Biomass Power Plant Location and Distribution Planning System

Jakkawan Patomtummakan and Narameth Nananukul*

Abstract— *This research focuses on the supply chain planning of biomass in Thailand. The objective is to create a complete planning system for biomass plant site selection, and also biomass allocation to each plant. Three components of the biomass supply chain are being considered; which are suppliers, bio-power plants, and customer. Biomass is an organic material which can be used as a source to generate bioenergy. The left-over biomass from agricultural activities will be purchased and used as raw material to generate electricity. A mixed-integer linear programming is developed as an optimization tool to decide the amount of biomass that should be ordered from different suppliers in each time period, and where bio-power plants should be located considering a set of related constraints. The objective of the optimization model is to minimize the total cost at selected bio-power plants by considering four cost components, including the fixed opening of proposed bio-power plants, material cost from purchasing biomass, transportation cost between suppliers and bio-power plants, and inventory holding cost. The model has the ability to identify the potential of biomass as an alternative source of energy in Thailand. Moreover, the research will be further developed by including disruption management as one of its conditions. With disruption management, the optimization model can provide a decision support solution to make an adjustment to the decision variables as a countermeasure towards uncertainties within the supply chain.*

Keywords— **Alternative energy, biomass, location and distribution planning system, supply chain optimization.**

1. INTRODUCTION

Thailand is a country which is located at the center of Indochinese Peninsula in Southeast Asia. The geographical property of the country consists of five regional parts, including northern, northeastern, central, western, eastern, and southern regions. The total area of the country is approximately 513,00 km^2 and the population is estimated to be over 68.8 million people (as of 2016). According to the data from Department of Alternative Energy Development and Efficiency published in the year 2016, biomass is ranked after large hydropower as the second largest source of alternative energy to generate electricity for consumption, and biomass is expected to be utilized even more in the future.

Every region of Thailand is supplied with biomass [12] whereas the majority of supply is from the northern region and followed by the northeastern region. Biomass can be obtained from agricultural activities and by-products from processing agricultural product. Despite the availability of several types of biomass in the country, the research focuses mainly on the majorities of the group. The biomass considered in this research is from activities regarding plantation and processing of rice, sugarcane, cassava, palm, peanuts and beans, rubber tree, and coconut. In general, there would be some remaining of biomass left unused after being utilized for a purpose (e.g. some rice mills would use rice husk in combination with other substances to make fertilizer while some would leave it wasted), and this proportion of remaining biomass can be used to generate bioenergy in biomass power plant. Some examples of common biomass available in Thailand are represented in Figure 1:

Fig.1. Examples of common biomass in Thailand.

Each biomass consists of the different degree of heat value. The heat value is a number which indicates how much energy, in terms of heat, can be extracted from a biomass. For instance, rice straw, on average, would have a heat value of 12.33 MJ/kg which is equivalent to 3.425 kWh of electricity enough to operate a 60-Watt light bulb for five to six hours. This different degree of heat value will be one of the factors that determine which types of biomass should be selected to order from the available suppliers, in order to be as economically efficient as possible. There are several methods [10] which can be applied to convert the amount of biomass into electricity. One of the methods, which is quite straightforward, is direct combustion (Figure 2). In direct combustion, biomass will be burnt in a combustor to generate hot gas. The hot gas will then be used in the second stage which is to boil water to generate hot steam. At the last stage, the hot steam is used to run a turbine to generate electricity.

J. Patomtummakan is with Sirindhorn International Institute of Technology, Thammasat University, 99 Moo 18, Km. 41 on Paholyothin Highway, Khlong Luang, Pathum Thani 12120, Thailand.

N. Nananukul is with Sirindhorn International Institute of Technology, Thammasat University, Thailand.

*Corresponding author: N. Nananukul; Phone: +66-86-4164919; E-mail: narameth@siit.tu.ac.th.

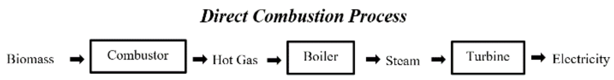

Fig.2. Direct combustion process flow.

Despite the fact that there is carbon dioxide generated and released into the environment during the process of converting biomass into bioenergy, biomass is still considered as a clean energy. This is because the released carbon dioxide will eventually be absorbed by the newly grown plants. Hence, in this sense, the combustion process of biomass is different from the combustion process of fossil fuel, in which the latter releases carbon dioxide into the environment without any means to absorb it back.

In this research, the objective is to create a complete planning system for biomass plant site selection, and also biomass allocation to each plant. The proposed decision support system consists of three main components, user interface (UI), server, and database. The user interface (UI) provides functions to import data (biomass availability, list of existing biomass plants, etc.) from a database or from reliable sources. The UI also has functions to display different types of data and results. The database stores all input data and also the results from the optimization modules. At the server, the optimization module is implemented. The module is a site selection and allocation module for building biomass plants. The module determines the optimal locations and allocation based on different key factors that affect the decision. The factors are electricity consumption in each region, land cost, industrial zoning, available biomass, and risk of having disruption [4] of biomass.

Problem statement

Thailand is enriched with biomass, and there is a considerable amount of biomass left unused after being utilized. This left-over biomass can be considered as an alternative source of energy to generate electricity for consumption. However, it raises some questions regarding the design of biomass supply chain for electricity generation. For instance, in each time period, what types of biomass should be purchased? the amount of biomass? and from which available sources? It is also crucial to identify the suitable location for the bio-power plant by considering major related costs (e.g. land cost, machine cost, and transportation cost). Moreover, it is important to take disruption management into consideration, since agricultural supply chain usually faces many uncertainties at the supply side (i.e. supply shortage due to unusual seasonal effects). Hence, a good decision should be made, and by having a decision support system, the decision maker will be equipped with necessary information to make a good and profitable decision.

Objective

The objective of this research is to create a complete planning system which can identify the optimal biomass power plant locations and the optimal allocated amount of different types of biomass, inventory level, and the usage of each biomass at each candidate for biomass power plant under a 12-month time frame.

2. LITERATURE REVIEW

There have been many studies regarding the application and implementation of optimization techniques for biomass supply chain. One of the common techniques is to develop a mathematical model, by considering related constraints and solve the problem using an optimization software. There is a number of studies which prefer to focus their applications on one particular element rather than the whole supply chain. This depends on the area of focus of the study. Since in some scenarios, a supply chain could be very complex that the problem would be too large to model and solve with all details included. Hishamuddin, H., Sarker, R. A., and Essam, D. L. [1] put their focus on a single stage production-inventory system (i.e. an input raw material will have to go through just one manufacturing process to become the finished goods). A constrained non-linear optimization program was developed to use in a production system by including a recovery model for disruption. The optimization program can provide two answers of interest; which are optimal production size and optimal recovery time window. Paul, S. K., Sarker, R. A., and Essam, D. L. [2] extended their co-members previous study by considering a two-stage batch production-inventory system while concerning reliability. The problem gets more complex by just adding one more stage into the production-inventory system. A disruption would require a different countermeasure depending on which stage is being disrupted. A non-linear constrained optimization program was developed with an objective function to maximize the total profit of the system subjects to capacity, demand, and stage linking constraints. Reliability is being considered by taking in the possibility of having defective finished goods in the system, which adds, even more, complexity to the supply chain problem.

Disruption management has become one of the areas of focus for many researchers. A disruption is an unexpected event that occurs and interferes with general habits of a system. Disruption management is one of many approaches to equip the system with a countermeasure towards the unexpected events. A study from Brouer, B. D., Dirksen, J., Pisinger, D., Plum, C. E.M., and Vaaben, B. [3] about vessel schedule recovery problem is an example of the application of disruption management in logistics aspect. A mixed integer programming was developed to handle disruptions in liner shipping business. Traditionally, a decision to deal with disruptions would be decided individually by the operator in charge. However, with the availability of disruption management in a decision support system, the operator can decide, with a better reason, to select an optimal recovery action for their operation. A book named “Disruption Management: Framework, Models, and Applications” was published by Yu, G. and Qi, X. [4] in 2004. The book addresses many examples of how to model an optimization program inclusively with disruption management aspect. The application of disruption management can be applied to various types of business scenarios, including a supply chain. More studies have tried to include disruption management perspective into their supply chain problems since the application of disruption management is capable of providing a more realistic solution to support the decision maker. A robust supply chain network design has been developed by Baghalian, A., Rezapour, S., and Farahani, R. Z. [5] to determine the optimal network structure, in which they try to keep a certain service level against disruptions and demand uncertainties. A mixed integer non-linear program was developed under a stochastic mathematical model while considering a multi-product supply chains integrating with a number of capacitated production facilities, distribution centers, and retailers. Piecewise linearization and robust optimization techniques were implemented in their work, and the authors also applied their model to a real-life case in the rice industry of a Middle East country. Jabberzadeh, A., Fahimnia, B., Sheu, J., and Moghadam, S. H. [6] put their effort in designing a supply chain resilience to cope with disruptions and supply-demand interruption. A stochastic mathematical model was used to minimize the total cost of establishing a supply chain network while maximizing the supply chain resilience (i.e. the flexibility to respond to disruptions). Unlike the work from [5] where the distribution of probability in stochastics models are known, this study assumes to have an unknown distribution, thus robust optimization was applied to deal with the unknown distribution. A recent work from Paul, S. K., Sarker, R. A., and Essam, D. L. [7] was to develop a quantitative model which aims to mitigate disruptions in a supply chain. Three-stage supply chain network is considered with multiple manufacturing plants, distribution centers, and retailers. Three approaches were applied to their work. The first approach is to develop an updated supply chain plan for a finite period to incorporate any change in the data. The second approach is to develop a predictive mitigation planning for obtaining a better supply chain plan using a Fuzzy Inference System. The third approach is to develop a mathematical model for managing sudden production disruptions which cannot be predicted in advance. They also consider a series of disruptions, which occur consecutively, in their third approach.

Biomass has been taken into consideration by many researchers due to the urge of finding solutions towards the on-going energy crisis. One of the aspects which researchers have paid their attention to is the optimization of biomass supply chain. A study of biomass-based industrial district heating networks in Italy was conducted by Chinese, D. and Meneghetti, A. [8]. System analytic models were developed as an optimization tool to support decisions under the district heating networks scenario. They formulated two optimization programs and integrated them as a systematic optimizer for the whole heating district networks. The first program was developed as a mixed integer linear programming with an objective to maximize profit for a utility company. The second program was developed as a linear programming which aims to minimize the net balance between CO_2 emissions and the configuration of the energy supply. Kazemzadeh, N. and Hu, G. [9] developed a mathematical modeling framework to design a biofuel supply chain network considering uncertainty in the system. A two-stage programming model was formulated with a goal to maximize profit in a supply chain. The first stage is used to decide decisions regarding variables prior to the occurrence of uncertainty. After the realization of uncertainty, a corrective action is performed by the second stage programming to optimize the objective of the system. In 2016, Donskoy, I. G., Keiko, A. V., Kozlov, A. N., Shamansky, V. A., and Svishchev, D. A. [10] published a research about mathematical modeling of the fixed-bed gasification process. A mathematical model was formulated to simulate the optimal condition for the fixed-bed staged biomass gasification process. Heat flux and air ratio are two key variables considered in the model. The model is useful for determining the conditions in which staged gasification can be efficiently operated. Moreover, a good supply chain planning can indirectly contribute to a better environment by reducing the number of emergency shipment due to poor planning. Dekker, R., Bloemhof, J., and Mallidis, I. [11] proposed an overview of aspects, issues, contributions, and challenges in the application of operation research for green logistics, they gave an overview of the present and possible future developments with a focus on designing, planning, and controlling in a supply chain for transportation, inventory, and facility decisions.

Thailand is a country which many of its regions are suitable for plantation, hence biomass is distributed and available throughout all parts of the country. Papong, S., Yuvaniyama, C., Lohsomboon P., and Malakul, P. [12] portrayed the overview of biomass utilization in Thailand through their study in 2004. Biomass is considered to be the second largest energy source in the country whereas sugarcane, rice, oil palm, and wood wastes are the major sources. The major potential resources of biomass, biomass production, and biomass utilization in the country have been discussed in details together with possible uncertainties within the biomass supply chain. Based on the literature review, there is a potential research gap between the application of disruption management and the optimization of biomass supply chain under a certain context. At the current stage, this research tends to grab this research opportunity by trying to optimize the biomass supply chain in Thailand through creating a system which is capable of identifying suitable biomass locations and planning the distribution of different types of biomass. For the future stage, the work will be further developed by including disruption management into the system.

3. METHODOLOGY

Data

Characteristics of biomass supply chain under the context of Thailand is studied and relevant data is collected to be used in the optimization model. The data used in this research can be classified into three main groups; which are biomass supply-related data, biomass power plant related data, and electricity demand related data.

Biomass Supply Related Data

Twenty-five types of biomass (Table 1) are considered. The availability of biomass from each district in Thailand is collected from Department of Alternative Energy Development and Efficiency, Thailand (DEDE). The number of biomass in each area depends on the geographical property of the plantation area, thus it differs among each district. For instance, the southern region of Thailand is enriched with coconut-based biomass since the area is suitable for growing such plant, in contrast with the northern region, where the area is suitable for growing other types of plant, thus making the northern region abundant with other types of biomass rather than coconut-based biomass.

As shown in Table 1, different types of biomass consist of the different degree of heat value. Heat value is a number which indicates how much heat can be extracted from a biomass. The data of different degree of heat value is also collected from DEDE. The amount of biomass ordered from each supplier, which is decided by the optimization model, will be multiplied by the degree of the heat value of its type and a conversion constant to be equivalent to kilowatt-hours unit, which is the unit used for the demand of electricity in each time period.

Table 1. Types of biomass and heating value

Index	Biomass	Heat value (MJ/kg)	Index	Biomass	Heat value (MJ/kg)
1	Rice straw	12.33	14	Coconut empty bunch	15.4
2	Rice husk	13.52	15	Coconut bract and husk	16.23
3	Off-season rice straw	12.33	16	Cashew nut shell	5.49
4	Off-season rice husk	13.52	17	Palm shell	1.47
5	Corn cob	9.62	18	Cassava residue	1.49
6	Corn leaves and stem	9.83	19	Cassava roots	5.49
7	Palm trunk	7.54	20	Rubber tree sawdust and wood chips	6.57
8	Palm shell	16.9	21	Rubber tree wood ends	6.57
9	Palm empty bunch	7.24	22	Rubber tree slabs	6.57
10	Palm leaves	1.76	23	Rubber tree stumps, roots, and branches	6.57
11	Palm fiber	11.4	24	Bagasse	7.37
12	Peanuts, soybeans, and green beans stems and leaves	16.23	25	Sugarcane leaves	15.48
13	Coconut shell	17.93			

Apart from the data related to biomass supply locations, availability, and heat values, data of cultivation period and prices are also collected. Some types of biomass are not available in some periods of a year. For instance, rice can only be cultivated during October to December. If rice-based biomass is to be purchased by the power plant to be used as raw material for generating electricity, they will only be available for purchase in their cultivatable period. The cultivation period referred in this research is collected from the Energy Environment Foundation. The price of each biomass is collected from various sources, including from the Energy Environment Foundation and biomass markets in the country. Nonetheless, the prices used in this research is assumed to be constant and not to be subjected to real life factors (e.g. inflation rate and seasonal effect).

Biomass Power Plant Related Data

One objective of the optimization model is to identify the best locations to establish biomass power plants. Data of factors regarding the justification of establishment is collected from several sources. In a power plant, transportation cost and fixed opening cost are the two major costs which mainly affect the decision of establishment. Transportation cost is the cost of moving biomass from suppliers to power plants. The cost is computed by multiplying transportation rate in monetary unit (e.g. Thai baht) per ton-kilometer, which is collected from a fleet transportation company, with the distance between each supplier and the power plant. Coordinates of districts and provinces in Thailand are obtained from the Electronics Government Agency (Public Organization). The coordinates of a supplier and a power plant are used to calculate the distance between the two components by applying the spherical law of cosines. The current stage of this research, however, assumes the transportation rate to be the same for any biomass type. Hence, distance is the main factor to illustrate the difference in transportation cost. The fixed opening cost of a power plant is calculated from the combination of land cost and boiler cost. In all provinces of the country, the land cost of the urban area is more expensive than the land cost of the rural area. The data of land cost of each district in Thailand is collected from the Treasury Department. The cost of boiler depends on the desired capacity of the power plant. In this research, the maximum capacity of a biomass power plant is expected to be 100 MW, which would require two 260 ton/hour boilers. The cost of a 260 ton/hour boiler is approximately 100,000 USD. The referred price and specification are collected from a boiler supplier based in China. The research does not take operating cost into consideration. Since the operating cost should be the same for any biomass power plant, thus the cost does not justify the decision regarding the establishment of a power plant.

Electricity Demand Related Data

The annual electricity demand of each province in Thailand is collected from the National Statistics Office. The historical data between 2006 to 2015 is used to forecast a new annual demand of the observing province. Historical electricity demands of different provinces are observed, and they tend to follow a linear trend model. This can be implied that the usage of electricity in Thailand will likely increase in the future. An example of linear trend behavior from the historical data of electricity usage is illustrated in Figure 3:

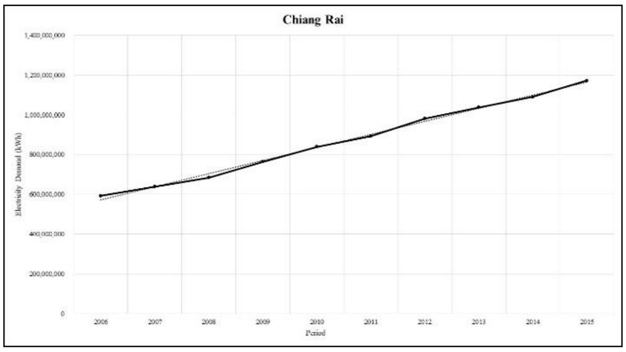

Fig.3. Annual electricity demand of Chiang Rai province from 2006 to 2015.

Different linear trend models are compared to find the most suitable technique to forecast a new annual electricity demand for each province. The mean squared error will be used as an indicator to identify the technique. Since the optimization model considers one-year time horizon which is divided into twelve periods, the annual demand must be aggregated into monthly basis. The historical data of each province is only available on annual basis. However, there exists a data of electricity demand of the whole country in monthly basis available form Electricity Generating Authority of Thailand. The historical data starting from 2002 to 2016 was used to compute seasonality index of each month which represents the percentage of electricity usage in each month compared with the average usage of the whole year. The seasonality index is multiplied with the forecast data to obtained monthly demand of electricity of each province.

Optimization model

A mathematical model is formulated to represent the biomass supply chain optimization problem. Details of how indices, parameters, and decision variables are defined are shown in Nomenclature section. The objective function and the constraints are represented in Table 2.

Table 2. Objective function and constraints

minimize

$$\left(\sum_{k=1}^{p} FC_k \times Y_k\right) + \left(\sum_{t=1}^{12}\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{p}\left(X_{tijk} \times BP_{tj}\right)\right) + \left(\sum_{t=1}^{12}\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{p}\left(X_{tijk} \times TR_{jk} \times d_{jk}\right)\right) + \left(\sum_{t=1}^{12}\sum_{i=1}^{m}\sum_{k=1}^{p}\left(I_{tik} \times HC_{ik}\right)\right)$$

subject to

$\sum_{k=1}^{p} I_{0ik} \le BI_i$;	$\forall i \in m$	(1)
$I_{tik} = I_{t-1ik} + \sum_{j=1}^{n} X_{tijk} - U_{tik}$;	$\forall t = 1..12$, $\forall i \in m$, $\forall k \in p$	(2)
$\sum_{i=1}^{m}\sum_{k=1}^{p} (U_{tik} \times W_i) \ge D_t$;	$\forall t = 1..12$	(3)
$\sum_{k=1}^{p} X_{tijk} \le S_{tij}$;	$\forall t = 1..12$, $\forall i \in m$, $\forall j \in n$	(4)
$\sum_{i=1}^{m} (U_{tik} \times W_i) \le C_k \times Y_k$;	$\forall t = 1..12$, $\forall k \in p$	(5)
$X_{tijk}, U_{tik}, I_{tik} \ge 0$;		(6)
Y_k is binary ;		(7)

The objective function of the model aims to minimize the summation of four cost components. These cost components represent majority costs which lay significant impact towards the establishment of a biomass power plant. The costs being considered are fixed opening cost of biomass power plant, purchasing of raw material cost, transportation cost, and holding cost of biomass inventory.

There are seven constraints which restrict the model's feasible boundary and define its conditions. Constraint (1) initializes the initial inventory of biomass to be available before the establishment of any bio-power plant in order to satisfy the demand of the first period. Constraint (2) defines how inventory level in each period is accumulated by considering the summation between the beginning inventory, which is the ending inventory of the prior period, and a new portion of incoming purchased biomass in the period. The inventory level is depleted at the end of the period by subtracting the amount of biomass which has been used to generate electricity during the period. Constraint (3) converts the amount of biomass in ton unit to kilowatt-hour unit, by multiplying the amount with its particular conversion constant. The total generated electricity from all biomass power plants must be enough to satisfy the demand in the period. Constraint (4) requires that the purchased biomass at every power plant must not exceed the amount that suppliers can provide in each time period. Constraint (5) requires that the electricity generated at each power plant must not exceed the capacity of the plant. Constraints (6) and (7) are boundary constraints of the decision variables.

4. CASE STUDY: UPPER-NORTHERN THAILAND

Characteristics of the region

The mathematical model was applied to a case study of the upper-northern Thailand. The upper-northern region consists of nine provinces, including Chiang Rai, Chiang Mai, Phayao, Maehongsorn, Lampang, Lampoon, Nan, Phrae, and Uttaradit. The upper-northern region is part of the northern region, which is considered to have the highest biomass potential among all regions of the country. In terms of population, the total population of the region is approximately 6.2 million (as of 2012), where Chiang Mai is the most populated province followed by Chiang Rai and Lampang. In terms of land area, Chiang Mai still acquires the largest total area followed by Lampang and Chiang Rai.

Applying the system

Relevant data of the upper-northern region was collected to be applied to the mathematical model. The mathematical model was transformed into an optimization model and run in IBM ILOG CPLEX software. The available supply of 25 types of biomass in each province was collected and sorted monthly depending on their cultivatable periods. There are 112 districts within the nine provinces. The coordinates of these districts were collected and will be considered as the candidates to establish biomass power plants. The demand considered in the study is the monthly demand of nine provinces. The demand from all provinces was consolidated together into one monthly demand to be satisfied by the model. In conclusion, the dimension of the optimization problem would consist of 12 periods, 25 types of biomass, 9 suppliers, and 112 bio-power plant location candidates.

Results

The optimization model aims to minimize the summation of fixed opening cost, raw material purchasing cost, transportation cost, and inventory holding cost regarding the relevant data of the upper-northern Thailand. The decision variables are the amount of purchased biomass, inventory level, and used biomass in each period. The values of decision variables which yield the optimal result were obtained from the optimization model. The black stars in Figure 4 represent the suggesting candidates, which are the best locations for establishing biomass power plants in the upper-northern Thailand. The suggesting candidates are: 1) Phayamengrai District, Chiang Rai 2) Wiangchai District, Chiang Rai 3) Samoeng District, Chiang Mai 4) Chiangkham District, Phayao 5) Pong District, Phayao 6) Mueang Pan District, Lampang 7) Thung Hua Chang District, Lampoon 8) Phu Phiang District, Nan 9) Mae Charim District, Nan 10) Santisuk District, Nan 11) Denchai District, Phrae 12) Thongsaenkhan District, Uttaradit 13) Tha Pla District, Uttaradit and 14) Nam Pat District, Uttaradit.

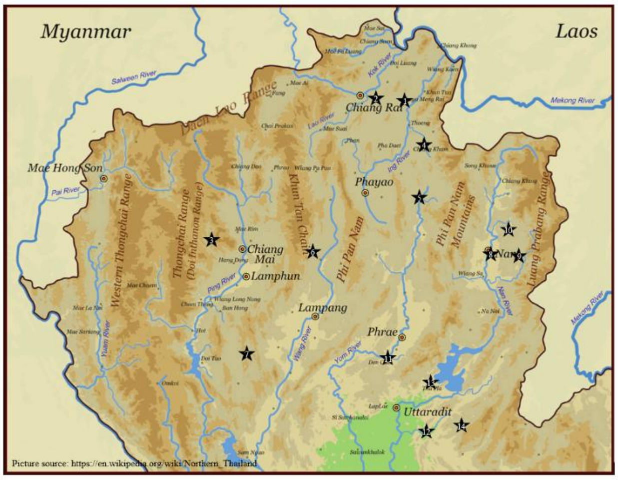

Fig.4. Optimal locations to establish biomass power plant.

Types of biomass which are used to generate electricity in each time period are illustrated by black boxes in Table 3. It is shown that the most frequently used biomass is corn leaves and stem followed by palm trunk and peanuts, soybeans, and green beans leaves and stem. The inventory level of the most frequently used biomass, corn leaves and stem, is observed and illustrated in Figure 5.

Table 3. Usage of different types of biomass

Period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1			■			■				■						■	■		■						
2			■			■																			
3		■				■	■																		
4	■	■			■	■	■					■													■
5	■	■				■	■					■													■
6	■	■				■	■					■													
7	■			■		■	■					■								■			■		■
8	■			■	■	■	■		■		■	■	■										■		■
9					■	■	■		■			■								■			■		■
10					■	■	■		■			■								■			■		
11				■	■	■	■					■								■			■		
12				■	■	■	■					■								■			■		■

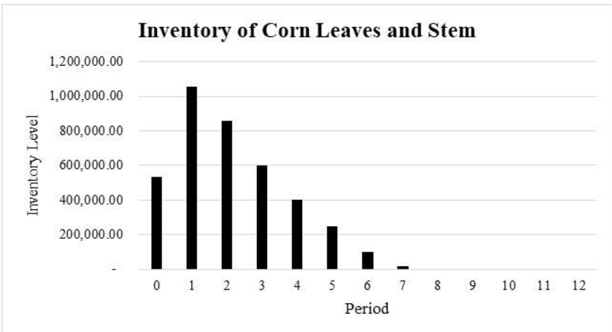

Fig.5. Change in inventory level of corn leaves and stem.

5. DISCUSSION

After performing an optimization analysis with the model, the decision variables are assigned with optimal values which together yield the minimum total cost of the biomass supply chain problem.

The optimization model suggests that the demand for electricity of the upper-northern Thailand can be satisfied with 14 one-hundred-megawatt biomass power plants. The power plants are operated under the conditions in which they are required to run the generator 24 hours a day, 330 days annually, and at 20% efficiency on average. Nan and Uttaradit are the only two provinces which are suggested by the model to establish three power plants within the province territory. Chiang Rai and Phayao are suggested to establish two power plants in their provinces and the rest are suggested with one power plant, except for Maehongsorn province which is not to be established any power plant in its area. Each biomass power plant is selected mainly based on the distance between the power plant and suppliers around the suggesting area. Despite the fact that Chiang Mai contains the largest land area, its supply of biomass is relatively low when compared with other provinces. In addition to the preference towards Nan and Uttaradit, both provinces are enriched with biomass supply of many types, especially for Nan which contains the highest amount of corn leaves and stem, which is the most frequently use biomass based on the result from the optimization model.

18 out of 25 types of biomass were selected to use for electricity generation at the power plants. The most frequently used biomass is corn leaves and stem, palm trunk, peanuts, soybeans, and green beans leaves and stem, respectively. The main reason behind these choices of biomass is the specific heat value, which represents the effectiveness of each biomass, and the supply within the area. In the upper-northern Thailand, the availability of corn leaves and stem is the highest among other types of biomass. Therefore, even the specific heat value of the biomass is not the most effective one, its availability tends to justify the decision of the model by, instead, reducing the transportation cost.

The inventory level throughout a year of corn leaves and stem at all established power plants is observed. It is shown that the model tries to keep the biomass in stock from period one to period six then it stops storing the biomass. The reason behind this behavior is because of the cultivatable period of the biomass. The cultivation period of corn is from September to January. Therefore, the biomass will not be available for purchase from February to August. The optimization model responds to this restriction by trying to keep inventory level of the biomass to be used later during its uncultivatable period. This decision is possible since the shelf-life of each biomass is long and considered without limit. Once the cultivation period of corn begins, the fact that the model does not want to keep the storage anymore can be implied that the availability of corn leaves and stem, in its cultivation period, in combination with other types of biomass is enough to satisfy the demand of electricity in the period. Moreover, another assumption in the model is that each biomass power plant does not have a limit for its storage which makes it possible for the power plants to keep a high level of different types of biomass at once during each time period. These assumptions, however, could be manipulated in the future research in order for the optimization model to become more realistic towards the biomass supply chain problem.

6. CONCLUSION

The research can be applied as a fundamental concept to develop a decision support system which is capable of providing useful solutions for decisions regarding the biomass supply chain problem. The optimization model developed in this research can be used to identify suitable locations to establish biomass power plants, as a mean to satisfy the demand of electricity within the region. The model can also be used to determine the optimal amount of biomass to be purchased and stored in each time period.

Future research

The research will be further developed by considering more conditions for the planning and distribution system. A wider scale of data regarding the availability of biomass in new regions, the electricity demand, and the restriction such as requirement from industrial zoning, will be considered to improve the capability of the system. The next step of this research will also include disruption management technique in the optimization model, which will enable the model to response and provide solutions by taking into account risk management and uncertainties. The model may also consider the shelf life of each biomass as one of the constraints in providing the optimal solution. The system will be able to work in a more realistic environment of input data, thus resulting in a more realistic solution. Furthermore, the optimization model will be integrated with other software applications to be equipped with necessary tools, for instance, user-interface and map visualization which will make the system become easier and more effective for its users.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the financial support provided by the Thammasat University Research Fund under the TU Research Scholar, Contract No. 2/25/2560 and national budget fund in fiscal year 2018, Contract No. 26/2561.

NOMENCLATURE

Define Indices:

Number of time periods (t) = 1, 2, …, 12
Number of biomass types (i) = 1, 2, …, m
Number of suppliers (j) = 1, 2, …, n
Number of biomass power plants (k) = 1, 2, …, p

Define Parameters:

FC_k = fixed cost for opening biomass power plant k
C_k = capacity of biomass power plant k

HC_{ik} = holding cost of biomass i at biomass power plant k
d_{jk} = distance between supplier j and bio power plant k
TR_{jk} = transportation rate per ton per kilometer between supplier j and biomass power plant k
D_t = demand of electricity in period t in kilowatt-hour unit
S_{tij} = available supply of biomass i from supplier j in period t
BP_{ij} = buying price of biomass i from supplier j
W_i = weight conversion constant to transform ton unit of biomass i to kilowatt-hour unit
BI_i = available inventory of biomass i in period 0

Define Decision Variables:

X_{tijk} = number of biomass i purchased in period t from supplier j to biomass power plant k
U_{tik} = number of biomass i to be used in biomass power plant k to generate electricity in period t
I_{tik} = inventory level of biomass i holding in biomass power plant k in period t
Y_k = 1 if biomass power plant k is to be located
= 0 otherwise

REFERENCES

[1] Hishamuddin, H., et al. 2012. A disruption recovery model for a single stage production-inventory system. *European Journal of Operational Research* 222(3): 464-473.
[2] Paul, S. K., et al. 2014. Real time disruption management for a two-stage batch production–inventory system with reliability considerations. European Journal of Operational Research 237(1): 113-128.
[3] Brouer, B. D., et al. 2013. The Vessel Schedule Recovery Problem (VSRP) – A MIP model for handling disruptions in liner shipping. European Journal of Operational Research 224(2).
[4] Yu, G. and Qi, X. 2004. Disruption management: framework, models and applications. World Scientific.
[5] Baghalian, A., et al. 2013. Robust supply chain network design with service level against disruptions and demand uncertainties: A real-life case. European Journal of Operational Research 227(1).
[6] Jabbarzadeh, A., et al. 2016. Designing a supply chain resilient to major disruptions and supply/demand interruptions. Transportation Research Part B: Methodological (Supplement C) 94: 121-149.
[7] Paul, S. K., et al. 2017. A quantitative model for disruption mitigation in a supply chain. European Journal of Operational Research 257(3): 881-895.
[8] Chinese, D. and Meneghetti, A. 2005. Optimisation models for decision support in the development of biomass-based industrial district-heating networks in Italy. Applied Energy 82(3).
[9] Kazemzadeh, N., and Guiping, H. 2013. Optimization models for biorefinery supply chain network design under uncertainty. Journal of Renewable and Sustainable Energy 5(5): 053125.
[10] Donskoy, I. G., et al. 2016. Mathematical modeling of the fixed-bed staged biomass gasification process. Renewable Bioresources 4(1).
[11] Dekker, R., et al. 2012. Operations Research for green logistics – An overview of aspects, issues, contributions and challenges. European Journal of Operational Research 219(3).
[12] Papong, S., et al. 2004. Overview of biomass utilization in Thailand. In Proceedings of the ASEAN Biomass Meeting.