black et al., 2016)
Wood chips and straw pellets	Logistics analysis	(Wiśnicki et al., 2014)
Multiple biomass	Network design	(Yue and You, 2014)
Empty fruit bunches	Optimal allocation	(Foo et al., 2013)
Multiple biomass	Network design	(Thanarak, 2012)

Table 5-1 shows that the technical approaches adopted in the previous studies are solely targeting on enhancing one's competence in their own sphere without highlighting the competition within the industry. These attempts, nevertheless, might not necessarily contribute to higher profit or to serve the plant owner's best interest. Instead of merely focusing on increasing efficiency of processing biomass, this thesis opines that it is equally crucial to pay attention on sourcing strategy for effective procurement within such a competitive environment. Ultimately, strategic procurement would be a complement to the aforementioned optimisation steps and further enhance the overall efficiency.

Above all, biomass industry is competitive, particularly in terms of security and sustainability of biomass supply. In order to gain a competitive advantage over the other competitors, recognition of their interests and moves are important to enhance leverage in getting the most cost-effective biomass supply (Eu and Studies, 2014).

5.4 Methodology

This thesis adopts game theory approach in analysing Malaysia current competitive biomass industry, wherein multiple players are involved, often with conflicting objectives. In terms of procurement, they compete among each other to acquire the most cost-effective biomass supply and to maximise profit. Strategic form is the most appropriate method to analyse the above scenario. All possible strategies from every competitor are listed out while the outcomes for each possible combination of choices are also defined. The outcomes represent separate payoff for each competitor or also call player in terms of game theory. The payoff is a value to measure how likely a player prefers that outcome.

A non-cooperative game need to be constructed in strategic form by defining:

i. The involved players.
ii. Available strategies by each player.
iii. Payoff of each strategy

The formal representation of strategic game is:

a) Number of players involve,

$$\mathrm{i} = 1, \cdots, \mathrm{n} \tag{5-1}$$

b) A set of strategies for player i,

$$s = (s_1, \cdots, s_n) \text{ where } s_i \in S_i \text{ for } i = 1 \cdots, n \tag{5-2}$$

c) A function,

$$\pi_i \rightarrow: S \rightarrow R \text{ for player } i = 1 \cdots, n \tag{5-3}$$

where S is the strategy profiles set.

$$\text{player i's payoff} = \pi_i(s) \tag{5-4}$$

Nash equilibrium is a condition where each player knows the best strategy of each other and no player will get any further benefit by changing their current strategy. In the context of biomass supply competition, each biomass industry player is adjusting their best strategy to countermeasure the shortage crisis in belief of his opponent is also taking the best response.

$$\forall i, s_i \in S_{i,}: \pi_i(s_i^*, s_{-i}^*) \geq \pi_i(s_i^*, s_{-i}^*) \tag{5-5}$$

After the strategic form of the players' game has been constructed, the best strategy which gives the best response (favourable payoff) to other strategies is identified. Nash equilibrium is achieved if each of the players is making the best decision possible by taking into account the decision of opponents.

5.5 Case study

Case study is demonstrated in a specific oil palm plantation area which has two individual biomass processing plants. To further demonstrate the application of game theory in palm industry, a competitive environment criterion has been set up for the analysis which is short of biomass supply. It is defined in a specific region where its empty fruit bunches are running low due to 2 major factors:

a) Low harvest season of oil palm fruits therefore leads to drop in available EFB.
b) Raining season is affecting the quality of usable EFB. High moisture EFB are not desirable as biomass feedstock as more preprocessing procedures are needed and efficiency drop in the plant process.

They are competing each other for biomass supply and market share (both players are assumed to have same customers base). Both players have to compete each other to survive in these tough situations. In order to countermeasure these challenges, optimal strategies (Nasiri and Zaccour, 2009) need to be made by the players. In the worst case, lower competitiveness player is likely to be eliminated from the market (Sun et al., 2013).

5.6 Strategy priority ranking

The Analytic Hierarchy Process (AHPs), introduced by Thomas Saaty (1980), is a structured method to organise and analyse complex choices which are difficult to quantify in the process of decision-making (Saaty, 2001). AHP has been recognized as a useful aid in deciding priorities and making the best decision. Through computing the vector of criteria weights and the matrix of option scores, and lastly by ranking the options, AHP can usefully contribute to the decision-making process.

This method has been widely adopted in various settings and sectors, including public administration, customer service, student admissions, conflict analysis, disaster relief, military strategy planning and so forth (Saaty, 2008).

The pairwise relative evaluations, which compare a set of evaluation criteria to a set of alternative options, enable the most appropriate decision to be made. That being said, the most suitable decision is not necessarily the best option which optimises each single criterion, but the one which achieves the most suitable trade-off among the different criteria, considering some of the criteria could be contrasting.

It has been used in biomass supply chain analysis (How and Lam, 2017) to generate sustainability index based on the input priority (Saaty, 2000). This specific case of strategy prioritisation involves five criteria to rank out seven possible strategies.

There are seven suggested strategies (extracted from biomass industry players) for each player to consider in countering the shortage crisis. These strategies are:

1) Attempting to secure all the existing available biomass supply from a specific region without changing transportation mode and without additional handling method. However, there is possibility of purchasing price hike due to sudden demand surge.
2) Searching for the biomass supply in shortage from another region. There will be additional logistics cost and handling cost as it is located farther from the plant. The quality of raw biomass (such as EFB) may deteriorate due to longer expose hour after harvesting. Furthermore, the purchase price is not guaranteed to be the same with the existing pricing because of switching to new supplier.
3) Looking for different biomass which has similar performance to the current one. For the case of EFB, PKS or mesocarp fiber would be a suitable substitute. However, additional process modification is needed to accommodate the different type of biomass. Logistics, handling and storage would also need to be reconfigured. Therefore, more cost incurs in the entire process.
4) For the case of unsuccessful sourcing, increasing the current product selling price would temporarily conserve the supply. The drawback will be the possible dissatisfaction amongst customer and may affect future or potential business opportunity in the long run.

5) Reducing production output can conserve the supply yet leaving behind unmet demand. Customer dissatisfaction will be the tradeoff of this strategy.
6) A total shutdown to stop production is impossible from business perspective. A temporary shutdown is only possible for service and maintenance work or annual stock check. Normally, these activities only take a limited time frame. During this time frame, it is a total lost as there is no production to fulfill the demand while additional cost incurs for the service works.
7) Switching production process of the current plant is unlikely unless there is a reboot or upgrading equipment to adapt new technology. The cost is sky-high as this involves capital expenditure and is comparable to the setting up of a completely new plant.

These strategies are ranked and prioritised in advance to reduce difficulty in analysis, so that it can converge to a conclusive result. The prioritisation is done by accessing the level of feasibility of each strategy. This strategy feasibility study is based on the accumulative scoring on the involved operational execution procedures.

Table 5-2: Strategies scoring standards

No	Considering points	Explanation
1	Procurement cost	Extra cost is needed to make special or additional purchase due to urgency or last-minute purchase.
2	Logistics	Irregular transportation route and schedule for the new acquire supply
3	Service and maintenance	Production may stop for routine equipment service and maintenance.
4	Storage and handling	Additional handling and storage efforts in the warehouse for the non-scheduled supply.
5	Process modification	Different biomass supply requires different settings on the process. Extra time and cost related to equipment tuning will incur.
6	Customer satisfaction	Supply shortage will increase the unsatisfied demand of customers. Negative feedback from customers place a toll in upcoming business opportunity.
7	Plant start-up	Obsolete the current production line and upgrade to new line to adapt new technology.

Points from Table 5-2 are categorised into 5 selection criteria:

i. Implementation complexity
ii. Financial cost
iii. Process flexibility
iv. Output quality
v. Time frame

The questionnaire (Appendix D) was distributed to 15 biomass companies to acquire sufficient scoring data on strategies prioritisation. It was designed based on five criteria to prioritise seven proposed strategies. After the survey was done, AHP was implemented to create a pairwise comparison data in three simple consecutive steps:

i. Computing the criteria weights vector
ii. Computing the alternatives scores

iii. Ranking the alternatives

Matrix A was constructed as Equation 5-6.

$$matrix\ A = m \times m \tag{5-6}$$

m is the number of criteria in the pairwise comparison. There are five criteria in this study. Each a_{jk} in the matrix A represents the importance of the jth criterion relative to the kth criterion.

The constraint of the entries in matrix A is shown as Equation 5-7

$$a_{jk} \cdot a_{kj} = 1 \tag{5-7}$$

The example of relative importance measurement scale between two criteria is shown in Table

Table 5-3: Example of importance measurement scale

a_{jk} **scale**	**Definition**
1	j and are equally important k
3	j is slightly more important than k
5	j is more important than k
7	j is strongly important than k
9	j is absolutely more important than k

After matrix A is built, normalised pairwise comparison matrix A_{norm} is computed using Equation 5-8.

$$\overline{a_{jk}} = \frac{a_{jk}}{\sum_{l=1}^{m} a_{lk}} \tag{5-8}$$

Criteria weight vector is calculated by averaging the entries on each row of A_{norm} as Equation 5-9.

$$w_j = \frac{\sum_{l=1}^{m} \overline{a_{jl}}}{m} \tag{5-9}$$

Next, matrix B is constructed for the alternatives which are strategies in this chapter.

$$matrix\ B = n \times n \tag{5-10}$$

n is the number of alternatives.

Same steps (Equations 5-8 and 5-9) are applied to the matrix B on each entry to obtain the vector $s^{(j)}$ as Equation 5-11.

$$S = \left[s^{(1)} \cdots s^{(m)}\right] \tag{5-11}$$

Finally, the alternatives ranking is calculated using Equation 5-12.

$$v = S \cdot w \tag{5-12}$$

Based on the scoring from biomass plant players, the strategies rankings (Table 5-4) are calculated using AHP technique.

Table 5-4: Strategy score ranking

Strategy Profile	**Ranking**
Purchase all possible source from local market	0.44904
External sourcing (same biomass from other area)	0.21582
Alternative sourcing (different biomass)	0.12643
Increase selling price	0.06398
Production reduce	0.06170
Production stop	0.05066
Process change	0.03236

Table 5-5: Palm biomass business strategy for low supply

Decision priority	Available strategy
1	Purchase all possible source from local market
2	External sourcing (same biomass from other area)
3	Alternative sourcing (different biomass)
4	Increase selling price
5	Production reduce
6	Production stop
7	Process change

Table 5-5 shows the priority of strategy is made based on the possible cost incurred if it was executed by the team. The first priority involves the least cost compared to others. However, the first priority does not signify the best strategy. Without taking into account the opponents' decision, it is difficult to make the best decision. Therefore, the priority ranking of the strategy is served for the simplicity of analysis. The analysis has yet to include all available strategies to avoid complication in decision making.

Payoff of the strategy is determined by the inter-relationships between the consequences of opponent's strategy. In general, payoff is not necessarily to be in monetary value. Social and psychological factors might influence payoffs and decisions.

In this case study, the payoff that are listed in each strategy combination are assumed to be the likelihood of players' acceptable profit margin and benefits after including the possible cost, market share changes and the difficulties of work progress. The higher number means the higher benefit to the player who takes that particular strategy. The payoff figures in the analysis were collected from questionnaires data (Appendix E) which were completed by those biomass companies mentioned above.

Rather than analysing all of the strategies in one strategic form, three steps strategy equilibrium search is proposed to eliminate the incompetent strategy and to identify the best response of one player can do by considering opponent's best move. It may reduce the complexity of analysis itself. Game theory tool, Gambit 16 (McKelvey, McLennan, and Turocy 2016) is used to analyse the case study and to determine Nash equilibrium in each analysis step.

5.6.1 First step analysis for priority 1 and 2

The first two business options to countermeasure the low local biomass supply source are:

i. To procure whatever supply leftover from local market.

   This would increase the supply pricing if both players are competing each other.

ii. To source supply from other area.

   There are external, internal and network risks in supply chain (Mitkowski and Zenka-Podlaszewska 2014) which are no guarantee of sourcing success, additional logistic and handling cost since from different area. In the current scenario, the success rate of sourcing is assumed high where the proximity of biomass sources is as close as possible (Sun et al. 2011).

		Player 1	
	Strategy	**Purchase all**	**External procure**
Player 2	**Purchase all**	30 30	60 40
	External procure	40 60	50 50

Figure 5-1: step 1 strategic game

Figure 5-1 shows the strategic game form of step 1 and the payoff of each strategy set. If player 1 chooses "purchase all" strategy, he is not gaining benefit from this strategy if player 2 takes "external procure" strategy (40 VS 60). Meanwhile, if player 1 decides to choose "external procure" strategy, his payoff would not be in anywhere lesser than player 2 regardless of how player 2 reacts. The same situation applies to player 2. The achieved Nash equilibrium (Figure 5-2) is to go for second sourcing from external area, regardless of the opponent's strategy. The possible explanation for the situation is that: given the local biomass supply is in shortage, there are no guarantee that the market demand could be fulfil even if the player attempted to procure all available supply in that area.

		Player 1	
	Strategy	**~~Purchase all~~**	**External procure**
Player 2	**~~Purchase all~~**	~~30~~ ~~30~~	60 ~~40~~
	External procure	~~40~~ 60	50 50

Figure 5-2: step 1 dominance strategy

5.6.2 Second step analysis for priority 3 and 4

Following step 1, same type of biomass is unable to be sourced from any other area (due to weather condition, harvesting period and logistic issue) and local available supply are out of stock due to the competition from previous step assumption.

The two available options to countermeasure this issue are as stated below (Figure 5-3):

i. Alternative supply source of different biomass.

   This might increase the cost of purchase (Dumortier 2013), logistic, handling and process modification since this is a different properties of material.

ii. To avoid any further cost incureed, maintain the current supply but increase the selling price.

		Player 1	
	Strategy	**Alternative source**	**Increase pricing**
Player 2	**Alternative source**	30 30	40 40
	Increase pricing	40 40	50 50

Figure 5-3: step 2 strategic game

Raising price would be the best solution (Figure 5-4) as there is no additional cost incurred and the additional profit margin could offset the possible demand decrease due to higher selling price.

		Player 1	
	Strategy	**~~Alternative source~~**	**Increase pricing**
Player 2	**~~Alternative source~~**	~~30~~ ~~30~~	40 ~~40~~
	Increase pricing	~~40~~ 40	50 50

Figure 5-4: step 2 dominance strategy

5.6.3 Third step analysis

Based on step 1 and 2, possible strategies are external sourcing (same type of biomass) and increasing selling price (Figure 5-5). The best solution among these two is to increase the product's selling price (Figure 5-6) which yield an acceptable payoff for both players. The explanation would be that there are no additional cost incurred if this decision is made. Again, the only risk that might happen is the possibility of demand decrease due to price hikes. However, this would be the best-case scenario considering that the supply from local area is limited, and it is not logical to further boosting demand. This is only matter if either player can get external sourcing successfully with all the possible risks are being overcame, especially of the issues pertinent to biomass harvesting and transportation. These two factors contribute 29 % and 18 % respectively of the total capital cost (You and Yue, 2014).

		Player 1	
	Strategy	External procure	Increase pricing
Player 2	External procure	40 40	40 30
	Increase pricing	30 40	50 50

Figure 5-5: step 3 strategic game

After identifying the best strategy (Figure 5-6), further optimisation can be applied to it. For this particular strategy, there are two possible sub-options. First, optimizing supply chain by utilising a satellite biomass plant (Rogers and Brammer, 2009) to reduce the biomass transportation cost. Second, transforming the biomass into higher efficiency material such as energy pack (Ng et al., 2014). These can be used to negate the effect of demand decrease due to selling price increase.

		Player 1	
	Strategy	External procure	Increase pricing
Player 2	External procure	40 40	40 30
	Increase pricing	30 40	50 50

Figure 5-6: step 3 dominance strategy

5.6.4 Further explanation on priority 5, 6, 7 strategies

Strategy 5, 6 and 7 are not included in the aforementioned game analysis. These 3 strategies are unlikely to be deployed by the management team. Stopping production cycle can be directly translated as no income while at the same time, the process equipment is experiencing depreciation day by day. Furthermore, no output from the plant will give chance to opponent to monopoly the whole market shares. This is a total negative payoff to the player and this option is the least favourable. If the player chose to reduce the production rate to conserve supply source, the outcome would be equally disappointed as it would adversely decrease the commitment to the market demand. Again, this enables the opponent to monopoly the local market. However, during lower production rate, service and maintenance of the plant can be carried out. There would be an additional 10% of the operating expenses ("Presentation of 25 MW Biomass Power Plant in Kozani Area", 2012) incurred but in the sense of long term strategy, this is advisable although it does not generate profit at that moment. There is a short-term risk and long-term benefit that needed to be weighted and balanced. Last strategy would be changing the process mode to cope with new type of biomass processing. This is not an encouraging option as setting-up a new plant would be costly. For instance, even the cheapest option such as co-firing plant (IRENA, 2012) would cost USD 600 /kW for the equipment per se. This can be considered as a new investment and a detailed business profiling should be run. In case of co-firing plant where the player can retrofit (Cuéllar, 2012), the process for different biomass also cost USD 640 /kW/y compared to direct (USD 150 /kW/y) and indirect (USD 139 /kW/y) co-firing. This results in a higher fitting cost. Therefore, it is the last resort for the player as this can be regarded as quitting the market and re-entering it again in a brand new start.

5.7 Conclusion

Palm biomass business is a value-added sector in the existing palm-related industry; the management policy tends to be cost-orientated. Against this backdrop, game theory offers some of the most comprehensive and sophisticated tools in analysing and modelling a better strategy within a competitive biomass business environment through gaining insights into competitors' objective and interest, as well as their psyche (Bhattacharya, 2013). The entire procurement process is a dynamic action which needs to be constantly adjusted according to opponent's reaction. By structuring an analogous situation to identify appropriate and feasible strategy, further engineering optimisation can then be targeted on the specific strategy. Rather than optimising the entire process cycle, it emphasizes specifically on key areas and thus is more effective on decision making without wasting time and resources and can even achieve rapid payback.

6 CHAPTER 6 CONCLUSION

Malaysia has been proactively taking step in generating wealth from the biomass industry. Being one of the world's dominant palm oil producers, Malaysia is indeed having a distinct advantage to fully access to and utilise the abundance of biomass. The onus is on the industry to flourish, and importantly to contribute to the national wealth and sustainable development; yet there are challenges that need to be faced and solved. Amongst all, the absence of an integrated and dynamic system to support and monitor the biomass supply chain is highlighted in this thesis as the most significant barrier that has impeded the development of biomass industry.

The present thesis is a laboratory- and simulation-based research, which nevertheless has also taken an empirical and realistic approach to the current development status of biomass industry in Malaysia. In this thesis, a comprehensive sustainable framework, namely BSVC, has been proposed to address the deficiencies of the prior studies in the field of biomass studies to fill in the gap. BSVC comprised of: (a) BCI to classify the biomass properties for optimum utilisation; (b) artificial neural network to manage 3Vs (volume, velocity and variety) big data for aiding effective decision-making; and (c) game theory approach to elicit strategic sourcing options specifically on the procurement phase within a competitive environment. The suggested framework has ventured into a new direction by shedding light on the possibilities of a value-added supply chain for the biomass industry, enabling biomass to be deliver in an effective, proactive and timely manner, and simultaneously continue to preserve the continuity of the life-support system where the prospect of the biomass industry premised on.

6.1 Limitations and recommendations

The BSVC framework is built on three separate analysis systems to enable them to work independently and to serve for the purpose to ease the subtle adjustment on each module to achieve a functionable framework. Such separation, nonetheless, may render the possibilities that the input-output of these systems might not be correlated. The accuracy of the outcome at the final stage may therefore be affected. Furthermore, the errors occurred may propagate from one system to another system. Due to this limitation, the analysis system may assume the inputs are without mistake. This assumption, however, should not be conveniently made as variables and uncertainties are inevitable in the real-world situation.

Next, the BCI requires massive data inputs to generate accurate output. However, when historical and literature data are used to replace the actual data of those unavailable biomass, the consistency and precision of the output may be compromised. It is also important to take into account that the characteristics of the same biomass such as palm biomass may even be different due to different origins. Therefore, assumption is made to uniform the data of the same biomass to provide a general model to BCI. In addition, the moisture content – one of the biomass properties that determines the BCI– can hardly be accurately measured in an open-air environment. In order to improve the BCI's accuracy to be more realistic, oven drying is used to simulate the different level of palm biomass moisture. Calorific value of palm biomass is an approximation value as some of the biomass is difficult to be measured for its calorific value in natural raw condition unless it is processed into standard feedstock with industry specification.

Artificial neural network consists of a number of different learning algorithms. The decision criteria to select the appropriate algorithm is based on experience and the desired output. Learning rate stopping criteria, neuron weight assignment and loss function definition can be different from case to case basis. The input taken by neural network model may not be directly correlated to output like those in proximate analysis. Therefore, industry experience needs to be pin-pointed and picked out as reliable inputs for the prediction model. Anyhow, the selected inputs may not necessarily be the most influential parameters. There are possibilities that other parameters also play a role to determine the output. Moreover, even when the model is proven to be functional, the equation is not inevitably unquestionable and cannot be assumed as a fixed theory. Another limitation of the artificial neural network is that it requires a huge volume of data, including historical data, for the training algorithm of the model. There is no limit on the data range, given that it can generate the anticipated output. Therefore, the database needs to be constantly updated and compared with real-world data for verification. Every correction and adjustment can possibly lead to better and more accurate prediction in the future.

Last but not least, the accuracy of game theory analysis is also relied on the quality of the constructed database, wherein every input might affect the calculated payoff of the player. Besides, the result of the game theory approach cannot be generalised but is based on specific case scenario. The considerations and payoff acceptancy of different players may vary; hence, the strategic options generated by the model will also be different according to different case scenario.

6.2 Future works

The BCI framework can be enhanced by taking account into more types of biomass and larger sets of data of each biomass.

It is possible for BCI to be extended to specific biomass BCI according to the clustering show in the work. Moreover, the analysis on BCI can be done by using multivariate regression to provide a comprehensive model on the relationships of bulk density, moisture contents and calorific value. Computer aided programming will potentially enhance the efficiency of analysis. This will improve the accuracy of BCI prediction on biomass appearance properties. All these estimated biomass values can be applied in sustainable and life cycle studies and energy total site analysis.

Next, neural network application in biomass procurement is a modest attempt to embark the trend of big data in biomass supply chain. There are numerous of learning algorithms can be tested in wide range of biomass supply chain scenario. In the near future, the analysis can venture into two directions for deep learning and reinforcement learning method. Deep learning can achieve higher performance in data representation task. Meanwhile, reinforcement learning allows the system to adjust the preference of the action according to the level of rewards. Both algorithms involve complex mathematical calculation and higher computation time which required sophisticated hardware infrastructure. Besides, the establishment of a comprehensive input database is critical for the system to learn from valuable industry experience.

Finally, further analysis can be carried out to explore more strategic options. Feedbacks from the experienced industry players in multiple area can be extended to enhance the strategy profiles. Payoff of the strategy can also be improved by incorporating pragmatic real-life scenario. In addition, more factors can be adopted to the strategy analysis such as supply uncertainty risk management (Shabani et al., 2014) and natural environment factors. Furthermore, in-depth study on the chosen strategy such as analysis on single or multiple sourcing (Sawik, 2014) can be carried out to improve the efficiency of procurement process. Multi-criteria (Aplak and Sogut, 2013) can also contribute to complementing the decision-making process of biomass industry owners.

Another suggestion will be the conduct of a more complex two-level analysis: first, several different case scenario analyses can be constructed, and second, performance of the analysed strategy from each scenario can be correlated with the analytic network process. Results or outcomes can then be compared to evaluate the performance of optimisation, and also feasibility and efficiency of the chosen strategy.

The ultimate goal is to integrate all modules into a single system that is capable of performing multiple tasks to function like a live procurement strategist.

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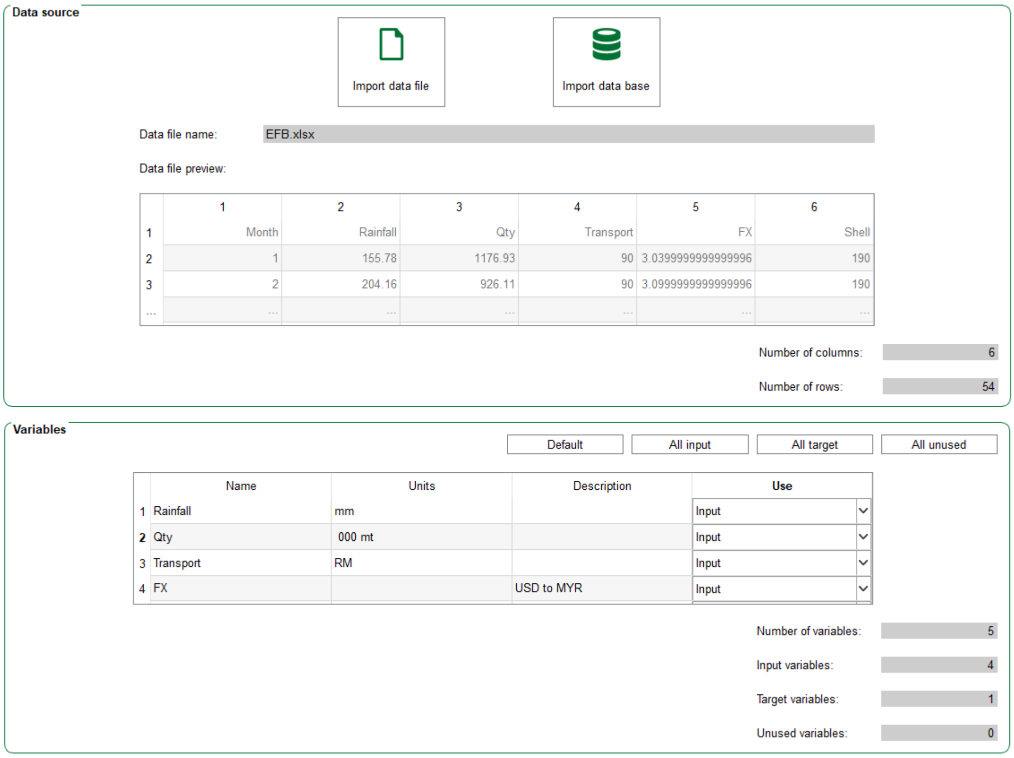
APPENDIX A: ANN system initialisation



APPENDIX B: ANN output mathematical expression

The mathematical expression represented by the neural network is written below. It takes the inputs Rainfall, Qty, Transport and FX to produce the output Shell.

```
scaled_Rainfall=2*(Rainfall-23.59)/(267.36-23.59)-1;
scaled_Qty=2*(Qty-815.11)/(1674.59-815.11)-1;
scaled_Transport=2*(Transport-67.5)/(111.5-67.5)-1;
scaled_FX=2*(FX-3.02)/(4.47-3.02)-1;
y_1_1=tanh(0.164395
-0.540898*scaled_Rainfall
-1.44268*scaled_Qty
-0.02819*scaled_Transport
-0.021397*scaled_FX);
y_1_2=tanh(-1.43287
+0.729369*scaled_Rainfall
-3.54323*scaled_Qty
+1.21995*scaled_Transport
-1.66633*scaled_FX);
y_1_3=tanh(-0.616402
-1.77617*scaled_Rainfall
+1.37181*scaled_Qty
+3.72995*scaled_Transport
-1.16425*scaled_FX);
y_2_1=tanh(-0.233937
+1.37643*y_1_1
-0.206941*y_1_2
+0.464519*y_1_3);
y_2_2=tanh(1.96727
-3.13389*y_1_1
+5.99401*y_1_2
+2.94535*y_1_3);
y_2_3=tanh(0.842991
-5.31494*y_1_1
+1.43398*y_1_2
+2.7718*y_1_3);
y_3_1=tanh(2.70493
+1.34163*y_2_1
-0.0493426*y_2_2
-0.343124*y_2_3);
y_3_2=tanh(2.91579
```

```
+1.16349*y_2_1
+0.0224741*y_2_2
-0.379653*y_2_3);
y_3_3=tanh(2.70822
+1.28504*y_2_1
-0.0412898*y_2_2
-0.252848*y_2_3);
y_3_4=tanh(-2.60925
-1.24198*y_2_1
+0.111273*y_2_2
+0.07972*y_2_3);
y_3_5=tanh(-3.66503
+4.41258*y_2_1
-2.6556*y_2_2
+4.08659*y_2_3);
y_3_6=tanh(-3.10988
-2.18538*y_2_1
+0.651383*y_2_2
-1.34177*y_2_3);
y_3_7=tanh(-1.63505
-0.767731*y_2_1
+3.44815*y_2_2
+2.54236*y_2_3);
y_3_8=tanh(-2.07839
-1.97468*y_2_1
+2.43305*y_2_2
-1.21397*y_2_3);
y_3_9=tanh(-2.65411
-1.30289*y_2_1
+0.111704*y_2_2
+0.262235*y_2_3);
scaled_Shell=(25.0013
+24.9513*y_3_1
+24.9444*y_3_2
+24.9512*y_3_3
-24.9531*y_3_4
-22.7876*y_3_5
-24.9479*y_3_6
-21.138*y_3_7
-24.3596*y_3_8
-24.9515*y_3_9);
(Shell) = (scaled_Shell);
```

APPENDIX C: Python expression

The mathematical expression represented by the model can be exported to Python programming languages, in the so called production mode.

```
#!/usr/bin/python

from math import tanh

def expression (Rainfall, Qty, Transport, FX) :

    scaled_Rainfall=2*(Rainfall-23.59)/(267.36-23.59)-1
    scaled_Qty=2*(Qty-815.11)/(1674.59-815.11)-1
    scaled_Transport=2*(Transport-67.5)/(111.5-67.5)-1
    scaled_FX=2*(FX-3.02)/(4.47-3.02)-1
    y_1_1=tanh(0.164395
    -0.540898*scaled_Rainfall
    -1.44268*scaled_Qty
    -0.02819*scaled_Transport
    -0.021397*scaled_FX)
    y_1_2=tanh(-1.43287
    +0.729369*scaled_Rainfall
    -3.54323*scaled_Qty
    +1.21995*scaled_Transport
    -1.66633*scaled_FX)
    y_1_3=tanh(-0.616402
    -1.77617*scaled_Rainfall
    +1.37181*scaled_Qty
    +3.72995*scaled_Transport
    -1.16425*scaled_FX)
    y_2_1=tanh(-0.233937
    +1.37643*y_1_1
    -0.206941*y_1_2
    +0.464519*y_1_3)
    y_2_2=tanh(1.96727
    -3.13389*y_1_1
    +5.99401*y_1_2
    +2.94535*y_1_3)
    y_2_3=tanh(0.842991
    -5.31494*y_1_1
```

```
+1.43398*y_1_2
+2.7718*y_1_3)
y_3_1=tanh(2.70493
+1.34163*y_2_1
-0.0493426*y_2_2
-0.343124*y_2_3)
y_3_2=tanh(2.91579
+1.16349*y_2_1
+0.0224741*y_2_2
-0.379653*y_2_3)
y_3_3=tanh(2.70822
+1.28504*y_2_1
-0.0412898*y_2_2
-0.252848*y_2_3)
y_3_4=tanh(-2.60925
-1.24198*y_2_1
+0.111273*y_2_2
+0.07972*y_2_3)
y_3_5=tanh(-3.66503
+4.41258*y_2_1
-2.6556*y_2_2
+4.08659*y_2_3)
y_3_6=tanh(-3.10988
-2.18538*y_2_1
+0.651383*y_2_2
-1.34177*y_2_3)
y_3_7=tanh(-1.63505
-0.767731*y_2_1
+3.44815*y_2_2
+2.54236*y_2_3)
y_3_8=tanh(-2.07839
-1.97468*y_2_1
+2.43305*y_2_2
-1.21397*y_2_3)
```

```
y_3_9=tanh(-2.65411
-1.30289*y_2_1
+0.111704*y_2_2
+0.262235*y_2_3)
scaled_Shell=(25.0013
+24.9513*y_3_1
+24.9444*y_3_2
+24.9512*y_3_3
-24.9531*y_3_4
-22.7876*y_3_5
-24.9479*y_3_6
-21.138*y_3_7
-24.3596*y_3_8
-24.9515*y_3_9)
(Shell) = (scaled_Shell)

return Shell
```

APPENDIX D: Pairwise Questionnaires

The University of Nottingham
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Survey Participation Consent Form

Prioritise strategy options to handle biomass supplies shortage in a competitive environment with Analytic Hierarchy Process Approach

Dear participant,

I am a PhD student, under the supervision of Associate Professor DDr. Lam Hon Loong in the Department of Chemical and Environmental Engineering, University of Nottingham Malaysia Campus. I am conducting a research study to prioritise the strategy to deal with biomass supplies shortage in a competitive situation.

I am requesting your participation, which will involve filling questionnaires that will take approximately 10 minutes in total. Your participation in this study is completely voluntary and you may withdraw at any time. We want to assure you that all responses to this survey will be kept completely anonymous and confidential. The results of the survey will be reported only in the aggregate.

If you have questions or want a copy or summary of the study results, please contact me at *012-366 2431* or *kebx3tjn@nottingham.edu.my*.

Thank you in advance for your contributions to this important study. Return of the questionnaire will be considered your consent to participate.

Thank you.

Sincerely,

TANG JIANG PING
kebx3tjn@nottingham.edu.my

The University of Nottingham
UNITED KINGDOM · CHINA · MALAYSIA

Instruction

Please compare the pair of variable in the same row, and indicate the level of importance based on the scale of 1, 3, 5, 7, 9 with a sign "X". The description of the scale level is as below:

1 – equally   *3 – moderately*   *5 – strongly*   *7 – very strongly*   *9 – extremely*

For example, if A is ***very strongly*** more important than B, please insert the tick sign on the "7" column closer to A, vice versa.

A is more important than B ← 9 7 5 3 1 3 5 7 9 → B is more important than A

A		X								B

Based on your expertise and experience, please make the pairwise comparison judgement by comparing the two variables in the same row.

Background:

Area: same district as your industry location.

Player A: yourself.

Player B: your direct competitor.

Crisis: biomass supplies shortage within 2 months.

Part I: Strategy prioritization criteria

Criteria definition:

1. Implementation Complexity
   a. Storage and handling
   b. Service and maintenance
   c. Process modification
2. Financial Cost
   a. Procurement cost
   b. Logistics
   c. Plant start-up capital
   d. Process modification cost

3. Process Flexibility
    a. Logistics
    b. Storage and handling
4. Output Quality
    a. Feedstocks reliability
    b. Customer satisfaction
5. Time Frame
    a. Customer satisfaction
    b. Logistics

To determine the importance of the selection criteria in strategy options prioritization.

Risk factor	9	7	5	3	1	3	5	7	9	Risk factor
Implementation complexity										Financial cost
Implementation complexity										Process flexibility
Implementation complexity										Output quality
Implementation complexity										Time frame
Financial cost										Process flexibility
Financial cost										Output quality
Financial cost										Time frame
Process flexibility										Output quality
Process flexibility										Time frame
Output quality										Time frame

Part II: Risk factor vs risk factor

To rank the importance of **strategy** options in biomass supplies shortage crisis under competitive environment.

Risk factor	9	7	5	3	1	3	5	7	9	Risk factor
Purchase all the available biomass supplies										Change the plant process

Purchase all the available biomass supplies										Source for alternative biomass supplies
Purchase all the available biomass supplies										Purchase biomass supplies from adjacent area
Purchase all the available biomass supplies										Reduce production output
Purchase all the available biomass supplies										Stop production
Purchase all the available biomass supplies										Increase output selling price
Change the plant process										Source for alternative biomass supplies
Change the plant process										Purchase biomass supplies from adjacent area
Change the plant process										Reduce production output
Change the plant process										Stop production
Change the plant process										Increase output selling price
Source for alternative biomass supplies										Purchase biomass supplies from adjacent area
Source for alternative biomass supplies										Reduce production output
Source for alternative biomass supplies										Stop production
Source for alternative biomass supplies										Increase output selling price
Purchase biomass supplies from adjacent area										Reduce production output
Purchase biomass supplies from adjacent area										Stop production
Purchase biomass supplies from adjacent area										Increase output selling price
Reduce production output										Stop production
Reduce production output										Increase output selling price
Stop production										Increase output selling price

APPENDIX E: Payoff Questionnaires

The University of Nottingham

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Survey Participation Consent Form

Strategy payoff with Game Theory Approach

Dear participant,

I am a PhD student, under the supervision of Associate Professor DDr. Lam Hon Loong in the Department of Chemical and Environmental Engineering, University of Nottingham Malaysia Campus. I am conducting a research study to quantify the strategy payoff which are related to competitor's action in biomass supplies shortage case scenario.

I am requesting your participation, which will involve filling questionnaires that will take approximately 10 minutes in total. Your participation in this study is completely voluntary and you may withdraw at any time. We want to assure you that all responses to this survey will be kept completely anonymous and confidential. The results of the survey will be reported only in the aggregate.

If you have questions or want a copy or summary of the study results, please contact me at *012-366 2431* or *kebx3tjn@nottingham.edu.my*.

Thank you in advance for your contributions to this important study. Return of the questionnaire will be considered your consent to participate.

Thank you.

Sincerely,

TANG JIANG PING
kebx3tjn@nottingham.edu.my

Page **1** of **3**

Instruction

Please indicate the level of advantages based on the scale from 10 to 100 with a sign circle. The description of the scale level is as below:

10 – least advantage ***50 – moderately advantage*** ***100 – most advantage***

For example, if you take strategy A is ***very strongly*** more advantage that your opponent takes strategy B, please circle "70", vice versa.

10	20	30	40	50	60	70	80	90	100

Based on your expertise and experience, please make the payoff judgement by comparing the two strategies given in the question.

Step I: Purchase all the available biomass supplies VS Procure the biomass supplies from adjacent area

1. To what extend do you think you will be gaining advantages if you were trying to purchase all the available biomass supplies in the local market while opponent was also doing the same thing?

10	20	30	40	50	60	70	80	90	100

2. To what extend do you think you will be gaining advantages if you were trying to procure the biomass supplies from adjacent area while opponent was also doing the same thing?

10	20	30	40	50	60	70	80	90	100

3. To what extend do you think you will be gaining advantages if you were trying to purchase all the available biomass supplies in the local market while opponent was trying to procure the biomass supplies from adjacent area?

10	20	30	40	50	60	70	80	90	100

4. To what extend do you think you will be gaining advantages if you were trying to procure the biomass supplies from adjacent area while opponent was trying to purchase all the available biomass supplies in the local market?

10	20	30	40	50	60	70	80	90	100

Step II: Source for alternative biomass supplies VS Increase the plant output price

1. To what extend do you think you will be gaining advantages if you were trying to source for alternative biomass supplies replace the shortage supplies while opponent was also doing the same thing?

10	20	30	40	50	60	70	80	90	100

2. To what extend do you think you will be gaining advantages if you were trying to increase the plant output price while opponent was also doing the same thing?

10	20	30	40	50	60	70	80	90	100

3. To what extend do you think you will be gaining advantages if you were trying to source for alternative biomass supplies replace the shortage supplies while opponent was trying to increase the plant output price?

10	20	30	40	50	60	70	80	90	100

4. To what extend do you think you will be gaining advantages if you were trying to increase the plant output price while opponent was trying to source for alternative biomass supplies replace the shortage supplies?

10	20	30	40	50	60	70	80	90	100

The University of Nottingham

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Survey Participation Consent Form

Strategy payoff with Game Theory Approach

Dear participant,

I am a PhD student, under the supervision of Associate Professor DDr. Lam Hon Loong in the Department of Chemical and Environmental Engineering, University of Nottingham Malaysia Campus. I am conducting a research study to quantify the strategy payoff which are related to competitor's action in biomass supplies shortage case scenario.

I am requesting your participation, which will involve filling questionnaires that will take approximately 10 minutes in total. Your participation in this study is completely voluntary and you may withdraw at any time. We want to assure you that all responses to this survey will be kept completely anonymous and confidential. The results of the survey will be reported only in the aggregate.

If you have questions or want a copy or summary of the study results, please contact me at *012-366 2431* or *kebx3tjn@nottingham.edu.my*.

Thank you in advance for your contributions to this important study. Return of the questionnaire will be considered your consent to participate.

Thank you.

Sincerely,

TANG JIANG PING

kebx3tjn@nottingham.edu.my

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Instruction

Please indicate the level of advantages based on the scale from 10 to 100 with a sign circle. The description of the scale level is as below:

10 – least advantage ***50 – moderately advantage*** ***100 – most advantage***

For example, if you take strategy A is ***very strongly*** more advantage that your opponent takes strategy B, please circle "70", vice versa.

10	20	30	40	50	60	70	80	90	100

Based on your expertise and experience, please make the payoff judgement by comparing the two strategies given in the question.

Step III: Procure the biomass supplies from adjacent area VS Increase the plant output price

1. To what extend do you think you will be gaining advantages if you were trying to procure the biomass supplies from adjacent area while opponent was also doing the same thing?

10	20	30	40	50	60	70	80	90	100

2. To what extend do you think you will be gaining advantages if you were trying to increase the plant output price while opponent was also doing the same thing?

10	20	30	40	50	60	70	80	90	100

3. To what extend do you think you will be gaining advantages if you were trying to procure the biomass supplies from adjacent area while opponent was trying to increase the plant output price?

10	20	30	40	50	60	70	80	90	100

4. To what extend do you think you will be gaining advantages if you were trying to increase the plant output price while opponent was trying to procure the biomass supplies from adjacent area?

10	20	30	40	50	60	70	80	90	100

APPENDIX F: Payoff survey responses