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RESEARCH ARTICLE

Optimizing Palm Oil Biomass Supply Chain Logistics through Multi-Objective Location-Routing Model

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Abstract Malaysia can convert agricultural wastes (biomass) into biofuel to reduce fossil fuel dependency and solve the disposal problem. As one of the largest palm oil producers, Malaysia has an abundance of palm oil biomass, but the biomass has high humidity, low energy density, and is scattered geographically. Establishing collection facilities with pretreatment operations is suggested to collect the biomass and improve its quality. Nevertheless, the facility placement and vehicle routing decisions significantly affect the total cost and operational efficiency. Hence, this study develops a model to address the location-routing problem and quantifies the pretreatment operation to customize the process in the biomass supply chain. This research also addresses sustainability from all dimensions through multi-objective optimization. The model minimizes costs, reduces negative social impacts by considering population densities, and measures environmental performance through CO_2 emissions. The study first optimized each objective function separately and then conducted a multi-objective optimization using a weighted sum approach. Optimizing each objective function individually will achieve the best outcome for each dimension, but enhancing one objective would impair the others. However, multi-objective optimization shows some compensation for the performances where economic, social, and environmental indicator values decreased by 0.36%, 6.58%, and 15.28%, respectively. The results demonstrate that the model adjusts the locational and routing decisions based on different goals.

Keywords: Location-routing problem, biomass supply chain, palm oil biomass supply chain, mixed integer linear programming, multi-objective optimization.

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Introduction

Malaysia is rich in agricultural products, but their wastes cause disposal problems where they are disposed of at landfill sites, burned, or incinerated directly at farms. Modern technology provides an alternative for dealing with these wastes by converting them into biofuels (biomass energy), which could also help Malaysia become less dependent on fossil fuels. Nevertheless, the geographical scattering of biomass resource sites, coupled with biomass characteristics like high moisture content, bulkiness, and low energy content, has caused transportation, storage, and energy conversion difficulties. It is necessary to have an appropriate structure biomass supply chain (BSC) to coordinate all parties in the industry and manage the biomass characteristics problem. In BSC, decisions such as facility location, allocation, and vehicle routing affect the efficacy of biomass energy production and total cost. Researchers have shown considerable interest in BSC models. Nonetheless, these BSC models have traditionally solved facility location and vehicle routing problems separately, which may cause suboptimality in the solution [1].

As one of the largest palm oil producers [2], [3], the palm oil industry in Malaysia generates tons of waste from the oil extraction process from fresh fruit bunches (FFB). The palm oil wastes are empty fruit bunches (EFB), palm oil mill effluent (POME), palm kernel shell (PKS), and mesocarp fiber (MF). Generally, PKS and MF are incinerated at mills to generate steam and electricity for disposal instead of optimally used to produce energy [4], whilst EFB is used either directly as mulch [5] or in combination with POME for mulching [6], [7]. This study proposes using EFB as the feedstock for solid biofuel production due to its abundant availability and establishing collection facilities to collect EFB from mills to resolve the issue of geographically scattered resources. However, the locational decision of the collection facilities affects establishment and transportation costs, and the tour trips (routing) of vehicles from collection facilities to mills also influence transportation costs. Since the facility location and vehicle routing decisions are significant in BSC, it is necessary to have an optimization model to address the location-routing problem (LRP) simultaneously.

Although using EFB as biomass energy can bring advantages, its characteristics cause problems in BSC management and energy conversion. The bulkiness of EFB consumes more space for transportation and storage, and burning it results in the emission of substantial white smoke, which is high in water vapor and fly ash due to high humidity [4]. Hence, this study proposes to equip collection facilities with pretreatment operations such as pelletizing to reduce the humidity content in biomass and transform it into a compact form of higher energy density [8]. The pellet forms of EFB could increase the efficiency of transportation, storage, and combustion. Nevertheless, few BSC articles considered including and quantifying the pretreatment operation in the optimization models. Thus, this study quantifies the pretreatment operation in the optimization model, which tailors the LRP to the conversion process in BSC.

While most BSC models prioritize economic performance, specifically cost-effectiveness, it is crucial to recognize that decisions within the BSC also influence the environment and surrounding community. Transportation activities release CO_2, which is one of the causes of global warming. The CO_2 emissions relate not only to travel distance but also in relation to vehicle load, which influences fuel consumption. This study proposes to relate CO_2 emissions to travel distance and vehicle loading to measure environmental sustainability. Apart from environmental sustainability, social sustainability should also be a concern of the BSC. Commonly, the facilities might release harmful chemicals, produce heat, and create noise, which makes facility establishments unwelcome by the local community. The decisions on facility placement should address this negative social impact when designing the network structure. This research addresses social performance by reducing the population affected by locational decisions. Facility establishments should prioritize areas with the fewest people living in the vicinity, resulting in fewer individuals being exposed to potential pollutants. This approach prevents the concentration of adverse environmental impacts on the population, potentially mitigating the negative social consequences associated with facility location decisions.

Overall, this study builds a mixed-integer linear programming model to optimize the locational decisions of collection facilities and vehicle routing decisions of trucks collecting EFB from mills. This study quantifies the pretreatment operation in the model and simultaneously addresses the sustainability of the BSC by optimizing the economic, environmental, and social performances. In a nutshell, this research proposes a multi-objective LRP model to manage BSC that converts EFB into solid biofuels (palm pellets).

The novelties of this study are as follows. Firstly, the proposed mathematical model is versatile and applicable to optimize facility locations, biomass allocation, and vehicle routing in any BSC network. Secondly, the model can handle both single-objective and multi-objective scenarios, providing a foundational framework for addressing diverse sustainability goals in BSC networks. Thirdly, the incorporation of pretreatment operations, specifically pelletizing, into the collection facilities distinguishes the proposed model from general LRP models. Additionally, the model is not confined to networks featuring collection facilities with pelletizing technology. It can be applied to optimize networks with various facilities utilizing different technologies. The structure of this paper is as follows. Section 2 provides a literature review. Section 3 defines the problem and introduces the mathematical model. Section 4 presents the results and discussion. Finally, Section 5 outlines the conclusions and limitations.

Literature Review

In recent years, articles contributing to the BSC have increased substantially. Table 1 lists and analyzes the relevant literature, their goals (objective functions), and decisions to be optimized to evidence the gap in the works.

A substantial amount of research has been conducted on solving locational and allocation decisions simultaneously. Works that focus on the location-allocation problem are described as follows. Sarker *et* *al.* [9] and [10] solved a location-allocation problem of the bio-methane gas supply chain constituted by multiple residues, hubs, and reactors. Saadati and Hosseininezhad [11] designed a bagasse-based bioethanol supply chain for locating hubs by considering road and rail transport. Serrano-Hernandez and Faulin [12] optimized the number and capacity of biorefineries and different storage policies. Some researchers also used the Geographic Information System (GIS) to solve the location-allocation problem (e.g., Schröder *et al.* [13]; Zhang *et al.* [14]; Soha *et al.* [15]; Sahoo *et al.* [16]; Jayarathna *et al.* [17]; Razm *et al.* [18]; Zhang *et al.* [19]).

Table 1. Articles Relevant to the Biomass Supply Chain

Reference	LD	AD	RSD	PO	Eco	Env	Soc	Obj
León-Olivares *et al.* [20]	•	•			•			Min total cost
Castro-Peña *et al.* [21]	•	•			•			Min total cost
Galanopoulos *et al.* [22]	•	•			•			Max annual profit
San Juan *et al.* [23]	•	•		•	•	•		Min total cost, Min CO_2 emissions
Chugh *et al.* [24]	•	•			•			Max net present value
Rabbani *et al.* [25]	•	•			•	•	•	Min total cost, Min greenhouse gas emissions, Max job creation
Park *et al.* [26]	•	•			•	•		Min total cost, Min CO_2 emissions
Gital Durmaz and Bilgen [27]	•	•			•			Max profit, Min total distance
Rabbani *et al.* [28]	•	•			•	•	•	Min total cost, Min environmental impact, Max job creation
Ganev *et al.* [29]	•	•			•	•	•	Min total cost, Min total CO_2 emissions, Job creation as a constraint
Mahjoub *et al.* [30]	•	•			•			Min total cost, Max the energy produced
Ivanov [31]	•	•			•			Min total cost
Hosseinalizadeh *et al.* [32]	•	•			•	•		Min total cost, Min fuel emissions
Sarker *et al.* [9]	•	•			•			Min total cost
Sarker *et al.* [10]	•	•			•			Min total cost
Saadati and Hosseininezhad [11]	•	•			•	•		Min total cost, Min CO_2 emissions
Serrano-Hernandez and Faulin [12]	•	•			•			Min total cost
Schröder *et al.* [13]	•	•			•			Max return on investment
Zhang *et al.* [14]	•	•			•	•		Min total cost and emission cost
Soha *et al.* [15]	•	•			•			Min amount of manure to be transported
Sahoo *et al.* [16]	•	•			•			Min total cost or Min total distance
Jayarathna *et al.* [17]	•	•			•			Min total distance
De Meyer *et al.* [33]	•	•		•	•			Max net energy output
Arabi *et al.* [34]	•	•			•			Min total cost
Arabi *et al.* [35]	•	•		•	•	•		Max total profit, Max carbon absorption
Mohseni and Pishvaee [36]	•	•			•			Min total cost
Ghaderi *et al.* [37]	•	•			•	•	•	Min total cost, Min environmental impact, Max employment and economic indicators
Razm *et al.* [18]	•	•			•			Min total cost
Zhang *et al.* [19]	•	•			•			Min total cost
Kwon and Han [38]	•	•			•			Min ethanol levelized cost
Zhao and Li [39]	•				•	•		Min total logistics cost, Min CO_2 emissions
Salleh *et al.* [40]	•				•			Min total distance
Woo *et al.* [41]	•				•			Min transportation cost
Sahoo *et al.* [42]	•				•			Min total distance
Laasasenaho *et al.* [43]	•				•			Min total distance
Rivera-Cadavid *et al.* [44]		•			•			Max total profit
Wang *et al.* [45]		•			•			Min total distance
Tiammee and Likasiri [46]		•			•	•	•	Max total profit, Min total transportation cost, Min environmental

Reference	LD	AD	RSD	PO	Eco	Env	Soc	Obj
She *et al.* [47]		●			●	●		Max net revenue of log sales, Max net revenue of bioenergy, Max GHG emission savings of log, Max GHG emissions savings of bioenergy
How and Lam [48]		●			●	●		Max net profit, Max satisfaction degree of environmental sustainability
Torjai and Kruzslicz [49]			●		●			Min number of trucks or Min total trucks' idle
Soares *et al.* [50]			●		●			Min total transportation cost
Pinho *et al.* [51]			●		●			Min total distance, Min remaining distance
Fokkema *et al.* [52]			●		●			Min transportation time
Malladi *et al.* [53]			●		●			Min transportation cost
Cárdenas-Barrón and Melo [54]			●		●			Min transportation distance and cost
Vahdanjoo *et al.* [55]			●		●			Min distance
Zamar *et al.* [56]			●		●			Max energy returned
Cao, Wang, *et al.* [57]	●	●	●		●			Min total cost
Cao, Zhang, *et al.* [1]	●	●	●		●			Min total cost
Li *et al.* [58]	●	●	●		●			Min total cost
Habibi *et al.* [59]	●	●	●		●			Min total cost
Asadi *et al.* [60]	●	●	●		●	●		Min total cost, Min total system pollution
Morales Chavez *et al.* [61]	●	●	●		●	●	●	Max net present value, Min environmental impact, Max positive impact (job creation and food security)

Note: LD = Locational Decision, AD = Allocation Decision, RSD = Routing or Scheduling Decision, PO = Pretreatment Operation, Eco = Economic Performance, Env = Environmental Performance, Soc = Social Performance, Obj = Objectives

Some available studies focus mainly on a single type of decision in the BSC problem. The articles that concentrate on locational decisions are reported as follows. Zhao and Li [39] solved the problem of identifying the location of the power plants. Salleh *et al.* [40] used a least-square regression method to identify a location for biomass processing facility. The combination of multi-criteria analysis and GIS is also commonly used by researchers in solving the locational problem (e.g., Woo *et al.* [41]; Sahoo *et al.* [42]; Laasasenaho *et al.* [43]). The papers that optimize the allocation decision are described as follows. Rivera-Cadavid *et al.* [44] developed a model to identify the plots of the day whose sugarcane wastes should be transported. Wang *et al.* [45] presented a model for assessing biomass supply and calculating co-firing ratios for each retrofit power plant. Tiammee and Likasiri [46] solved the distribution and disposal problems of corn kernels and residues. She *et al.* [47] inspected the wood residue salvage operations under sequential and integrated scenarios. How and Lam [48] proposed considering vehicle capacity constraints in planning biomass allocation.

Besides, some articles examine the routing or scheduling decision alone. Torjai and Kruzslicz [49] developed a model to schedule trucks to deliver biomass from satellite storage locations to a central biorefinery. Soares *et al.* [50] investigated the synchronization of trucks' movement and operation in a full truck pick and delivery problem. Pinho *et al.* [51] propounded a predictive control model to plan vehicle routing. Fokkema *et al.* [52] proposed a continuous-time inventory routing model for a biogas logistic network. Malladi *et al.* [53] developed a model to plan the transshipment and routing of the forest SC. Cárdenas-Barrón and Melo [54] solved reverse logistics' selective and periodic inventory routing problem in managing waste vegetable oil collection. Vahdanjoo *et al.* [55] formulated and solved the bale collection problem with a vehicle routing model. Zamar *et al.* [56] considered biomass availability and moisture contents in planning the route for the sawmill residue collection problem.

Table 1 shows that few articles investigate location, allocation, and routing decisions simultaneously (e.g., Cao, Wang, *et al.* [57]; Cao, Zhang, *et al.* [1]; Li *et al.* [58]; Habibi *et al.* [59]; Asadi *et al.* [60]; Morales Chavez *et al.* [61]). Table 1 also indicates that few optimization models incorporate the pretreatment operation. San Juan *et al.* [23] incorporated the feedstock quality and quantified the pretreatment into the model. De Meyer *et al.* [33] proposed including pretreatment operation and biomass loss in the model. Arabi *et al.* [35] considered the pretreatment rate and deterioration percentage in their algae-based SC model. Besides, the objective functions listed in Table 1 also demonstrate that not many articles inspect the sustainability of the BSC. A sustainable BSC would aim to optimize economic, environmental, and social performance simultaneously, but these goals might often conflict [62]. Aside from that, minimizing the total cost, minimizing CO_2 emissions, and optimizing job creation are the famous metrics for evaluating economic, environmental, and social performances.

The following observations are identified in the literature:
a) Few studies have considered optimizing locational, allocation, and routing decisions simultaneously.
b) There is a limited multi-objective location routing model for the BSC problem.
c) No existing location-routing model optimizing the BSC performance considers minimizing CO_2 emission and reducing the negative social impact of facility establishment.
d) Few BSC research projects include the pretreatment operation and quantify them into the model.

This research aims to fill the gaps found in the existing literature by developing a sustainable LRP model. The model is designed to identify the optimal decisions for opening collection facilities and tour trips of trucks visiting mills. These tour trips are the vehicle routing that will consider the truck loading along routes. The proposed BSC network also includes the pretreatment operation in the collection facilities and quantifies it as an additional parameter. Lastly, the suggested model is also a multi-objective model that addresses the sustainability of BSC by minimizing the total cost (economic performance), CO_2 emissions (environmental performance), and total affected population (social performance).

This research shares similarities with the study conducted by Cao, Wang, *et al*. [57], addressing a single economic objective two-echelon location-routing problem within a BSC network structure involving resource sites, collection facilities, and biorefineries. However, there are notable distinctions in the proposed model. Firstly, the proposed model focuses on a multi-objective problem within a single echelon network comprising resource sites and collection facilities. Consequently, this act allows the model to address scenarios requiring consideration of sustainable goals. Secondly, the notable difference resides in the model constraints, where additional constraints related to connecting the transverse route with facility assignment, vehicle load capacities, and subtour elimination have been introduced. The additional constraints are crucial to depict the interdependencies among facility assignment, vehicle routing, and vehicle loads in the pursuit of minimizing costs, CO_2 emissions, and the affected population. Moreover, the model incorporates parameterization of pretreatment operations.

This study also bears some resemblance to the research by Karaoglan and Altiparmak [63], which addressed a cost minimization single-echelon LRP in a general distribution network with depots and customers. Their model involved an unlimited fleet of homogeneous vehicles and scenarios encompassing both pickup and delivery demands from customers. However, the proposed model in this research differs by limiting the fleet size of homogeneous vehicles in the BSC and considering only pickup demands from resource sites (customers). Consequently, there are variations in the model constraints. The proposed model stipulates that a facility must serve at least one resource site (customer) when open and relates biomass flow to vehicle loads, focusing solely on the pickup scenario. Additionally, there are slight differences in subtour elimination constraints. Moreover, this proposed model deals with multi-objective functions and integrates pretreatment operations, aspects not included in Karaoglan and Altiparmak [63]'s work.

Less closely related research works are found in studies conducted by Theeraviriya *et al*. [64] and [65], which addressed the LRP in the palm oil supply chain. Theeraviriya *et al*. [64] focused on a single-echelon network involving palm oil fields and palm oil collection centers. Meanwhile, Theeraviriya *et al*. [65] extended their study to a two-echelon network, including palm oil fields, depots, and extraction plants, considering direct shipment scenarios. Both studies focus on collecting palm oil or FFB rather than biomass or waste, the collection centers or depots are used for collecting purposes without pre-equipped pretreatment operations. Additionally, both studies targeted a single economic objective, specifically total cost minimization. In Theeraviriya *et al*. [64], fuel consumption costs dependent on road conditions and vehicle types were considered as one of the cost components. In Theeraviriya *et al*. [65], emission and congestion costs were included. Even if the emission cost was employed to quantify the environmental impact, it only related to the rate of fuel consumption brought on by the road conditions. Notably, they did not investigate CO_2 emissions caused by vehicle loads along the route, as suggested by this proposed research. Moreover, the negative social impact was overlooked in these studies. Lastly, substantial differences in model constraints exist between the current proposed model and the models in the articles of Theeraviriya *et al*. [64] and [65].

This research has introduced innovative contributions to the field of interest in the following ways. First, the developed model could be applied to all kinds of BSC networks intended to optimize the decisions of facility locations, allocation, and vehicle routing simultaneously. Second, the model could be optimized individually for the proposed objective functions and produce optimal decisions for situations considering conflicting sustainable goals. In addition, this model can be viewed as a framework of the multi-objective LRP optimization model for the BSC. Finally, the suggested model incorporates the changes in biomass characteristics resulting from pretreatment operation, which tailors the model to the procedure in BSC and is hence distinct from the general LRP model.

Problem Definition and Mathematical Model

This section describes the problem definition, assumption, and mathematical model, including the equations for performance indicators, model constraints, and multi-objective optimization.

Problem Definition and Assumption

This paper designs a BSC model that only considers two main players in the palm oil industry: mills (resource sites) and collection facilities. Figure 1 shows an overview of the investigated palm oil BSC. The EFB will be pre-processed into wet short fibers (WSF) by sieving and separation in the mills. Then, trucks collect the WSF from mills and deliver it to an assigned collection facility. In the collection facility, the WSF will be pretreated by pelletizing technology to produce solid biofuels, palm pellets. Since the locations of the collection facilities affect the total cost and the surrounding population, it is necessary to determine their optimal locations. In addition, optimizing the route used by trucks visiting the mills is important to reduce total costs and CO_2 emissions. The act of optimizing locational and routing decisions, along with the minimization of costs, total population, and CO_2 emissions, has made the investigated BSC fall under the multi-objective location routing problem (MOLRP).

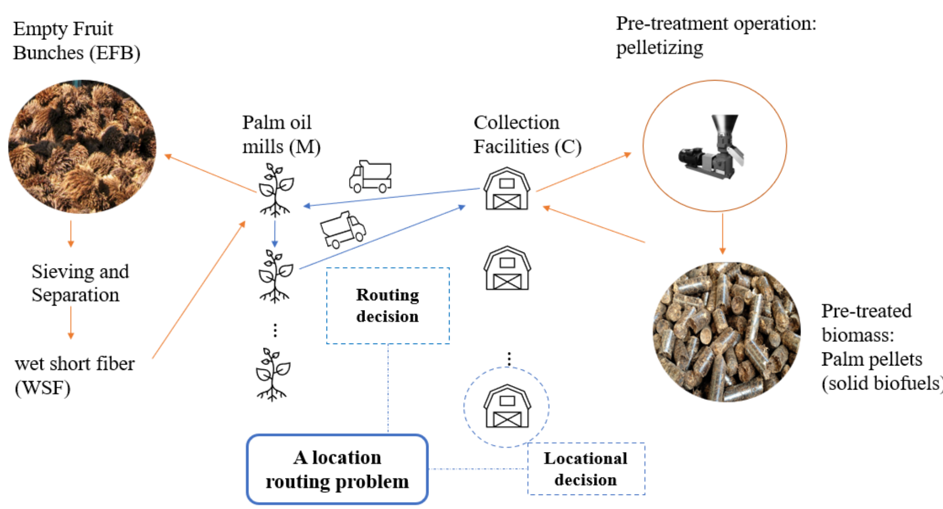

Figure 1. An overview of the investigated palm oil biomass supply chain

This research proposes a MOLRP model and quantifies the pretreatment operation into the model. This study has customized the model to the processing in palm oil BSC and made a disparity from the general LRP model. Figure 2 illustrates the network consisting of mills and collection facilities by nodes, and the routes between facilities are portrayed by arcs. Tables 2, 3, and 4 present the sets, decision variables, and parameters of the MILP model, respectively. The assumptions for the proposed model are stated as follows:

(a) Each mill can only be visited by one truck.
(b) A truck will start its route from an opened collection facility and back to the same facility after picking up the biomass from the mills.
(c) A truck could visit different mills if the total loading is less than the truck capacity.
(d) The candidate locations of collection facilities and their capacities are known.
(e) There is no flow between collection facilities.

Table 2. Sets

Notation	Description
M	Mills
C	Collection Facilities
H	Trucks

Table 3. Decision Variables

Notation	Description
z_i	1, if collection facility i is opened; 0, otherwise.
α_{ij}	1, if mill i is assigned to collection facility j; 0, otherwise.
x_{ijh}	1, if truck h travels from node i to node j; 0, otherwise.
LP_{ijh}	Loading on truck h from node i to node j
q_j^C	Amount of biomass received by collection facility j
q_j^{CP}	Amount of pretreated biomass produced in collection facility j

Table 4. Parameters

Notation	Description	Unit
q_i^G	Amount of biomass generated in mill i	metric ton/day
q_i^M	Amount of preprocessed biomass produced by sieving and separation in mill i	metric ton/day
t_i^M	Capacity of mill i	metric ton FFB/hour
t_i^C	Capacity of pretreatment in collection facility i	metric ton/day
c_h	Capacity of truck h	metric ton
d_{ij}	Distance between nodes i and j	km
f_i^{EC}	Establishment cost of collection facility	RM/day
f_i^{PC}	Unit operating cost of pretreating the biomass	RM/metric ton
v_h	Cost per km of truck h	RM/km
ρ^G	Biomass generation rate	EFB/FFB
ρ^{MO}	Rate of the biomass used for mulching and other purposes	-
θ^S	Conversion rate for separating and sieving EFB into WSF	WSF/EFB
θ^P	Conversion rate for pelletizing the biomass	pellets/WSF
γ^{h1}	CO_2 emission rate per kilometer	$kgCO_2$/km
γ^{h2}	CO_2 emission rate per metric ton per kilometer	$kgCO_2$/metric ton-km
Pop_i	The surrounding population at the collection facility	people
w	Daily operating hours	hour

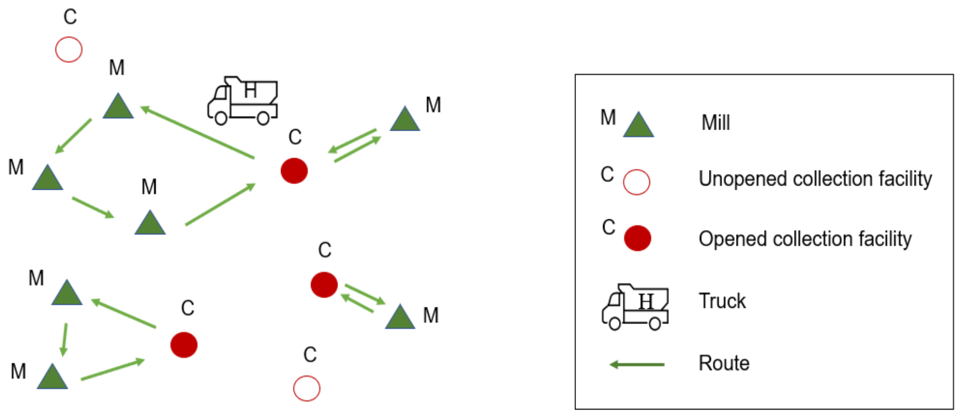

Figure 2. A network representation of the investigated location-routing problem

The Sustainable Performance Indicators

The cost function (Equation (1)) is calculated by adding the cost of opening collection facilities (first term), the cost of pretreating the biomass (2nd term), and the transportation cost of collection routes (last term).

$$\text{Minimize } f_1 = \sum_{i \in C} f_i^{EC} z_i + \sum_{i \in C} f_i^{PC} q_i^c + \sum_{i \in M \cup C} \sum_{j \in M \cup C} \sum_{h \in H} v_h d_{ij} x_{ijh} \quad (1)$$

This study uses the total number of people living in the vicinity of collection facilities as a measure of social performance metric (this concept was adopted from Tirkolaee *et al*. [66]'s work of solving LRP in applications other than BSC). Locations with lower surrounding populations are favored for facility placement, indirectly reducing the concentration of adverse social impacts on local communities. Using Equation (2), it is less likely that collection facilities would be opened in densely populated areas.

$$\text{Minimize } f_2 = \sum_{i \in C} Pop_i z_i \quad (2)$$

For environmental performance, this research only considers CO_2 released from transportation activities and assumes that emissions from the pretreatment operation are negligible. Equation (3) minimizes total CO_2 emissions consisting of two components. These two terms could represent CO_2 emissions under two different situations, trucks with loading and empty trucks. In the first term, this study proposes to consider the proportionality of CO_2 emissions with trucks' loading and travel distance, which this concept was adapted from Roni *et al*. [67]. The second term captures CO_2 emissions from the travel distance of empty trucks (trucks with no loading).

$$\text{Minimize } f_3 = \sum_{i \in M} \sum_{j \in M \cup C} \sum_{h \in H} \gamma^{h2} d_{1ij} LP_{ijh} + \sum_{i \in C} \sum_{j \in M} \sum_{h \in H} \gamma^{h1} d_{ij} x_{ijh} \quad (3)$$

Model Constraints

Equation (4) ensures that each mill must be visited by one truck exactly once. Equation (5) guarantees the balance of incoming and outgoing arcs of each node. Equation (6) states that a maximum of one truck can transport biomass from a mill to a collection facility. Equation (7) asserts no path between the same node, while Equation (8) ensures no connection between collection facilities. Equation (9) implies that at least one mill is served if a collection facility is opened.

$$\sum_{j \in M \cup C} \sum_{h \in H} x_{ijh} = 1, \quad \forall i \epsilon M \quad (4)$$
$$\sum_{i \in M \cup C} x_{ijh} = \sum_{i \in M \cup C} x_{jih}, \quad \forall j \epsilon M \cup C, \forall h \in H \quad (5)$$
$$\sum_{i \in M} \sum_{j \in C} x_{ijh} \leq 1, \quad \forall h \in H \quad (6)$$
$$x_{ijh} = 0, \quad \forall i,j \in M \cup C, \ \forall h \in H, \ i = j \quad (7)$$
$$\sum_{h \in H} x_{ijh} = 0, \quad \forall i,j \in C \quad (8)$$
$$\sum_{j \in M} \sum_{h \in H} x_{ijh} \geq z_i, \quad \forall i \in C \quad (9)$$

Equation (10) is the flow conservation constraint for each mill's biomass amount. Equation (11) asserts that a truck's load should be less than its capacity. Equation (12) ensures that the total pickup load entering a collection facility equals the total biomass pickup from the mills assigned to the corresponding collection facility. Equations (13)-(14) are the bounding constraints for the pickup load. Equation (15) ensures that the pickup load of the truck is zero when dispatched from the collection facility.

$$\sum_{j\in M\cup C}\sum_{h\in H} LP_{ijh} - \sum_{j\in M\cup C}\sum_{h\in H} LP_{jih} = q_i^M, \forall i \in M \quad (10)$$
$$LP_{ijh} \le C_h x_{ijh}, \forall i,j \in M\cup C, i\neq j, \forall h \in H \quad (11)$$
$$\sum_{j\in M}\sum_{h\in H} LP_{jih} = \sum_{j\in M} \alpha_{ji}\, q_j^M, \forall i \in C \quad (12)$$
$$LP_{ijh} \le \left(C_h - q_j^M\right) x_{ijh}, \forall i \in M\cup C, \forall j \in M, \forall h \in H \quad (13)$$
$$LP_{ijh} \ge q_i^M x_{ijh}, \forall i \in M, \forall j \in M\cup C, \forall h \in H \quad (14)$$
$$\sum_{j\in M} LP_{ijh} = 0, \forall i \in C, \forall h \in H \quad (15)$$

Equation (16) ensures that the total amount of biomass collected from mills is less than the capacity of a collection facility. Equation (17) states that the arc (i,j) is traversed if and only if a mill is assigned to a collection facility, while Equation (18) applies to the arc (j,i). Equation (19) forbids the route between two mills if they are assigned to two different collection facilities. Equations (20) and (21) refer to the amount of biomass that is allocated to the collection facility and the pretreated biomass (pellets) being produced. Equations (22)-(24) are the binary decision variables and Equations (25)-(27) ensure the non-negativity of the decision variables.

$$\sum_{i\in M} q_i^M \alpha_{ij} \le t_j^c z_j, \forall j \in C \quad (16)$$
$$\sum_{h\in H} x_{ijh} \le \alpha_{ij}, \forall i \in M, \forall j \in C \quad (17)$$
$$\sum_{h\in H} x_{jih} \le \alpha_{ij}, \forall i \in M, \forall j \in C \quad (18)$$
$$\sum_{h\in H} x_{ijh} + \alpha_{ik} + \sum_{n\in C, n\neq k} \alpha_{jn} \le 2, \forall i,j \in M, \forall k \in C \quad (19)$$
$$q_j^c = \sum_{i\in M}\sum_{h\in H} LP_{ijh}, \forall j \in C \quad (20)$$
$$q_j^{CP} = \theta^p q_j^c, \forall j \in C \quad (21)$$
$$z_i \in \{0,1\}, \forall i \in C \quad (22)$$
$$\alpha_{ij} \in \{0,1\}, \forall i \in M, \forall j \in C \quad (23)$$
$$x_{ijh} \in \{0,1\}, \forall i,j \in M\cup C, \forall h \in H \quad (24)$$
$$LP_{ijh} \ge 0, \forall i,j \in M\cup C, \forall h \in H \quad (25)$$
$$q_j^C \ge 0, \forall j \in C \quad (26)$$
$$q_j^{CP} \ge 0, \forall j \in C \quad (27)$$

Multi-Objective Optimization

The objective functions (f_1, f_2 and f_3) of the model are combined into a single objective function using the weighted sum approach. Equation (28) denotes all objective functions could be composited into a single objective function to be minimized by summing all objective functions with weights ($\omega_i, i = 1,2,3$). However, the dimension of each objective function is not necessarily the same. To solve this problem, this research optimizes each objective function individually to obtain its optimum values ($f_i^*, i = 1,2,3$) and divide objective functions by their optimum values (Equation (29)). This study assumes that all objectives are equally important, which implies that all the weights are equal.

$$Mf = \sum_i \omega_i f_i, \quad i = 1,2,3 \quad (28)$$
$$Mf = \sum_i \frac{\omega_i f_i}{f_i^*}, \quad i = 1,2,3 \quad (29)$$

Results and Discussion

This section describes the computational results obtained to assess the MOLRP model's ability to solve the palm oil BSC problem. The computational experiments were performed on a test instance consisting of ten mills and four potential collection facilities to verify the efficiency of the proposed model in dealing with sustainable goals. The test instance was generated using data and information related to the palm oil industry and pretreatment operation.

Data and Parameter Setting

Table 5 shows the locations and capacities of palm oil mills where the processing capacities (t_i^M) are taken from Lam *et al*. [68]. Table 6 lists information and parameters relevant to biomass. For every metric ton of FFB being processed, 0.234 metric tons of EFB is produced [68], this is defined as the biomass generation rate (ρ^G). By assuming 16 working hours (w) at each mill, the quantity of EFB available at each mill can be calculated by Equation (30). In current practice, the palm oil industry uses EFB for mulching and co-compositing. Since this study will utilize the EFB for biofuel conversion, this research assumes that rate of EFB used for mulching and co-compositing (ρ^{MO}) will change to 0.9 such that it will least impact the current practice in palm oil industry. Then, the remaining portion of EFB would be separated and sieved to produce WSF with a conversion rate (θ^{S}). Equation (31) states the amount of pre-processed biomass (WSF) that is available at each mill. The WSF will then be transported to the collection facility for pretreatment at a pelletizing rate (θ^{P}).

$$q_i^G = t_i^M \rho^G w, \ \forall i \in M \tag{30}$$
$$q_i^M = \theta^S (1-\rho^{MO}) q_i^G, \quad \forall i \in M \tag{31}$$

Table 5. The locations and capacities of palm oil mills

Mill	Cartesian coordinates	Processing capacity (t_i^M) (metric ton FFB/hour) Lam et al. [68]
M1	(25, 100)	80
M2	(60, 50)	90
M3	(100, 55)	90
M4	(90, 195)	40
M5	(115, 185)	100
M6	(160, 130)	100
M7	(225, 175)	65
M8	(260, 185)	80
M9	(255, 100)	90
M10	(305, 215)	100

Table 6. Parameters for biomass

Parameter	Value	Reference
Biomass generation rate (ρ^G)	0.234 EFB/FFB	Lam *et al.* [68]
Rate of the biomass used for mulching and co-compositing (ρ^{MO})	0.9	assumption
Conversion rate for separating and sieving (θ^S)	0.24 WSF/EFB	Lam *et al.* [68]
Conversion rate for pelletizing (θ^P)	0.33 pellets/WSF	Lam *et al.* [68]

Table 7 reports the annual investment cost for a collection facility with a capacity of 300,000 metric tons/year. This information will serve as the base value for adjusting the investment cost. This study designed all the potential collection facilities equipped with pelletizing technology of 15,000 metric tons/year (Table 8). Equation (32) calculates the daily pretreatment capacity (t_i^C)with an assumption of 300 working days. Equation (33) is an equation for adjusting the cost from one known (base) capacity to another [69], and the scale factor for a pelletizing facility is 0.6 [70]. Equation (34) describes the equivalent daily investment cost (f_i^{EC}) for the collection facility. Table 9 shows data for various potential collection sites and their population densities.

$$Daily\ pretreatment\ capacity = \frac{annual\ pretreatment\ capacity}{number\ of\ working\ days} \tag{32}$$
$$\frac{cost_a}{cost_{base}} = \left(\frac{size_a}{size_{base}}\right)^{Scale\ factor} \tag{33}$$
$$Equivalent\ daily\ investment\ cost = \frac{annual\ investment\ cost}{number\ of\ working\ days} \tag{34}$$

Table 7. The annual investment cost for a collection facility equipped with pelletizing technology [71]

Parameter	Size (base)
Pretreatment capacity	300,000 metric ton/year
Annual investment cost	3,476,219 USD /year

Table 8. Parameters for the collection facilities

Parameter	Value	Reference/Note
Pretreatment capacity	15,000 metric tons/year	Razm *et al.* [72]
Daily pretreatment capacity (t_i^C)	50 metric tons/day	Obtained using (32)
Unit operating cost (f_i^{PC})	USD 40 /metric ton MYR 176/metric ton*	Razm *et al.* [72] Currency conversion
Annual investment cost	USD 576,088.40	Obtained using (33)
Equivalent daily investment cost (f_i^{EC})	USD 1,920.29 MYR 8,449.28*	Obtained using (34) Currency conversion

Table 9. The potential collection facilities with their respective population densities

Collection facility	Cartesian coordinates	Population
C11	(90, 125)	9085
C12	(140, 90)	4312
C13	(160, 245)	5403
C14	(300, 150)	6042

Table 10 denotes data and parameters relevant to trucks used in the SC. The trucks in this LRP model are homogenous, which means all have the same capacity (c_h). Equation (35) denotes the number of trucks that exist in the palm oil BSC where the transportation cost (v_h) could be calculated using Equation (36). The CO_2 emission rate (γ^{h1}) for a 25 metric-ton truck is 0.7228 kg/km [73]. According to World Resource Institute and World Business Council for Sustainable Development, the emission rate (γ^{h2}) for a truck size over 17 metric tons with loading is 0.20027 kg/metric ton-km [74].

$$number\ of\ trucks = 2\left\lceil\frac{\sum_{i\in M} q_i^M}{c_h}\right\rceil \tag{35}$$

$$v_h = (fuel\ consumption)(fuel\ price) \tag{36}$$

Table 10. Parameters for the trucks

Parameter	Value	Reference
Capacity (c_h)	25 metric tons	How *et al.* [73]
Fuel consumption	0.278 L/km	How *et al.* [73]
Fuel price	RM2.15 /L	Official Portal of Ministry of Finance Malaysia [75]
CO_2 emission rate over every kilometer (γ^{h1})	0.7228 kg/km	How *et al.* [73]
CO_2 emission rate for the truck with loading over every kilometer (γ^{h2})	0.20027 kg/metric ton-km	Greenhouse gas protocol [74]

Result Analysis

This study coded the mathematical model in the General Algebraic Modeling System (GAMS) and solved it using the CPLEX optimization solver. First, the study conducted numerical experiments by optimizing each objective function individually to test how the model reacts to different sustainable goals and determine their optimum values. Figure 3 shows that the BSC attempts to minimize the total cost (f_1) should open collection facilities C11 and C14 and have four trucks in the network. Accordingly, C11 and C14 will be allocated 44.928 metric tons and 30.102 metric tons of biomass, producing 14.826 metric tons and 9.934 metric tons of pellets, respectively.

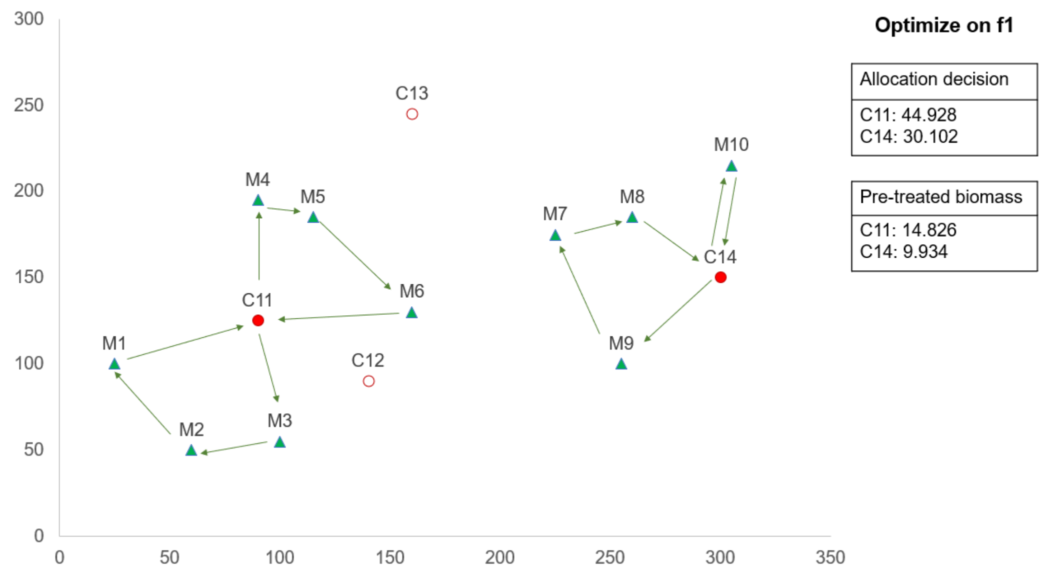

Figure 3. Graphical representation of optimal solutions optimizing the first objective function

Figure 4 illustrates that the collection facilities C12 and C13 are the optimal locations when the model attempts to minimize the surrounding population (f_2). This network requires eight trucks to transport the WSF, two trucks for C12 and six trucks for C13. C12 will receive 25.160 metric tons of WSF and produce 8.303 metric tons of pellets. Since C13 receives 49.870 metric tons of WSF, its pellet production is about twice that of C12.

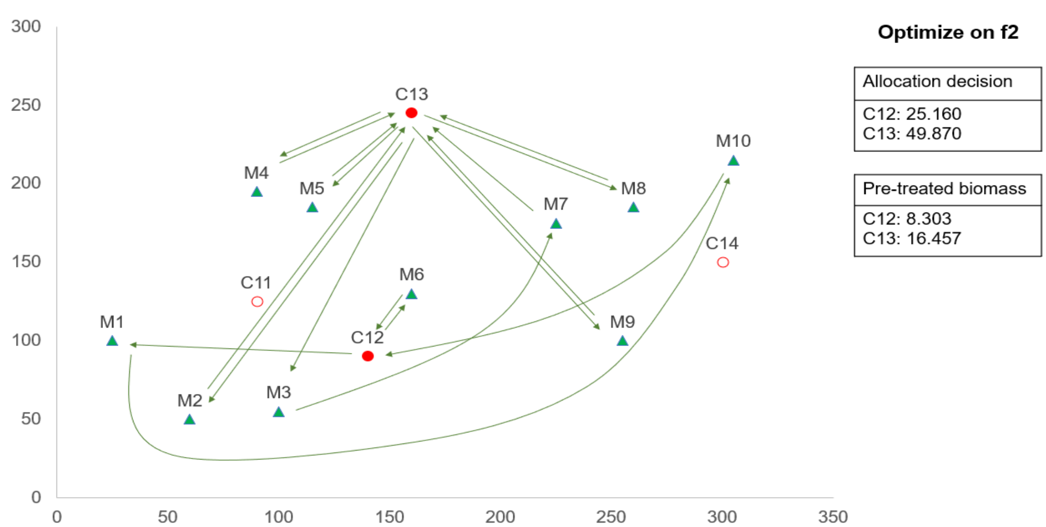

Figure 4. Graphical representation of optimal solutions optimizing the second objective function

When the model attempts to minimize total CO_2 emissions (f_3), the number of collection facilities increases to three, which are C11, C12, and C14 (Figure 5). As compared to the other objective functions (Figures 3 and 4), optimizing f_3 will provide the optimal solutions that minimize each truck's travel distance and loading (Figure 5 and Table 11). C11, C12, and C14 produce 6.524 metric tons, 8.303 metric tons, and 9.934 metric tons of pellets, respectively.

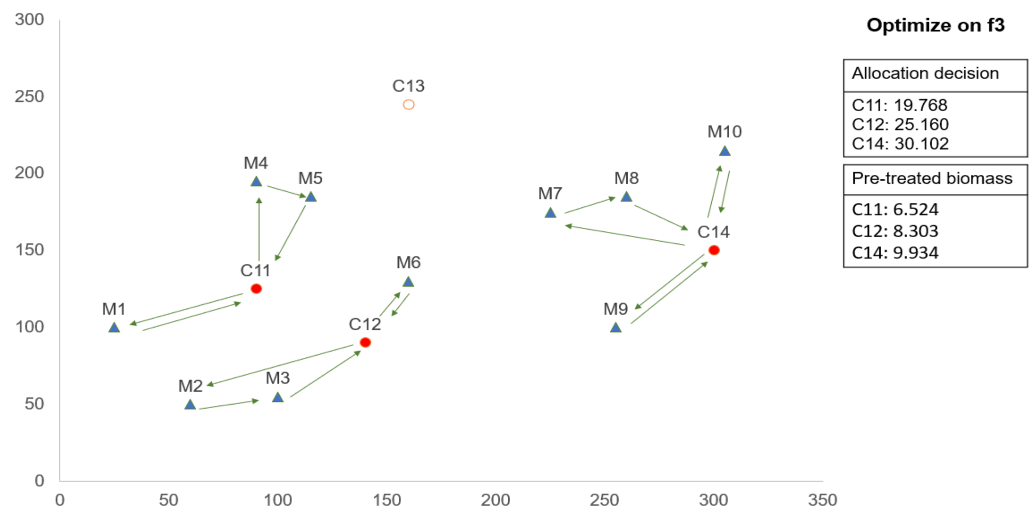

Figure 5. Graphical representation of optimal solutions optimizing the third objective function

By analyzing the results presented in Table 12, it can be concluded that the proposed objective functions are conflicting with one another. It is impossible to improve one objective without degrading the other objectives. Under the objective function of the total cost (f_1) minimization, the BSC needs to spend RM30610.524/day. But this means there will be 15127 people affected by this decision, and 1862.201 kg of CO_2 is emitted daily. Although optimizing the f_2 individually could reduce the total affected population to 9715 people, this decision will lead to the highest amount of CO_2 emissions, 3478.453 kg CO_2/day. The expenses will also be 3.27 % higher than the network design under total cost minimization. A similar situation is encountered when the model attempts to reduce total CO_2 emissions (f_3). Even though total CO_2 emissions could be reduced to 1359.636 kg CO_2/day, this network design might be unfavorable for economic and social dimensions. This design will cost a total cost of RM39154.981/day and affect a total of 19439 people.

Next, this study investigates how the model adjusts the strategy of facility establishment and truck routing under multi-objective optimization. Figure 6 and Table 13 report the results of multi-objective optimization. When all objective functions are equally important, the optimal decision is to open collection facilities C12 and C14. This network design requires six routes to transport biomass. C12 and C14 will receive 44.928 metric tons and 30.102 metric tons of WSF, respectively. As a result, C12 and C14 will produce 14.826 metric tons and 9.934 metric tons of pellets. The optimum value for the composite objective is 3.222.

The values of performance indices in Tables 12 and 13 also demonstrate the advantage of optimizing multi-objective functions simultaneously. Although the total cost needed is RM30722.001/day, it is only 0.36% higher than the model optimized under total cost minimization individually. This increment of 0.36% could be viewed as the price for having a network structure that considers the effect of negative social impact and CO_2 emissions together. Similarly, this network structure affects a population of 10354 people, slightly higher than the model optimized individually under total population minimization. Nonetheless, it is still better than optimizing the total cost and total CO_2 separately, affecting 15127 people and 19439 people, respectively.

Likewise, the CO_2 emissions of the network structure under multi-objective optimization (1567.424 kg CO_2/day) are higher than optimizing total CO_2 emissions alone (1359.636 kg CO_2/day). This amount is lower than the emissions from the network structure optimizing the total cost and total population separately, emitting 1862.201 CO_2/day and 3478.453 CO_2/day, respectively. Retrieving the third objective function intends to capture the emissions of empty and loaded trucks, computation experiments under this goal will reduce the CO_2 emissions caused by travel distance and truck loading. The network structures for optimizing multi-objective functions and the third objective function (total CO_2 emissions alone) will need six trucks and seven trucks, respectively. They are slightly better than the network structure under the total population minimization, which requires eight trucks. Nevertheless, the network structure considering cost minimization alone requires only four trucks since the relationship between CO_2 and truck loading is not the concern of this goal.

Table 11. The routes and loads of trucks for the different objective functions

Optimize	Route	Load
f_1	C11-M3-M2-M1-C11	23.363
	C14-M10-C14	8.986
	C14-M9-M7-M8-C14	21.116
	C11-M4-M5-M6-C11	21.565
f_2	C13-M4-C13	3.594
	C13-M3-M7-C13	13.928
	C13-M2-C13	8.087
	C13-M8-C13	7.189
	C13-M9-C13	8.087
	C12-M6-C12	8.986
	C12-M1-M10-C12	16.174
	C13-M5-C13	8.986
f_3	C14-M9-C14	8.087
	C14-M7-M8-C14	13.029
	C12-M6-C12	8.986
	C11-M4-M5-C11	12.580
	C12-M2-M3-C12	16.174
	C11-M1-C11	7.189
	C14-M10-C14	8.986
Mf	C12-M4-M5-C12	12.58
	C14-M10-C14	8.986
	C12-M1-M2-M3-C12	23.362
	C14-M9-C14	8.087
	C14-M7-M8-C14	13.029
	C12-M6-C12	8.986

Table 12. The values of performance measures when optimizing each objective function individually

Optimize	Total cost	Total population	Total CO_2 emissions
f_1	**30610.524**	15127	1862.201
f_2	31611.707	**9715**	3478.453
f_3	39154.981	19439	**1359.636**

Notably, there are some compensations for BSC performances under multi-objective function optimization. It would be the remuneration for a supply chain that would like to address all the sustainable dimensions as these (economic, environmental, and social) goals are conflicting. It is undeniable that optimizing the objective functions individually will always provide the best result for each dimension. Certainly, the single economic objective function optimization will produce the result that the industry players favor. Nonetheless, the construction of the network should not neglect sustainable development in the long term, where all the decisions made in the BSC would shape the lives of present and future generations.

Table 13. The performance indices for multi-objective optimization

Optimize	Composite Value	Total cost	Total population	Total CO_2 emissions
Mf	3.222	30722.001	10354	1567.424

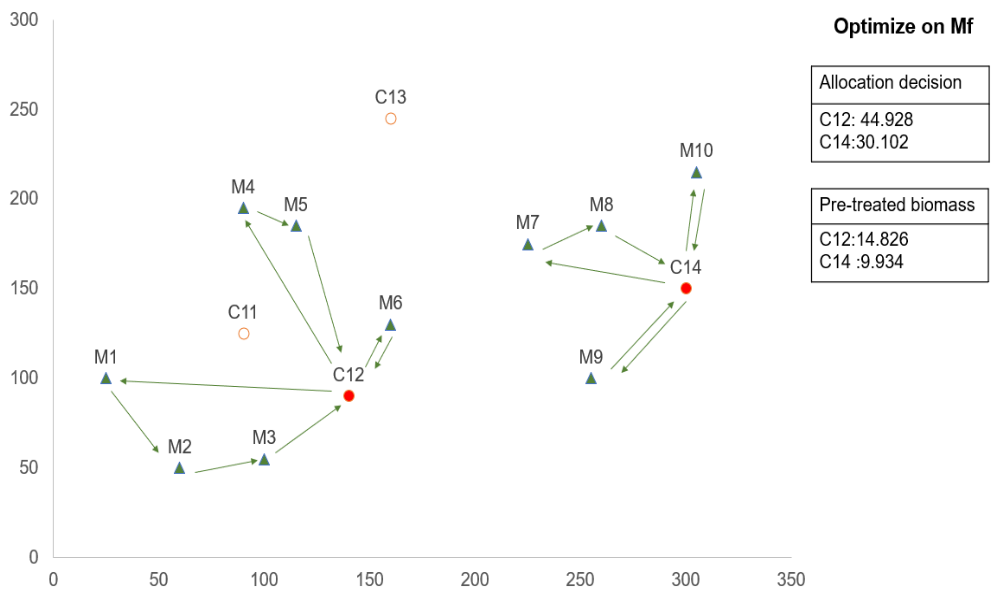

Figure 6. Graphical representation of optimal solutions optimizing the multi-objective functions

Conclusions

This paper investigates a sustainable palm oil BSC problem that simultaneously addresses locational and routing decisions. The main goal of this paper is to develop an effective BSC model that can handle the different needs of the BSC problem. The proposed LRP model has some important characteristics. The model is created to determine the best decisions for establishing collection facilities, allocating biomass, and vehicle routing. The pretreatment technology is also included in the proposed BSC network and quantified as an additional parameter. In addition, the suggested model is a multi-objective LRP model that attempts to address sustainability from all dimensions. The mowhodel optimizes economic performance through cost minimization. The model relates the CO_2 emissions of empty and loaded trucks to the environmental performance of the BSC. Minimizing the total population affected by locational decisions is the measure of social sustainability.

This research conducted numerical experiments to test how the model reacts under single and multi-objective optimization. The results of the single objective optimization show that the proposed objective functions are conflicting with one another in nature. Optimizing each objective function individually will provide the best outcome for its dimension, but improving one objective without degrading the others is impossible. In multi-objective optimization, all the objectives are composited into a single objective by the weighted sum approach. Compared to the results of single objective optimizing at its dimension, the indicator values of the multi-objective model are degraded by 0.36%, 6.58%, and 15.28% in the economic, social, and environmental performances, respectively. The results demonstrate that the model will adjust the facility establishment, allocation, and truck routing strategy accordingly.

Comparatively, the result of multi-objective optimization shows some remuneration for BSC performances. This reimbursement of model performances is unavoidable as these goals are conflicting. Optimizing each objective function separately will always produce the best solution for each dimension. Undoubtedly, the result of single economic objective optimization will be preferable by industry players. Nevertheless, the sustainability of the BSC in the long term should not be overlooked since the decisions made influence the lives of current and future generations.

This research has added novelties to the topics of interest in several ways. First, the developed model is workable with any BSC network that aims to optimize facility placement, resource allocation, and vehicle routing. Second, the model could be individually optimized for any stated objective function. It could also produce the best outcomes for scenarios that account for several sustainable goals, some of which might contradict one another. Moreover, this model set a framework for multi-objective optimization toward the sustainable development of the LRP model in BSC. By customizing the model to the operation in the BSC, this model differs from the general LRP model.

The limitations of the current proposed model are as follows. First, the model only allows one truck to visit each mill and has a homogenous fleet of trucks. Second, all objective functions are equally important, which might not be realistic in the industry. Last but not least, this research does not consider the stochasticity of the BSC. Future lines of research may consider improving the limitations of this model.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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References

[1] Cao, J. X., Zhang, Z. & Zhou, Y. (2021). A location-routing problem for biomass supply chains. *Comput Ind Eng.*, *152*, 107017.
[2] Aziz, N. F., Chamhuri, N. & Batt, P. J. (2021). Barriers and benefits arising from the adoption of sustainable certification for smallholder oil palm producers in Malaysia: A systematic review of literature. *Sustainability, 13*(18), 10009.
[3] Ismail, N. W., Kamal, S. N. M., Firdaus, M. & Hariri, N. M. (2022). Export demand of palm oil in Malaysia: Analysis using ARDL approach. *Asian Journal of Agriculture and Rural Development*, *12*(3), 157-163.
[4] Sukiran, M. A., Abnisa, F., Wan Daud, W. M. A., Abu Bakar, N. & Loh, S. K. (2017). A review of torrefaction of oil palm solid wastes for biofuel production. *Energy Convers and Manage.*, *149*, 101-120.
[5] Menon, N. R., Ab Rahman, Z. & Abu Bakar, N. (2003). Empty fruit bunches evaluation: Mulch in plantation vs. fuel for electricity generation. *Oil Palm Industry Economic Journal*, *3*, 15-20.
[6] Che Hamzah, N. H., Yahya, A., Che Man, H. & Samsu Baharuddin, A. (2018). Effect of pretreatments on compost production from shredded oil palm empty fruit bunch with palm oil mill effluent anaerobic sludge and chicken manure. *Bioresources*, *13*(3), 4998-5012.
[7] Kulim Malaysia. (2019). KULIM (Malaysia) Berhad Integrated Annual Report 2019. http://integrated-report.kulim.com.my/files/document/1080/KULIM (Malaysia) Berhad Integrated Annual Report 2019.pdf.
[8] Méndez-Vázquez, M. A., Gómez-Castro, F. I., Ponce-Ortega, J. M., Serafín-Muñoz, A. H., Santibañez-Aguilar, J. E. & El-Halwagi, M. M. (2017). Mathematical optimization of a supply chain for the production of fuel pellets from residual biomass. *Clean Technol and Envir., 19*(3), 721-734.
[9] Sarker, B. R., Wu, B. & Paudel, K. P. (2018). Optimal number and location of storage hubs and biogas production reactors in farmlands with allocation of multiple feedstocks. *Appl Math Model*, *55*, 447-465.
[10] Sarker, B. R., Wu, B. & Paudel, K. P. (2019). Modeling and optimization of a supply chain of renewable biomass and biogas: Processing plant location. *Appl Energ.*, *239*, 343-355.
[11] Saadati, M. & Hosseininezhad, S. J. (2019). Designing a hub location model in a bagasse-based bioethanol supply chain network in Iran (case study: Iran sugar industry). *Biomass and Bioenerg.*, *122*, 238-256.
[12] Serrano-Hernandez, A. & Faulin, J. (2019). Locating a biorefinery in Northern Spain: Decision making and economic consequences. *Socio Econ Plan Sci.*, *66*, 82–91.
[13] Schröder, T., Lauven, L. P. & Geldermann, J. (2018). Improving biorefinery planning: Integration of spatial

data using exact optimization nested in an evolutionary strategy. *Eur J of Oper Res.*, *264*(3), 1005-1019.
[14] Zhang, F., Wang, J., Liu, S., Zhang, S. & Sutherland, J. W. (2017). Integrating GIS with optimization method for a biofuel feedstock supply chain. *Biomass and Bioenerg.*, *98*, 194-205.
[15] Soha, T., Papp, L., Csontos, C. & Munkacsy, B. (2021). The importance of high crop residue demand on biogas plant site selection, scaling and feedstock allocation - A regional scale concept in a Hungarian study area. *Renew Sust Energ Rev.*, *141*, 110822.
[16] Sahoo, K., Hawkins, G. L., Yao, X. A., Samples, K. & Mani, S. (2016). GIS-based biomass assessment and supply logistics system for a sustainable biorefinery: A case study with cotton stalks in the Southeastern US. *Appl Energ.*, *182*, 260-273.
[17] Jayarathna, L., Kent, G., O'Hara, I. & Hobson, P. (2020). A Geographical information system based framework to identify optimal location and size of biomass energy plants using single or multiple biomass types. *Appl Energ.*, *275*, 115398.
[18] Razm, S., Dolgui, A., Hammami, R., Brahimi, N., Nickel, S. & Sahebi, H. (2021). A two-phase sequential approach to design bioenergy supply chains under uncertainty and social concerns. *Comput Chem Eng.*, *145*, 107131.
[19] Zhang, F., Johnson, D., Johnson, M., Watkins, D., Froese, R. & Wang, J. (2016). Decision support system integrating GIS with simulation and optimisation for a biofuel supply chain. *Renew Energ.*, *85*, 740-748.
[20] León-Olivares, E., Minor-Popocatl, H., Aguilar-Mejía, O. & Sánchez-Partida, D. (2020). Optimization of the supply chain in the production of ethanol from agricultural biomass using Mixed-Integer Linear Programming (MILP): A Case Study. *Math Probl Eng.*, *2020*, 6029507.
[21] Castro-Peña, M. Y., Peñuela, C. A. & González, J. G. (2019). Design of a supply chain to produce ethanol from one residuum and two coffee by-products. *Uncertain Supply Chain Management*, *7*(4), 767-782.
[22] Galanopoulos, C., Barletta, D. & Zondervan, E. (2018). A decision support platform for a bio-based supply chain: Application to the region of Lower Saxony and Bremen (Germany). *Comput Chem Eng.*, *115*, 233-242.
[23] San Juan, J. L. G., Aviso, K. B., Tan, R. R. & Sy, C. L. (2019). A multi-objective optimization model for the design of biomass co-firing networks integrating feedstock quality considerations. *Energies*, *12*(11), 2252.
[24] Chugh, S., Yu, T. E., Jackson, S. W., Larson, J. A., English, B. C. & Cho, S.-H. (2016). Economic analysis of alternative logistics systems for Tennessee-produced switchgrass to penetrate energy markets. *Biomass and Bioenerg.*, *85*, 25-34.
[25] Rabbani, M., Saravi, N. A., Farrokhi-Asl, H., Lim, S. F. W. T. & Tahaei, Z. (2018). Developing a sustainable supply chain optimization model for switchgrass-based bioenergy production: A case study. *J Clean Prod.*, *200*, 827-843.
[26] Park, Y. S., Szmerekovsky, J. & Dybing, A. (2019). Optimal location of biogas plants in supply chains under carbon effects: Insight from a case study on animal manure in North Dakota. *J Adv Transport*, *2019*, 5978753.
[27] Gital Durmaz, Y. & Bilgen, B. (2020). Multi-objective optimization of sustainable biomass supply chain network design. *Appl Energ., 272*, 115259.
[28] Rabbani, M., Momen, S., Akbarian-Saravi, N., Farrokhi-Asl, H. & Ghelichi, Z. (2020). Optimal design for sustainable bioethanol supply chain considering the bioethanol production strategies: A case study. *Comput Chem Eng.*, *134*, 106720.
[29] Ganev, E. I., Dzhelil, Y. R., Ivanov, B. B., Vaklieva-Bancheva, N. G. & Kirilova, E. G. (2020). Optimal design of a sustainable integrated biodiesel/diesel supply chain using first and second generations bioresources. *Chem Engineer Trans.*, *81*, 67-72.
[30] Mahjoub, N., Sahebi, H., Mazdeh, M. & Teymouri, A. (2020). Optimal design of the second and third generation biofuel supply network by a multi-objective model. *J Clean Prod.*, *256*, 120355.
[31] Ivanov, B. (2018). Multi-period deterministic model of sustainable integrated of hybrid first and second generation bioethanol supply chains for synthesis and renovation. *Bulg Chem Commun.*, *50*, 24-35.
[32] Hosseinalizadeh, R., Arshadi Khamseh, A. & Akhlaghi, M. M. (2019). A multi-objective and multi-period model to design a strategic development program for biodiesel fuels. *Sustainable Energy Technologies and Assessments*, *36*, 100545.
[33] De Meyer, A., Cattrysse, D. & Van Orshoven, J. (2015). A generic mathematical model to optimise strategic and tactical decisions in biomass-based supply chains (OPTIMASS). *Eur J of Oper Res.*, *245*(1), 247-264.
[34] Arabi, M., Yaghoubi, S. & Tajik, J. (2019). A mathematical model for microalgae-based biobutanol supply chain network design under harvesting and drying uncertainties. *Energy*, *179*, 1004-1016.
[35] Arabi, M., Yaghoubi, S. & Tajik, J. (2019). Algal biofuel supply chain network design with variable demand under alternative fuel price uncertainty: A case study. *Comput Chem Eng.*, *130*, 106528.
[36] Mohseni, S. & Pishvaee, M. S. (2016). A robust programming approach towards design and optimization of microalgae-based biofuel supply chain. *Comput Ind Eng.*, *100,* 58-71.
[37] Ghaderi, H., Moini, A. & Pishvaee, M. S. (2018). A multi-objective robust possibilistic programming approach to sustainable switchgrass-based bioethanol supply chain network design. *J Clean Prod.*, *179*, 368-406.
[38] Kwon, O. & Han, J. (2021). Waste-to-bioethanol supply chain network: A deterministic model. *Appl Energ.*, *300*, 117381.
[39] Zhao, X.-G. & Li, A. (2016). A multi-objective sustainable location model for biomass power plants: Case of China. *Energy*, *112*, 1184-1193.
[40] Salleh, S. F., Gunawan, M. F., Zulkarnain, M. F. B., Shamsuddin, A. H. & Abdullah, T. A. R. T. (2019). Modelling and optimization of biomass supply chain for bioenergy production. *Journal of Environmental Treatment Techniques*, *7*(4), 689-695.
[41] Woo, H., Acuna, M., Moroni, M., Taskhiri, M. S. & Turner, P. (2018). Optimizing the location of biomass energy facilities by integrating Multi-Criteria Analysis (MCA) and Geographical Information Systems (GIS). *Forests*, *9*, 585.
[42] Sahoo, K., Mani, S., Das, L. & Bettinger, P. (2018). GIS-based assessment of sustainable crop residues for optimal siting of biogas plants. *Biomass and Bioenerg.*, *110*, 63-74.

[43] Laasasenaho, K., Lensu, A., Lauhanen, R. & Rintala, J. (2019). GIS-data related route optimization, hierarchical clustering, location optimization, and kernel density methods are useful for promoting distributed bioenergy plant planning in rural areas. *Sustainable Energy Technologies and Assessments*. *32*, 47-57.
[44] Rivera-Cadavid, L., Manyoma-Velásquez, P. C. & Manotas-Duque, D. F. (2019). Supply chain optimization for energy cogeneration using sugarcane crop residues (SCR). *Sustainability-Basel*., *11*(23), 6565.
[45] Wang, R., Chang, S., Cui, X., Li, J., Ma, L., Kumar, A., Nie, Y. & Cai, W. (2021). Retrofitting coal-fired power plants with biomass co-firing and carbon capture and storage for net zero carbon emission: A plant-by-plant assessment framework. *GCB Bioenergy*, *13*(1), 143-160.
[46] Tiammee, S. & Likasiri, C. (2020). Sustainability in corn production management: A multi-objective approach. *J Clean Prod*, *257*, 120855.
[47] She, J., Chung, W. & Han, H. (2019). Economic and environmental optimization of the forest supply chain for timber and bioenergy production from beetle-killed forests in Northern Colorado. *Forests*, *10*(8), 689.
[48] How, B. S. and Lam, H. L. (2017). Integrated biomass supply chain in Malaysia: A sustainable strategy. *Chem Engineer Trans*, *61*, 1573-1578.
[49] Torjai, L. & Kruzslicz, F. (2016). Mixed integer programming formulations for the Biomass Truck Scheduling problem. *Cent Europ J Oper Re.*, *24*(3), 731-745.
[50] Soares, R., Marques, A., Amorim, P. & Rasinmäki, J. (2019). Multiple vehicle synchronisation in a full truck-load pickup and delivery problem: A case-study in the biomass supply chain. *Eur J of Oper Res.*, *277*(1), 174-194.
[51] Pinho, T. M., Coelho, J. P., Veiga, G., Moreira, A. P. & Boaventura-Cunha, J. (2017). A multilayer model predictive control methodology applied to a biomass supply chain operational level. *Complexity*, *2017*, 5402896.
[52] Fokkema, J. E., Land, M. J., Coelho, L. C., Wortmann, H. & Huitema, G. B. (2020). A continuous-time supply-driven inventory-constrained routing problem. *Omega (United Kingdom)*, *92*, 102151.
[53] Malladi, K. T., Quirion-Blais, O. & Sowlati, T. (2018). Development of a decision support tool for optimizing the short-term logistics of forest-based biomass. *Appl Energ.*, *216*, 662-677.
[54] Cárdenas-Barrón, L. E. & Melo, R. A. (2021). A fast and effective MIP-based heuristic for a selective and periodic inventory routing problem in reverse logistics. *Omega (United Kingdom)*, *103*, 102394.
[55] Vahdanjoo, M., Norremark, M. & Sorensen, C. G. (2021). A system for optimizing the process of straw bale retrieval. *Sustainability-Basel*, *13*(14), 7722.
[56] Zamar, D. S., Gopaluni, B. & Sokhansanj, S. (2017). Optimization of sawmill residues collection for bioenergy production. *Appl Energ.*, *202*, 487-495.
[57] Cao, J. X., Wang, X. & Gao, J. (2021). A two-echelon location-routing problem for biomass logistics systems. *Biosyst Eng.*, *202*, 106-118.
[58] Li, S., Wang, Z., Wang, X., Zhang, D. & Liu, Y. (2019). Integrated optimization model of a biomass feedstock delivery problem with carbon emissions constraints and split loads. *Comput Ind Eng., 137*, 106013.
[59] Habibi, F., Asadi, E. & Sadjadi, S. J. (2018). A location-inventory-routing optimization model for cost effective design of microalgae biofuel distribution system: A case study in Iran. *Energy Strateg Rev.*, *22*, 82-93.
[60] Asadi, E., Habibi, F., Nickel, S. & Sahebi, H. (2018). A bi-objective stochastic location-inventory-routing model for microalgae-based biofuel supply chain. *Appl Energ.*, *228*, 2235-2261.
[61] Morales Chavez, M. M., Costa, Y. & Sarache, W. (2021). A three-objective stochastic location-inventory-routing model for agricultural waste-based biofuel supply chain. *Comput Ind Eng.*, *162*, 107759.
[62] Delfani, F., Kazemi, A., Seyedhosseini, S. M. & Niaki, S. T. A. (2020). A green hazardous waste location-routing problem considering the risks associated with transportation and population. *International Journal of Engineering, Transactions B: Applications, 33*(11), 2272-2284.
[63] Karaoglan, I., and Altiparmak, F (2010). A hybrid genetic algorithm for the location-routing problem with simultaneous pickup and delivery. *The 40th International Conference on Computers and Industrial Engineering: Soft Computing Techniques for Advanced Manufacturing, and Service Systems*, CIE40 2010, Awaji, Japan, p. 1–6. IEEE.
[64] Theeraviriya, C., Pitakaso, R., Sillapasa, K. & Kaewman, S. (2019). Location decision making and transportation route planning considering fuel consumption. *Journal of Open Innovation: Technology, Market, and Complexity, 5*(2), 27.
[65] Theeraviriya, C., Ruamboon, K., & Praseeratasang, N. (2021). Solving the multi-level location routing problem considering the environmental impact using a hybrid metaheuristic. *International Journal of Engineering Business Management, 13*, 1-17.
[66] Tirkolaee, E. B., Abbasian, P. & Weber, G.-W. (2021). Sustainable fuzzy multi-trip location-routing problem for medical waste management during the COVID-19 outbreak. *SCI Total Environ., 756*, 143607.
[67] Roni, M. S., Eksioglu, S. D., Cafferty, K. G. & Jacobson, J. J. (2017). A multi-objective, hub-and-spoke model to design and manage biofuel supply chains. *Ann of Oper Res.*, *249*, 351-380.
[68] Lam, H. L., Ng, W. P. Q., Ng, R. T. L., Ng, E. H., Aziz, M. K. A. & Ng, D. K. S. (2013). Green strategy for sustainable waste-to-energy supply chain. *Energy, 57*, 4-16.
[69] Sultana, A., Kumar, A. & Harfield, D. (2010). Development of agri-pellet production cost and optimum size. *Bioresource Technol.*, *101*(14), 5609-5621.
[70] Mani, S., Sokhansanj, S., Bi, X. & Turhollow, A. (2006). Economics of producing fuel pellets from biomass. *Appl Eng Agric*, *22*(3), 421-426.
[71] Lamers, P., Roni, M. S., Tumuluru, J. S., Jacobson, J. J., Cafferty, K. G., Hansen, J. K., Kenney, K., Teymouri, F. & Bals, B. (2015). Techno-economic analysis of decentralized biomass processing depots. *Bioresource Technol.*, *194*, 205-213.
[72] Razm, S., Nickel, S., Saidi-mehrabad, M. & Sahebi, H. (2019). A global bioenergy supply network redesign through integrating transfer pricing under uncertain condition. *J Clean Prod.*, *208*, 1081-1095.
[73] How, B. S., Tan, K. Y. & Lam, H. L. (2016). Transportation decision tool for optimisation of integrated biomass

flow with vehicle capacity constraints. *J Clean Prod*, *136*, 197-223.
[74] Greenhouse gas protocol. (2017). Calculation tools. Emission factors from cross-sector tools. https://ghgprotocol.org/calculation-tools (accessed Dec. 31, 2022).
[75] Official Portal of Ministry of Finance Malaysia. (2022). *Retail Price of Petroleum Products from 8 December 2022 to 14 December 2022*. Press Release. https://www.mof.gov.my/portal/en/news/press-release/retail-price/retail-price-of-petroleum-products-from-1-december-2022-to-7-december-2022 (accessed Dec. 31, 2022).