

Synthesis of Multiple Biomass Corridor via Decomposition Approach: A P-graph Application

Bing Shen How^{*a}, Boon Hooi Hong^a, Hon Loong Lam^a, Ferenc Friedler^b

^aDepartment of Chemical and Environmental Engineering, Faculty of Engineering, University of Nottingham Malaysia Campus, Jalan Broga, 43500 Semenyih, Selangor Darul Ehsan, Malaysia.

^bDepartment of Computer Science and System Technology, University of Pannonia, Egyetem utca 10, Veszprém, H-8200, Hungary
 kebx4hbh@nottingham.edu.my

Nowadays, mankind is facing several environmental challenges such as climate change, pollutions, etc. In order to create a more sustainable future, an adequate waste management system is necessary. One of the major solid waste sources is biomass, which have the potential to be converted into energy and several kinds of value-added products. Therefore, it is suggested to develop a multi-biomass corridor in order to promote a global sustainable development of renewable energy. However, this large-scale problem normally requires longer computational duration due to its complexity. This paper develops a "Decomposition Approach" to simplify such problem and the effectiveness of the methodology has been illustrated by applying it to a case study in a state with abundant biomass, Johor.

1. Introduction

The increase of global population has a negative impact to the environment due to the direct correlation between the amount of solid waste generated and the population growth. Thus, a suitable waste management system is necessary in order to build a more sustainable future. One of the major solid waste sources is biological waste (biomass), which can be utilised as renewable energy and also has the potential to be further processed to valuable products. Therefore, it is suggested to develop a multi-biomass corridor in order to promote a global sustainable development of renewable energy.

Malaysia is the world second largest producer of palm oil around the world. It contributed 39 % of the world production and 44 % of world oil export (MPOC, 2014). With such amount of palm oil production, the amount of palm oil biomass is also tremendous. The palm oil biomass includes empty fruit bunch (EFB), palm kernel shell (PKS), fronds, trunks, etc. Besides, paddy is another commodity in Malaysia as rice is an important dietary carbohydrate. According to the Department of Agriculture Malaysia, paddy planted area in Malaysia is estimated to be 672,000 ha while the average paddy production is around 3,660 t/ha (DOA, 2014). The cultivation of rice results in two types of residues, i.e. paddy straw and rice husk. Both have attractive potential in term of energy due to their high energy content (10.04 MJ/kg for paddy straw and 12.55 MJ/kg for rice husk). Other than that, pineapple and sugar cane are another two important agriculture crops in Malaysia. The biomass wastes from these two sources (bagasse, pineapple solid residue and molasses) contain high potential of turning into renewable energy, value-added product and biochemical. In short, the increased interest in the utilisation of biomass waste not only reduces the environmental impact but also creates local business opportunity (Lam et al., 2010).

Generally, palm oil mill biomass (EFB and PKS) will be further processed into dried long fiber (DLF), Palm Pellet and Energy Pack (Ng et al., 2014). As mentioned previously, rice husk has relatively high energy content. It can be further converted into biochar, syngas and pyrolysis-oil via pyrolysis. Moreover, bagasse can be firstly pretreated prior to its conversion to bio-ethanol via fermentation. However, there are several types of pretreatment process that can be selected, e.g. dilute acid pretreatment, dilute alkaline pretreatment, hot water pretreatment and steam explosion pretreatment. Each method yields different amount of ethanol and will affect the overall operating and capital costs. Furthermore, pineapple waste has

a high potential to be reproduced into citric acid, formic acid and animal feed. At last, EFB, PKS, paddy straw and bagasse can be burned in boiler to generate high pressure steam (HPS). HPS will then be sent to steam turbine to generate electricity and medium pressure steam (MPS) which both are essential for the smooth operation of processes.

Recently, many researchers have gained interest in solving this biomass supply chain problem by using different techniques and approaches. For instance, Lam et al. (2013) has solved the supply chain synthesis problem by using a two-stage (micro and macro) optimisation model; Altıparmak et al. (2009) has solved the multi-product supply chain synthesis problem by using steady-state Genetic Algorithm (ss-GA); Yuce et al. (2014) has solved the multi-objectives optimisation problem in supply chain synthesis by using a modified Bees Algorithm (BA). However, the capability of using these methods to solve the supply chain synthesis problem with higher complexity still remains unknown. Also, the multiple biomass supply chain problem is a large-scale problem which normally required a longer computation period. Therefore, this paper introduces a novel approach namely "Decomposition Approach" to address the aforementioned issue. In the section of Methodology, the strategy of problem solving is presented. The methodology is illustrated by applying it to a case study in Johor, a state with abundant biomass, and the result will then be discussed.

2. Methodology

A "Decomposition Approach" is proposed to solve the multiple biomass supply chain problem. Basically, its conceptual idea is to decompose the complex problem into three smaller and simpler tasks. This simplifies the entire synthesis problem. Figure 1 shows the outline of Decomposition Approach.

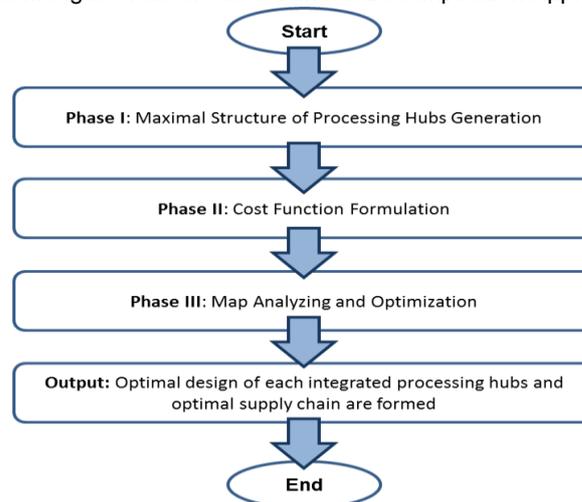


Figure 1: Synthesis of Multiple Biomass Supply Chain via Decomposition Approach

A noteworthy framework, P-graph which was introduced by Friedler et al. (1992), is applied in this work instead of employing the conventional mixed-integer linear programming (MILP) and superstructure approaches. Usually, the conventional approaches which present the selection of operating units by integer variables are less preferable to handle huge problem with high complexity. Besides, when a superstructure is created heuristically, certain low-cost option would be missed out which inclines to miss the true optimal solution. In addition, the conventional solvers normally will provide only one solution, which is the best solution that the solver can find. However, in some cases, the n-best suboptimal solutions are very useful in providing a wider overview of the entire problem.

2.1 Phase I: Maximal Structure of Processing Hubs Generation

The maximal structure of the model has to be built. The identification of related materials, streams and operating units are required in this phase. The cost of each raw material and the retail price of each product have to be pre-defined. Furthermore, the operating cost, capital cost and the conversion ratio of each unit have to be defined as well. With all of the required info, the maximal structure and all combinatorial feasible individual networks between the involved materials and streams will then be generated. This step can be performed internally by P-graph algorithm Maximal Structure Generator (MSG) & Solution Structure Generator (SSG) via PNS Studio (PNS Studio, 2015). It is worth to note that the transportations between layers are not considered in this step.

2.2 Phase II: Cost Function Formulation

In this phase, the correlation between the amounts of the raw material (input to the processing hubs) and gross profit which can be obtained has to be determined. This can be done by using P-graph Accelerated Branch-and-Bound (ABB) Algorithm. By inputting different amount of raw materials, the solver will provide n-best solutions for each case. Each solution indicates the maximal profit that can be obtained from different combinations of technologies (i.e. “structure”) which are installed in the processing hubs. After analysing these results, a cost function which correlates the amount of raw materials input with the maximal gross profit is formulated. Figures below are the graphical illustration of how the cost function can be obtained. Assume that there are only three possible combinations of technologies (structures) available in the processing hubs. The gross profit that can be obtained in each structure is shown in Figure 2(L). It can be clearly seen that, the graph is divided into three sectors. In sector 1, structure 1 is the most profitable combination of technologies among the three. However, structure 3 become more favourable when moving to the sector 2, while structure 3 is the most favourable process in sector 3. By removing all the non-optimal case in each sector, the overall optimal cost function can then be extracted. The result is shown in Figure 2(R). By using this cost function, the solver can directly determine the gross profit by using only the amount of each raw material. In other words, this will significantly reduce the number of binary variables and thus, shorten the computation time significantly.

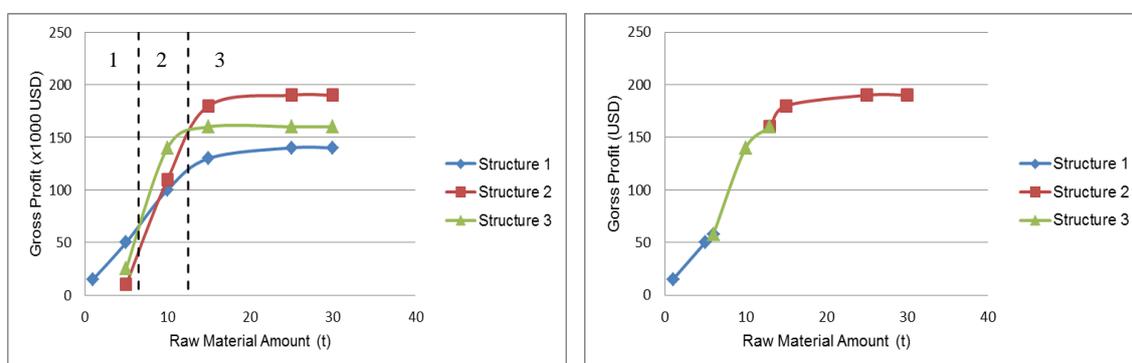


Figure 2: (L) Gross profit can be obtained in each structure; (R) Maximal gross profit cost function

2.3 Phase III: Map Analysing and Optimisation

This phase consists of four steps:

2.3.1. Area Fragmentation

In order to simplify the problem, the huge study area is divided into smaller zones. This is a pre-processing step for the following step 2.3.2 and step 2.3.3. Eventually, each “potential” zone will be assigned with a processing hub. Figure 3 is the illustration of area fragmentation.

2.3.2. Infeasibility Elimination

Remove the “Infeasible” zones which are not suitable or impossible to set up processing hubs, e.g. mountain area, residential area, etc. As a result, this will decrease the burden of the model by avoiding all unnecessary variables. For instance, the shaded areas in Figure 4 are mountain areas and protected forest areas. Therefore, all these zones have to be eliminated.

2.3.3. Connectivity Detachment

In the original model, each source point is connected to all possible destinations. All combinations of connectivity create a complex network with a huge number of variables and constraints which will lead to a longer computation time. However, in the actual case, each raw material has its own maximum allowable travelling distance due to its amount and economic potential. Generally, the maximum allowable travel distance (MATD) will be inversely proportional to the amount of the raw material to be travel and directly proportional to the economic potential of the raw material. It is expressed in Eq(1):

$$MATD = c \frac{EP}{r} \quad (1)$$

where, EP= economic potential, c= constant and r = amount of raw material

Figure 5 is an illustration of this step. The two source points supply the same type of biomass, therefore their EP will be same. In order to minimize the transportation cost, the one with less biomass stock is

allowed to travel a longer distance compared to the one with more biomass stock. The connectivity between zones which lies outside this searching range should be removed.

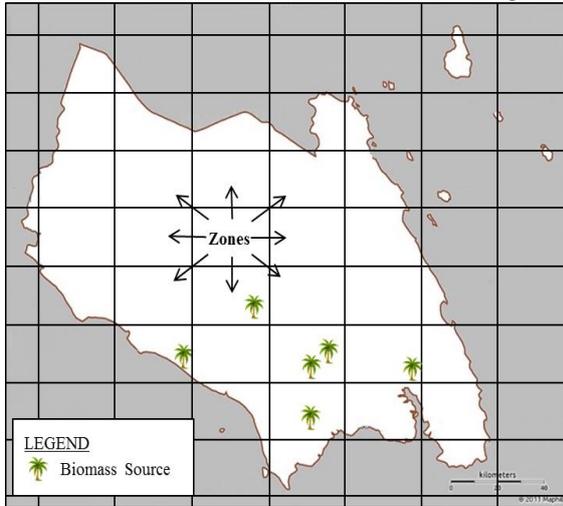


Figure 3: Area Fragmentation (Maphill, 2013)

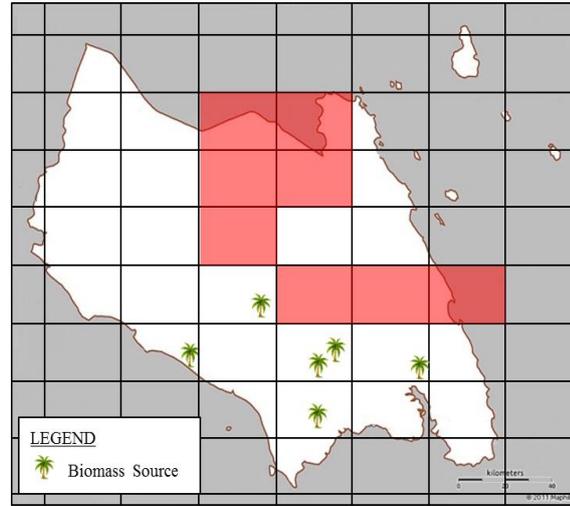


Figure 4: Infeasibility Elimination (Maphill, 2013)

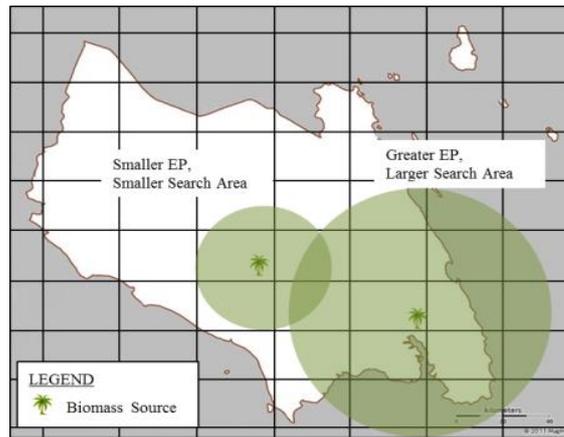


Figure 5: An illustration of Connectivity Detachment (Maphill, 2013)

2.3.4. Economic Study

After the previous steps, the remaining zones are the potential location to set up the processing hubs. In order to determine the optimal hub location, the formulated cost function is used. The hub(s) with the highest overall profit will be selected. This step can be done by using mathematical modelling technique. Note that the computation time is no longer an issue. The model formulation is stated below:

The biomass r supplied from each source i , is transported to centralized hub j to convert into energy or value-added product. The amount of biomass transferred from source i to all hub j , $\sum_j F_{i,j,r}$ can never exceed the amount of biomass available in source i , $F_{i,r}$. The material flow is defined as follow:

$$\sum_j F_{i,j,r} \leq F_{i,r} \quad \forall i \in I, \forall r \in R \tag{2}$$

The following constraint determine the selection of possible centralized hub j . $\sum_i F_{i,j,r}$ is the total amount of biomass transferred to hub j . Note that B_j is the binary variable to denote the selection of hub j while M is hub's capacity constraint.

$$\sum_i F_{i,j,r} \geq M \times B_j \quad \forall j \in J, \forall r \in R \tag{3}$$

As mentioned, the gross profit, C_{GP} can be determined by using the cost function formulated previously:

$$C_{GP} = \sum_j \sum_r (\sum_i F_{i,j,r} \times C_r) \tag{4}$$

Where C_r refer to the correlated cost constant. The value-added products p from hub b will then be transported to the demand, k . The total amount of value-added products p produced from hub j which sent to all demand k , $\sum_k F_{j,k,p}$ can never exceed the amount of value-added product p generated, $F_{j,p}$. The material flow is defined in Eq(5)-(6):

$$\sum_k F_{j,k,p} \leq F_{j,p} \quad \forall j \in J, \forall p \in P \quad (5)$$

$$F_{j,p} = \sum_i F_{i,j,r} \times X_{r,p} \quad \forall j \in J, \forall r \in R, \forall p \in P \quad (6)$$

where $X_{r,p}$ is the conversion factor for biomass r to be converted to value-added product p . Transportation cost, C_{Tr} is another important cost that has to be taken into consideration:

$$C_{Tr} = \sum_j \sum_r (\sum_i F_{i,j,r} \times d_{i,j} \times C_T) + \sum_k \sum_p (\sum_j F_{j,k,p} \times d_{j,k} \times C_T) \quad (7)$$

where $d_{i,j}$ and $d_{j,k}$ refer to the distance travelled between source i and hub j and distance travelled between hub j and demand k while C_T refer to the estimated transportation cost constant (\$/t/km). Besides, the total investment cost to set up hubs, C_{Inv} is also included in the model. It is annualized by using the capital recovery factor, CRF which converts a present value to a stream of equal annual cost over a life span, LS , at a specified discount rate, i_{Dis} . The formulations are shown as below:

$$C_{Inv} = \sum_j B_j \times C_{Hub} \quad (8)$$

$$C_{AN.Inv} = C_{Inv} \times \frac{i_{Dis}(1+i_{Dis})^{LS}}{(1+i_{Dis})^{LS}-1} \quad (9)$$

where C_{Hub} refer to the estimated investment cost (i.e. land cost, construction cost, etc.) required to set up a hub and $C_{AN.Inv}$ is the annualized investment cost. Finally, the model is structured to maximize the net profit, C_{NP} :

$$\max C_{NP} = C_{GP} - C_{Tr} - C_{AN.Inv} \quad (10)$$

This model can be solved by using global solver in Lingo v14.0 (Lingo, 2015).

3. Case Study

As mentioned above, palm oil biomass, paddy waste, sugar cane biomass and pineapple residues are the four chosen sources of biomass which will be utilised in the multiple biomass corridors. Due to its regional abundance of biomass, Johor is selected as the study area. There are 6 major palm oil mills, 5 major paddy plantations, 8 major sugar cane plantations and 6 major pineapple plantations in Johor (see Figure 6). The processing hubs should be set up in the strategic location in order to minimize the transportation cost of biomass from one point to another. Note that the value-added products will be exported from the port or will be consumed in the power plant to generate electricity.

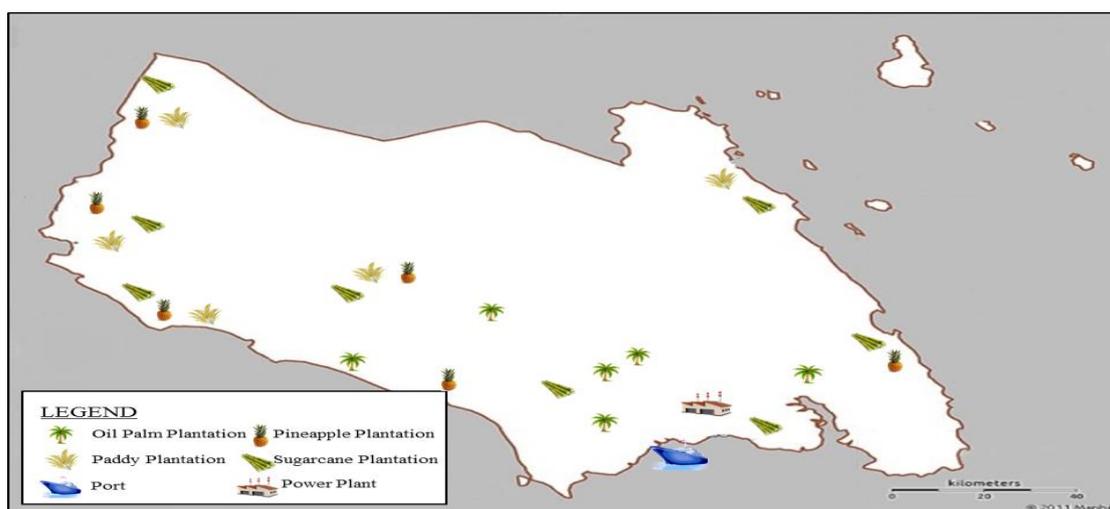


Figure 6: Geographical location for each biomass source, power plant and port (Maphill, 2013)

Table 1: Profit obtained from each potential processing hub

Ranking	Hub Location	Profit (USD/y)	Ranking	Hub Location	Profit (USD/y)
1	Simpang Renggam	1.66 E+7	4	Kulai	1.05 E+7
2	Ayer Hitam	1.39 E+7	5	Tenggara	9.79 E+6
3	Renggam	1.38 E+7			

4. Results and Discussions

The formulated cost function for this case study is shown below:

$$f(r_1, r_2, r_3, r_4) = 11.95r_1 + 72.42r_2 + 15.01r_3 + 14.71r_4 \quad \text{when } 2.94r_1 + r_2 + 4.41r_3 \geq 6.92r_4 \quad (11)$$

$$f(r_1, r_2, r_3, r_4) = 11.98r_1 + 72.43r_2 + 15.04r_3 + 14.77r_4 \quad \text{when } 2.94r_1 + r_2 + 4.41r_3 \leq 6.92r_4 \quad (12)$$

Note that r_1, r_2, r_3, r_4 represent the amount of harvested sugarcane, pineapple, oil palm and paddy in t, the constants in the cost function reflect the economic potential of the biomass while the constants in the condition function (behind the cost function) indicate the weight ratio. From Eq(11) and Eq(12), it shows that the amount of r_4 will affect the structure of the processing hub. Generally, r_4 which has the lower economic potential (r_1 is not suitable) will be combusted to generate electricity in order to overcome the utility cost used in other process (see Eq(11)). When the electricity generated is sufficient (Eq(12)), the excess r_4 will be converted to other value-added product in order to gain more profit. Therefore, the overall economic potential becomes higher.

The studied area was initially divided into 33 zones via Area Fragmentation. Then, 8 zones which located in mountain area are removed. In our illustration, we assume that only one hub can be set up. After considering MATD, only five of remaining zones are feasible. The profits which can be obtained from each potential processing hub are determined by using Eq(2)-Eq(10). The results are tabulated in Table 1. As a result, Simpang Renggam which generates the highest profit was selected as the hub location.

5. Conclusion

Decomposition Approach has been proposed in this paper in order to simplify the multiple biomass supply chain problem. The effectiveness and efficiency of this method were illustrated by applying it to the case study. With the aid of P-graph, the optimal hub location and biomass allocation pathway are identified and synthesised successfully. However, several further works will have to be followed up to increase the reliability and accuracy of the proposed method. For instance, the uncertainty analysis including seasonal availability of biomass, reliability of technology, etc. will have to be taken into consideration.

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