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Analysis of multi-objective vehicle routing problem with flexible time windows: The implication for open innovation dynamics

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ABSTRACT

Renewable energy has been a worldwide interest due to a growing energy demand as well as a mounting concern over the hostile impacts from traditional fuels. One of a direction for future renewable energy is the use of biofuel. In this research, we initially apply the K-means algorithm to evaluate the possible locations of collection sites at the upstream of the biofuel supply chain. Next, we propose the multi-objective vehicle routing problem model, in which flexible time windows are synchronized in the model. Additionally, our integrated model evaluates the perspective of socioeconomic by considering total cost – the surrogate criterion for economic aspect as well as the lateness for delivery and the maximum delivery time – the surrogate criteria for social aspect, into account. Finally, we apply a model to a regional case study based on the wood-biomass data of the biofuel supply chain in Thailand, in which the geographic information system is applied.

1. Introduction

Renewable energy has gained worldwide interest due to an increasing energy demand as well as a rising concern over the energy price and an environmental impact of traditional fuel consumption (United Nations, 2021). Renewable energy, in particular, is an energy that can be collected from natural resources and are produced by processes that can be constantly replenished. Additionally, renewable energy can be derived from various sources and forms, in which the renewable energy definition is inclusive of electricity and heat generated from solar, wind, ocean, hydropower, geothermal resources, biomass, and hydrogen (Ang et al., 2022). These days, the trend of renewable energy systems and development has been shown to be more efficient and economical, in which the share of total energy consumption is continuously increasing (Deloitte Insights, 2018; Li et al., 2020; Gawusu et al., 2022; Ransikarbum et al., 2022; Ransikarbum et al., 2023). Various countries have also taken thoughtful actions through strategic policies aiming at meeting energy needs more strongly and sustainably. Thailand, in particular, has also promoted a new economic model towards Industry 4.0 development plan by focusing on 10 targeted, S-curve industries – three of them are agricultural, logistics, and biofuel sectors (Thailand Board of Investment, 2021).

The Sustainable Development Goals (SDGs) have been considered the global goals for 2030, which call for development and action plans to balance social, economic and environmental sustainability. The 7th SDG, in particular, aims to ensure the universal access of reliable energy services, to substantially increase the share of renewable energy in the global energy mix, to improve in energy efficiency, and to enhance and expand infrastructure and innovation technology related to clean energy (Bali Swain and Yang-Wallentin, 2020; United Nations, 2022). Biofuel, in particular, can be obtained from several biomass sources including edible crops, non-edible lignocellulosic crops, crop residues, forests, waste, etc. In comparison to fossil fuels, biomass is easy to grow and can be replaced quickly without depleting natural resources (REN21, 2021). The advantages of using biomass are noted for its ability to be stored and used on demand, clean energy, renewable, and no carbon dioxide (CO_2) side effect. In addition, biomass also has the potential to reduce the reliance on fossil fuels, which are the main source of CO_2 release in the atmosphere (Lan et al., 2020). Challenges for biomass utilization as a renewable energy source are also noted for product quality, barrier properties of lignocellulosic biomass, biotechnological and physicochemical treatment technologies, and trade-offs between technological economic and environmental emission (Dey et al., 2022; Rout et al., 2022).

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The structure of biofuel supply chain (BFSC) involves several stakeholders from the upstream to the midstream, and the downstream process of the chain, including farms or suppliers providing biomass, pre-processing facilities or collection sites, bio-refinery or biogas facilities, blending facilities, and consumer points. Technical challenges related to the BFSC are inclusive of technology and human capital, policies and government, and logistics and supply chain issues. Additionally, there are also needs to evaluate alternatives of biofuel sources and the assessment for environmental impact and limitation of fuel source's availability (Kumar and Goga, 2023). Moreover, given that the process of transforming from biomass to biofuel is complex and involves various decision makers, a thorough assessment of the supply chain system for BFSC is desired. In this study, we investigate the BFSC by integrating the K-means algorithm to evaluate the locational decision and the optimization technique to analyze the last-mile distribution decision. The multi-objective vehicle routing problem (VRP) model, in which flexible time windows (VRPFTW) are considered, is synchronized in the model. Our integrated model evaluates the perspective of socioeconomic by considering the total cost – the surrogate criterion for economic aspect as well as the lateness for delivery and the maximum delivery time – the surrogate criteria for social aspect.

The remainder of this paper is structured as follows. In Section 2, we provide an overview of relevant literature. The proposed integrated K-Means algorithm and multi-objective mathematical model for VRPFTW is developed and presented in Section 3. Then, the biofuel case study and results are deliberated in Section 4. Finally, the research conclusions and directions for future research are presented in Section 5.

2. Literature review

The BFSC involves activities and flow of various biomass types at the upstream process to the biofuel production at the midstream, and last-mile delivery to end users at the downstream process. Given that the biomass source can be dispersed over a large area, the potential advantage depends greatly on cost evaluation along the BFSC (Lan et al., 2020). The complexity and structure of the BFSC typically involves biomass providing farms, preprocessing facilities with multi-modal depots, bio-refinery and biogas plants, blending facilities, as well as gas stations and consumer points. The preprocessing operations are also required to preprocess biomass from farms to mitigate density and to ease transportation operations (Aboytes-Ojeda et al., 2022; Albashabsheh and Stamm, 2021). Next, depending on the technology and physical network type, preprocessed biomass may be delivered via single- or multi-modal transportation to biorefinery and biogas facilities. Additionally, blending operations may be needed to mix and process gasoline products with different grades for consumers. Products from biogas facilities may also be distributed for electricity usage at the downstream process.

Numerous researchers have proposed the use of biomass for BFSC and addressed operational problems concerning the efficiency and effectiveness (e.g., Raychaudhuri and Ghosh, 2016, Darda et al., 2019, REN21, 2021). For example, Raychaudhuri and Ghosh (2016) discuss policy-related challenges of BFSC implementation. Operational challenges are noted for feedstock unavailability due to inefficient resource management and the government non-intervention approaches. Moreover, operational challenges include the regional and seasonal availability and storage of biomass, supply fluctuations, and fuel price variation, increased pressure on transportation sector to transport biomass from the supply source to the production site, inefficiencies of conversion facility as well as core technology, and under developed supply chain between the biomass owners, technology providers, investors, and potential users. Additionally, social challenges are noted for conflicting decisions from the lack of coordination between stakeholders on different levels of BFSC. Challenges related to marketing and other factors from biomass' growing conditions related to the weather, demand for biofuels in the producing countries, and import markets are also noted as further needs that should be evaluated by policymakers through development plans (REN21, 2021).

Challenges related to logistics and supply chain performance for BFSC have also been discussed and studied in the literature (e.g., Ekşioğlu et al., 2016, Roni et al., 2017, Ransikarbum and Pitakaso, 2021, Kumar and Goga, 2023). Ekşioğlu et al. (2016) evaluate the BFSC and suggest that larger quantities of biomass are required to substitute the equivalent quantities used in fossil fuel. In addition, biomass is typically in the form of agricultural products and is therefore bulky and heterogeneous. Roni et al. (2017) propose that various criteria impacting BFSC are inclusive of types of feedstock, resource unavailability, and complex logistics and network structure. Ransikarbum and Pitakaso (2021) have recently recommended that suppliers in the BFSC are typically geographically dispersed and operational efficiency of upstream suppliers is needed. Moreover, design and planning for preprocessing operations and locational selection are needed so that biomass can be properly accumulated and distributed to reduce transportation cost. In addition, competitiveness of logistics and supply chain system needs to be evaluated and optimized under various criteria for BFSC (Ransikarbum and Mason, 2021).

Studies in modeling BFSC initially focus on cost-benefit analysis and decision-making. Later, optimization-based mathematical models are recognized as a capable technique to support decision makers for handling complexity of the BFSC. A number of existing optimization-based studies for BFSC, however, are only concerned with an economic perspective. Thus, studies by recent researchers have shown that other criteria related to social requirements are also required for developing and designing BFSC with socioeconomic and sustainability approach (e.g., Agustina et al., 2018, Kamali et al., 2018, Mattioda et al., 2020, Albashabsheh and Stamm, 2021, Zarrinpoor and Khani, 2022). Social part of the socioeconomic is also inclusive of poverty reduction and effects on social resources. That is, investing in BFSC can contribute to poverty alleviation through provision of energy and an increase in income and economic per capita. Additionally, future model development for BFSC also requires that uncertainty for BFSC should be considered (e.g., Ransikarbum and Mason, 2016, Osmani and Zhang, 2017, Ransikarbum ***et al.*** 2017, Agustina et al., 2018, Ahmed and Sarkar, 2018, Abbasi et al., 2021, Ransikarbum et al., 2022). For example, Ahmed and Sarkar (2018) propose a model to assess the economic and environmental aspect of BFSC and allocation for agricultural zones by considering uncertain demand for market. Mattioda et al. (2020) also analyze social aspects and provide contextualization of the social life cycle assessment for biofuel production of the BFSC in their study.

In a business context, logistics play a key role to manage various aspects of a company's operations, from sales through production and distribution. Additionally, innovation and technology can be seen as business's competitive advantages to provide and deliver value products and services for customers. While companies engaging in the traditional innovation typically lie their work in a self-resource environment, open innovation methods suggest that external knowledge sources can be relied upon for innovation management strategies (Bigliardi et al., 2021; Lam et al., 2021). Additionally, the dynamic model of open innovation further integrates an open innovation concept with complex adaptive systems and evolutionary change. The dynamic effects are essential for also the selection process for companies' future competitive strategies (Yun et al., 2020). Moreover, the term 'inbound open innovation' and 'outbound open innovation' are also referred to for business strategies when companies buy or license technologies from other companies as well as when internal technologies not being used in a firm's business are taken outside the company, respectively (Chesbrough et al., 2014; Costa and Matias, 2020).

Open innovation and dynamic effects, in particular, offers several benefits for globalization competition inclusive of cost reduction for development, accuracy enhancement for market research, performance improvement for project delivery, and enhancement for digital transformation. In particular, business ecosystems can increasingly drive digital growth to make the innovation ecosystem work since it aligns various actors to achieve a mutually beneficial purpose as well. One of a good example for an ecosystem of using open innovation dynamics is also to combine e-commerce and social media with logistics and finance. Additionally, the impacts of open innovation dynamics have been discussed in a number of business applications inclusive of small and medium-sized enterprises (SMEs), E-marketplaces, and governmental units (Baierle et al., 2020; Fasnacht, 2021; Yigitcanlar et al., 2021; Cano et al., 2022). Specific logistics applications using technology and open innovation can also be seen from a number of recent studies inclusive of autonomous vehicle, metaheuristic approach, and hub modeling (Golbabaei et al., 2020; Abdirad et al., 2021; Shmatko et al., 2021; and Moonsri et al., 2022). Thus, there is a need to account for open innovation and technology to improve and integrate business operations inclusive of the operations for BFSC.

Vehicle routing problem (VRP), in particular, is one of the common models among several studies related to the use of innovation and technology to support transportation and distribution for logistics and supply chain. The VRP and its variance have been modeled in numerous applications. Regardless, existing studies typically evaluate only the economic aspect and there is a need to take other factors for sustainability paradigm into account (Asghari and Al-e, 2021; Lo et al., 2021; Ransikarbum et al., 2021a,2021b). Besides, locational analysis should be synchronized to the VRP problem as well (Ransikarbum and Mason, 2016; Ransikarbum and Mason, 2021; Ransikarbum and Madathil, 2022). In this research, we examine the delivery-route decisions for the delivery using a selective case study of transporting wood biomass-based biofuel in the BFSC from the upstream to the midstream points. Initially, we apply the K-means algorithm to evaluate the possible locations of collection sites at the upstream of the biofuel supply chain. Next, we propose the multi-objective VRP model, in which flexible time windows (VRPTW) are synchronized in the model. The total cost is modeled to reflect the economic perspective. Then, to model the driver perspective to deliver products and to capture urgent needs under time-control constraints, the minimax objective is applied as a surrogate objective function reflecting social perspective in this study.

Next, we further highlight our proposed study and discuss research contributions as follows:

- Existing studies are conducted on a single part at the upstream, midstream, or downstream of the BFSC and few studies evaluate key elements of the supply chain in an integrated way. In this study, we propose the integrated model to examine location of pre-processing facilities for wood chip processing sites and the decisions for delivery in our study.
- Present studies emphasize only a single aspect of the economic perspective and studies that evaluate social aspect as well as socioeconomic perspective are relatively scarce. Thus, studies that deal with multi-objective optimization by considering simultaneous criteria are called for. Our proposed study evaluates multiple objectives by considering total cost as well as the lateness for delivery and the maximum delivery time in the model.
- Our proposed research methodology integrates the K-means algorithm and the VRPFTW, in which the outputs of the K-means algorithm are used as input to a multi-objective optimization model. Additionally, given that present studies lack an integrated aspect of information technologies and a consideration for innovation, such as maps and geographic information systems (GISs). Our evaluated case study utilizes the QGIS software to illustrate an applicability of the model.

3. Methodology

3.1. Problem statement

We next present the problem statement of the BFSC model in this subsection. Our model evaluates the BFSC with two echelons, which are

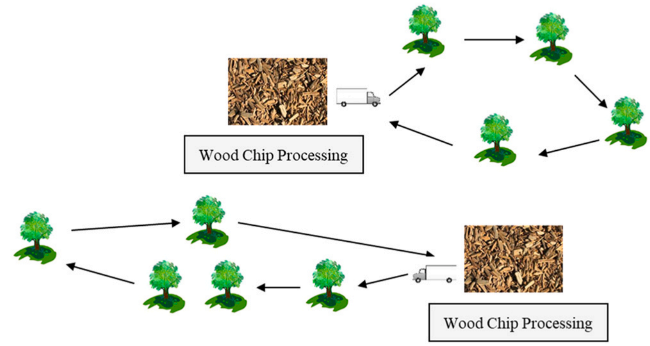

Fig. 1. The framework of problem statement in BFSC.

inclusive of wood-type biomass nodes and wood collection/wood chip processing nodes. In particular, our model seeks initially to evaluate possible locations for wood collection/wood chip processing nodes using the K-means algorithm. Then, the outputs obtained from the K-means algorithm are used as our inputs for the possible depots of the proposed mathematical optimization model. That is, the developed VRPFTW will seek to optimize the delivery trips from obtained wood chip processing nodes to biomass supply nodes in each cluster. Next, the integrated model will direct decision makers for locational selection and transportation flows of relevant commodity for wood and wood chip in the network such that the total cost, lateness, and worst-case final delivery time-related criteria will be optimized toward socio-economic outlook. Fig. 1 presents our problem statement for the design of BFSC in this study. Additionally, we summarize the high-level methodological flow chart as shown in Fig. 2.

In this paper, we propose the integrated K-means algorithm and the multi-objective optimization model. The K-means algorithm or K-means clustering algorithm are common interchangeably terms, which represent the popular unsupervised machine learning algorithms aiming to partition several observations into varied clusters. Each observation will belong to a specific cluster with the nearest mean or cluster centroid under the K-means evaluation. Additionally, multiple-objective optimization programming (MOOP) can be solved by using non-preemptive, preemptive, and epsilon-constraint methods (Ravindran, 2016; Ravindran et al., 2018; Wattanasaeng and Ransikarbum, 2021). The non-preemptive approach, in particular, can be solved as a single linear (weighted) objective model formulated with important criteria weights for each objective. In addition, common techniques to formulate and solve MOOP models involve objective normalization methods, which are used to investigate an inter-criterion comparison. Thus, one of the common normalization techniques called Linear Normalization (LN) is demonstrated in this study. Finally, the case study of the wood-biomass operations is evaluated and summarized using the QGIS software to illustrate an applicability of the proposed model.

3.2. K-means algorithm

We next discuss the classical K-means algorithm, which has been used to find the minimum-sum-of-squares clustering problem defined as in Equation (1). An aim of the algorithm is to partition the observational data into K sets, such that $S = \{S_1, S_2,., S_k\}$ that minimizes the sum of squares or variance. Benefits of the K-means algorithm are noted for a simplicity to implement, a scalability to a large dataset, and generalization to various cluster shapes. Additionally, there is no need for prior training, in which data points can be partitioned to a defined number of clusters. Thus, the algorithm can be applied by various levels of decision makers and thus chosen in this study. Some restrictions are also inclusive of the selection techniques for the value of K, the initial class center, and the capability to detect outliers (Ahmed et al., 2020; Ikotun et al., 2022). Since its development, many studies have attempted to improve the convergence behavior of the K-means

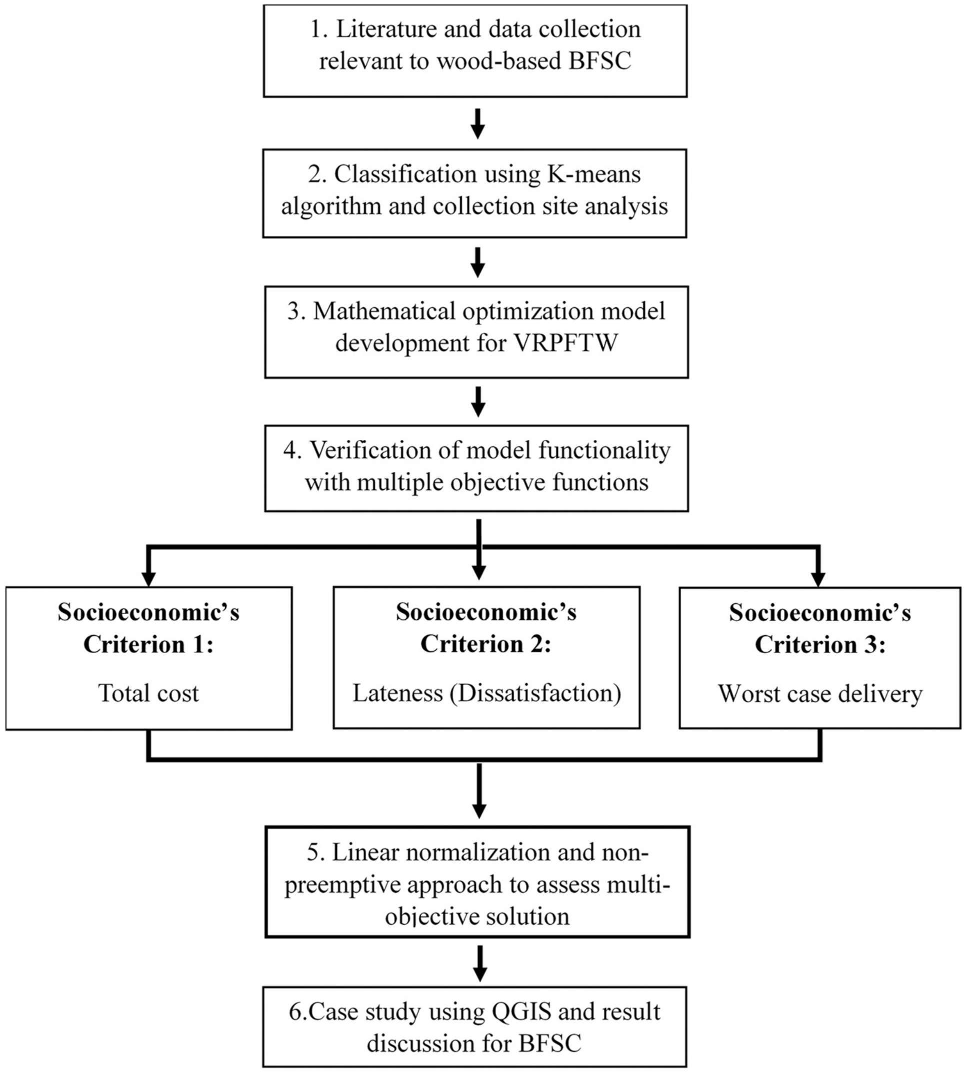

Fig. 2. The high-level methodology for the proposed model.

algorithm. K-means clustering requires the value of K or the number of clusters and the initial cluster center as input. A few techniques such as the Elbow method and the Silhouette method can evaluate appropriate K value based on within cluster sum of the squares, and similarity of data points within cluster respectively (Oh et al., 2019; Yildirim et al., 2019; Niemsakul et al., 2022). Then, the initial centroid can be computed. The objects are further moved to the closest cluster and the algorithm continues until the termination criterion is met. The schematic flowchart is presented in Fig. 3.

Additionally, the rectilinear minisum location method can be further used to determine the central location of a group of wood collection/wood chip processing facility in each cluster obtained from the K-means clustering technique. In particular, the rectilinear minisum approach seeks the optimal location that minimizes the summation of the distance and associated weight (i.e., supply amount). The rectilinear distance is used to capture the sum of the absolute difference in respective coordinates. Equations (2) – (3) show the mathematical notations, where Xor x, y is considered the optimal location of the wood collection/wood chip site, $P_i$or a_i, b_i is the existing location of each supply area of farmer growing fast-growing trees for biomass in the area, w_i is supply amount of possible woods categorized as weight in the model, and $d(X, P_i)$ is the computed rectilinear distance between the proposed location of wood collection/wood chip processing site and the existing location of each farmer, respectively.

$$Arg\ \min \sum_{i=1}^{k} \sum_{x \in S} \|X - \mu_i\|^2 \tag{1}$$

$$f(X) = \sum_{i} w_i d(X, P_i) \tag{2}$$

$$f(x, y) = \sum_{i} w_i |x - a_i| + \sum_{i} w_i |y - b_i| \tag{3}$$

3.3. Mathematical Notation for VRPFTW

3.3.1. Sets

$G(N, A)$ Graph consisting of node N and arc A.

N Set of all nodes in the BFSC, where 0 element denotes the analyzed wood collection.

sites/wood chip processing nodes.

A Set of all arcs of the transportation network.

V Set of the fleet of vehicle for transportation.

3.3.2. Parameters

n Total number of nodes points for farmers/suppliers growing wood trees in the BFSC.

m Number of available vehicles in the fleet under consideration.

c^f Fixed cost of using a particular vehicle in the fleet.

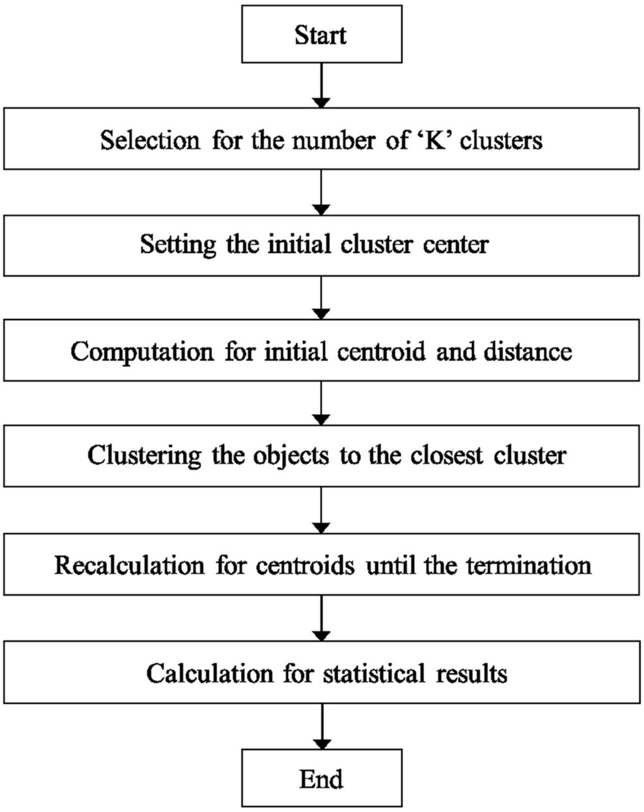

Fig. 3. The flowchart of K-means algorithm.

c^vVariable cost of transportation for a particular vehicle type in the fleet.

f^{trans} Rate of fuel consumption of a particular vehicle in the fleet.

$d_{i,j}$ Distance to transport/deliver between node location i and j, where $(i, j) \in A$.

p_i Amount of wood supplies to be picked up in each round for each node $i \in N$.

pq_k^{cap} Capacity of each vehicle k.

t^{beg} The start of the time horizon for the planning period.

t^{end} The end of the time horizon for the planning period.

t_i^s Service time for the wood loading at each node $i \in N$.

$t_{i,j}^t$ Travel time of the vehicle between location i and location j, where $(i, j) \in A$.

t_i^{ra} Agreed earliest time window for the pickup route at each node $i \in N$.

t_i^{rb} Agreed latest time window for the pickup route at each node $i \in N$.

i^{Z1} Auxiliary parameter denoting the ideal value of the first objective/criterion.

i^{Z2} Auxiliary parameter denoting the ideal value of the second objective/criterion.

i^{Z3} Auxiliary parameter denoting the ideal value of the third objective/criterion.

ai^{Z1} Auxiliary parameter denoting the antiideal value of the first objective/criterion.

ai^{Z2} Auxiliary parameter denoting the antiideal value of the second objective/criterion.

ai^{Z3} Auxiliary parameter denoting the antiideal value of the third objective/criterion.

α_l Relative weight of each objective function l under consideration.

3.3.3. Decision variables

$X_{i,j,k}$ Decision variable to assess whether to transport between locations i and j using a vehicle k, binary.

$Y_{i,j}$ Decision variable to account for cumulative amount of picking up wood supplies from node i in an arc $(i, j) \in A$, where $Y_{i,j}$ is within the vehicle capacity.

$W_{i,k}$ Decision variable to denote time to begin a loading service at node i by a vehicle k, where $W_{i,k}$ is between $t^{beg}$and t^{end}.

$S_{i,k}$ Decision variable to denote flexible time accounting for lateness from the agreed earliest time window to arrive at node i by a vehicle k.

W^{max} Decision variable to denote the worst case to arrive the last node of each vehicle trip (maximum time) with respect to all vehicles under consideration.

3.3.4. Multi-objective functions

We next discuss multiple objective functions of the proposed model. The first objective function (Equation (4)) represents the total cost minimization, in which both fixed cost of utilizing available vehicles and variable cost of transporting through the network are considered and evaluated. The next objective function in Equation (5) is to minimize lateness of picking up wood supplies, which is modeled as flexible earliest time to pick up wood products. Finally, the third objective function is to minimize the maximum time (i.e., minimax) of all drivers reaching the last wood supply node in each trip. This non-linear function of the objective function can be transformed to the linear function, in which the longest time (i.e., maximum time) of all drivers is subject to be minimized as shown in Equation (6) and (7). That is, the model will guarantee that the latest driver will not drive longer than W^{max}, subject to a number of requirements and restrictions.

$$Minimize\ Z_1 = \sum_{(0,j) \in A;\, k \in V} c^f X_{i,j,k} + \sum_{(i,j) \in A;\, k \in V} (c^v d_{i,j}/f^{trans}) X_{i,j,k} \tag{4}$$

$$Minimize\ Z_2 = \sum_{i \in N,\, k \in V} S_{i,k} \tag{5}$$

$$Minimize\ Z_3 = W^{max} \tag{6}$$

$$Subject\ To\ \ W^{max} \geq W_{i=n+1,k} - W_{o \in N,k} \quad ; \forall\, k \in V \tag{7}$$

3.3.5. Model constraints

Now that the above model's objection functions have been established, the model's constraints are next developed as follows. In particular, a constraint set in Equation (8) suggests that a vehicle will enter to a node only one at a trip time. A constraint set in Equation (9) also requires that a vehicle that enters a particular node must be the same one to leave that same node. The next set of constraints in Equation (10) ensures that each vehicle leaving the wood collection site/wood chip processing node will enter a particular node next.

$$\sum_{i \in N; i \neq j} \sum_{k \in V} X_{i,j,k} = 1;\ \forall\, j = 1, .,n \tag{8}$$

$$\sum_{i \in N;\, i \neq j} X_{i,j,k} = \sum_{i \in N;\, i \neq j} X_{j,i,k};\ \forall\, j = 1, .,n\ ;\ k \in V \tag{9}$$

$$\sum_{j \in 1,.,n} X_{0,j,k} \leq 1\ ;\ \forall\, k \in V \tag{10}$$

Next, combined constraint sets in Equations (11) and (12) compute the cumulative amount of pickup quantity at each node and help to guarantee that the cumulative amount up to a particular wood supply node will not exceed the vehicle capacity.

$$\sum_{(j,i) \in A} Y_{j,i} - \sum_{(i,j) \in A} Y_{i,j} = p_j;\ \forall\, j = 1, .,n \tag{11}$$

$$Y_{i,j} \leq \sum_{k \in V} pq_k^{cap} X_{i,j,k};\ \forall\, (i,j) \in A \tag{12}$$

The next set of constraint set in Equation (13) computes the starting time of the planning horizon for all vehicles. Next, the constraint set in

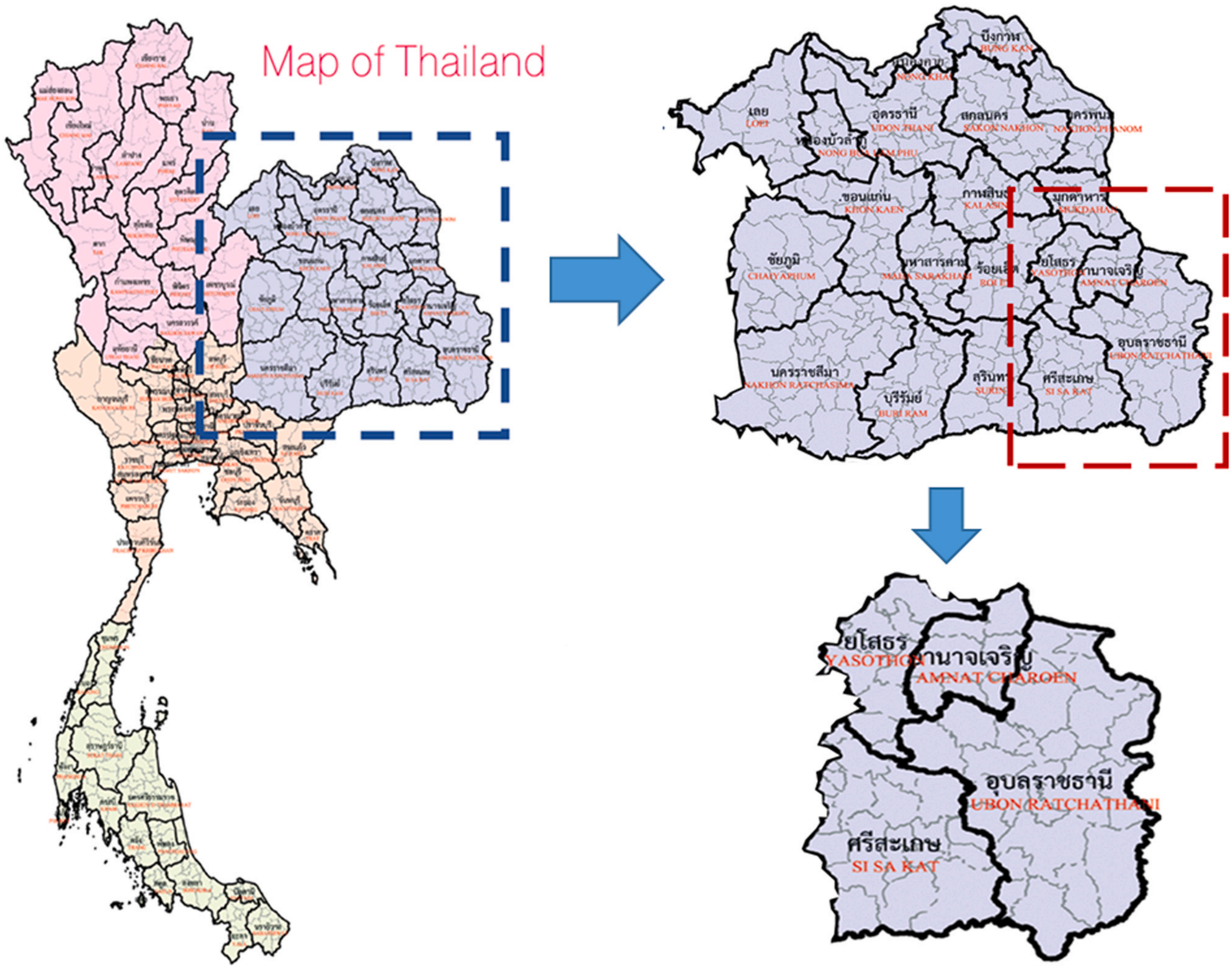

Fig. 4. Illustrated map for provinces to collect data.

Table 1
Area and supply data for the wood-type biomass supply nodes.

Wood Supply	Area in Rai (m^2)	Wood Supply	Area in Rai (m^2)	Wood Supply	Area in Rai (m^2)	Wood Supply	Area in Rai (m^2)
W1	5.30 (8476)	W23	9.90 (15,832)	W45	10.00 (16,000)	W67	10.00 (16,000)
W2	18.93 (30,292)	W24	19.35 (30,964)	W46	7.00 (11,200)	W68	5.00 (8000)
W3	11.42 (18,272)	W25	4.67 (7476)	W47	10.00 (16,000)	W69	1.00 (1600)
W4	13.09 (20,940)	W26	2.00 (3200)	W48	2.00 (3200)	W70	2.00 (3200)
W5	4.96 (7940)	W27	1.00 (1600)	W49	4.00 (6400)	W71	3.00 (4800)
W6	24.67 (39,468)	W28	2.00 (3200)	W50	2.00 (3200)	W72	1.00 (1600)
W7	2.47 (3948)	W29	2.00 (3200)	W51	2.00 (3200)	W73	1.00 (1600)
W8	21.89 (35,024)	W30	1.00 (1600)	W52	2.00 (3200)	W74	4.00 (6400)
W9	30.54 (48,868)	W31	12.00 (19,200)	W53	34.21 (54,740)	W75	2.00 (3200)
W10	1.11 (1780)	W32	1.00 (1600)	W54	7.00 (11,200)	W76	6.00 (9600)
W11	8.48 (13,572)	W33	2.00 (3200)	W55	18.98 (30,372)	W77	1.00 (1600)
W12	12.00 (19,200)	W34	13.50 (21,592)	W56	2.00 (3200)	W78	2.00 (3200)
W13	5.39 (8628)	W35	33.63 (53,808)	W57	2.00 (3200)	W79	10.00 (16,000)
W14	28.41 (45,448)	W36	2.50 (4000)	W58	2.00 (3200)	W80	2.00 (3200)
W15	16.01 (25,616)	W37	16.13 (25,800)	W59	1.00 (1600)	W81	1.00 (1600)
W16	4.05 (6472)	W38	7.00 (11,200)	W60	5.00 (8000)	W82	2.00 (3200)
W17	11.23 (17,968)	W39	1.00 (1600)	W61	1.00 (1600)	W83	2.00 (3200)
W18	35.91 (57,460)	W40	2.00 (3200)	W62	2.00 (3200)	W84	5.00 (8000)
W19	4.00 (6400)	W41	15.00 (24,000)	W63	1.00 (1600)	W85	2.00 (3200)
W20	14.87 (23,784)	W42	2.00 (3200)	W64	5.00 (8000)	W86	2.00 (3200)
W21	5.00 (8000)	W43	7.00 (11,200)	W65	5.00 (8000)	W87	2.00 (3200)
W22	11.34 (18,140)	W44	4.00 (6400)	W66	3.00 (4800)	W88	2.00 (3200)

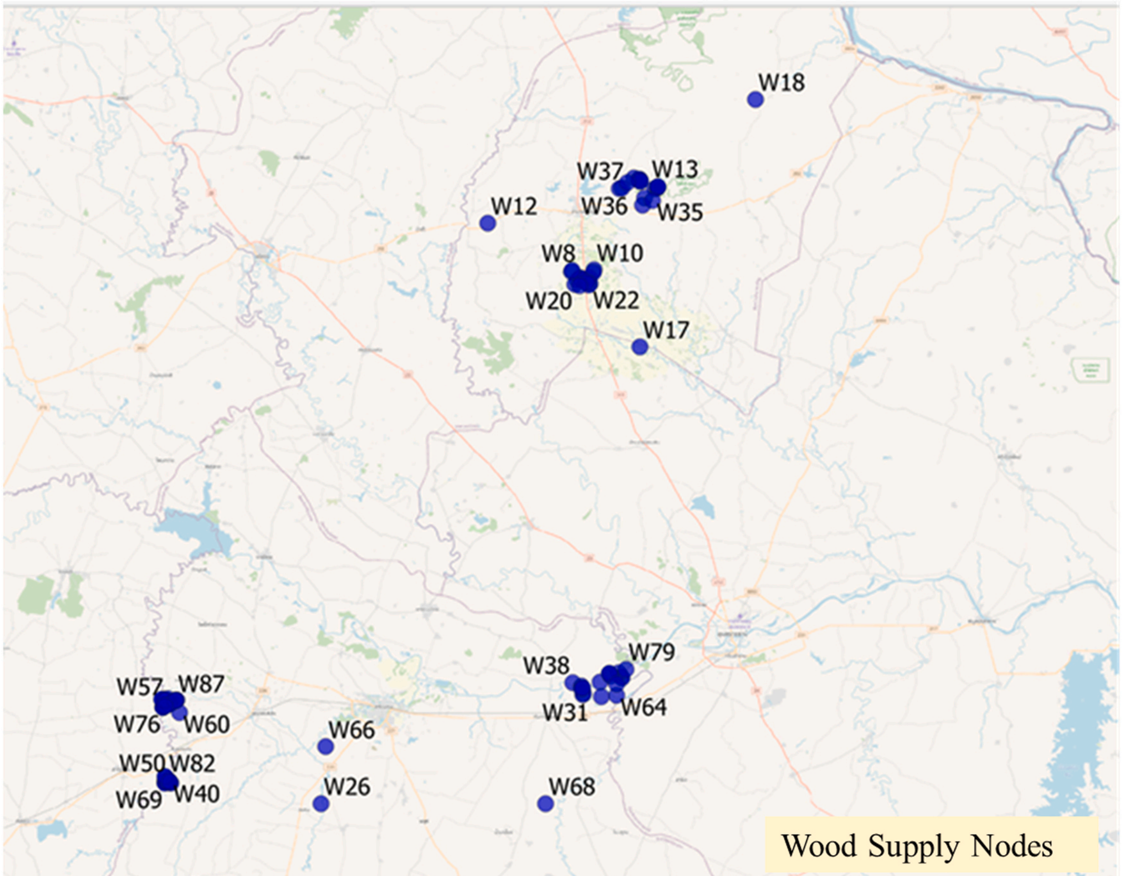

Fig. 5. Locational positions of the farmers/suppliers for wood-type biomass.

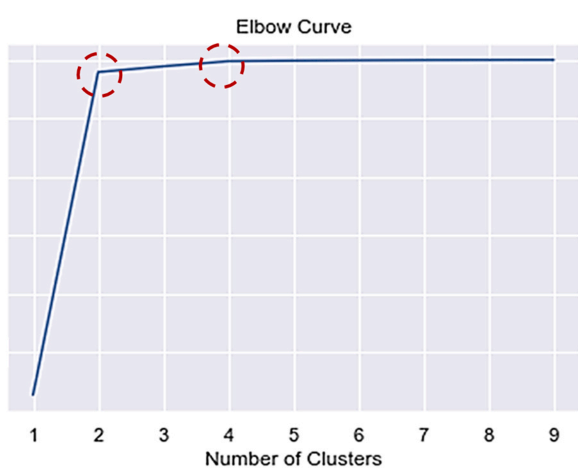

Fig. 6. Number of clusters for wood farmers analyzed using Elbow method.

Table 2
Analyzed K-means algorithm for farmers/suppliers of wood biomass.

Cluster (C)	No. of observations	Within Cluster Sum of squares	Ave. distance from Centroid	Max. distance from Centroid
C1	18	4.012	0.410	1.052
C2	10	7.079	0.784	1.349
C3	22	8.440	0.586	0.963
C4	38	3.504	0.248	0.949
	A list of members in each cluster			
C1	W27, W31, W38, W41 - W49, W64, W68, W71, W74, W79, W84			
C2	W2, W6, W8 - W9, W14, W18, W24, W35, W53, W55			
C3	W1, W3 - W5, W7, W10 - W13, W15 - W17, W19 - W23, W25, W34, W36 - W37, W54			
C4	W26, W28 - W30, W32 - W33, W39 - W40, W50 - W52, W56 - W63, W65 - W67, W69 - W70, W72 - W73, W75 - W78, W80 - W83, W85 - W88			
	Locational data (i.e., latitude and longitude) of analyzed wood collection sites			
C1	(15.1505030245, 104.6584878343)			
C2	(15.8787225908, 104.7182895657)			
C3	(15.8449394253, 104.6913502331)			
C4	(15.1151618204, 104.0034917605)			

Equation (14) computes the time that each vehicle arrives at each node in a BFSC network. The estimated arrival time of each vehicle is computed from the service time (i.e., loading time of wood supply) and the transportation time (i.e., the travel time between a pair of origin and destination locations). Then, the next set of constraints in Equations (15) and (16) combined restrict that each vehicle should arrive at each node during the agreed earliest and latest time window for the pickup operation. In our model, the flexible arrival time is modeled by using the soft constraint set with an aid of surplus variable as presented in Equation (15). That is, the surplus variable represents allowable lateness from the agreed earliest arrival time to allow for driver flexibility, whereas there is a need that the agreed latest time must me strictly met. Additionally, the constraint set in Equation (17) computes the bound of the estimated arrival time of each vehicle at each node.

$$W_{i=0,\, k\in V} = t^{beg};\ \forall\, k \in V \tag{13}$$

$$W_{i,\,k} + t_i^s + t_{i,j}^t - W_{j,\,k} \leq b(1 - X_{i,j,k});\ \forall\,(i,j) \in A\,,\ \ k \in V \tag{14}$$

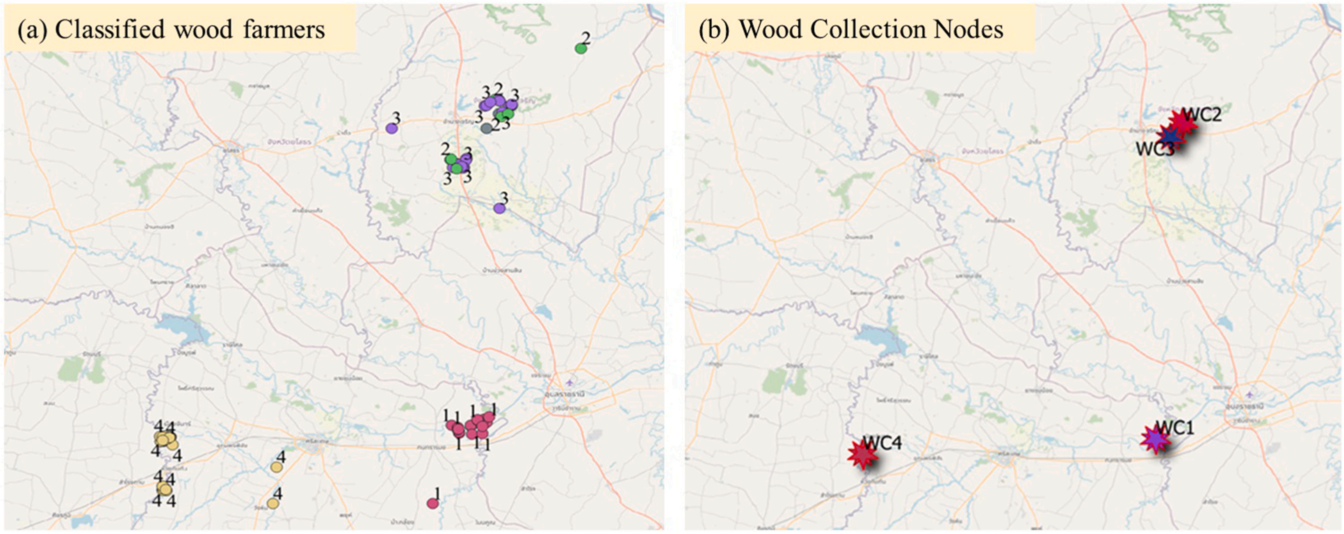

Fig. 7. (a) Four clusters of wood farmers (b) Four locations of wood collection nodes.

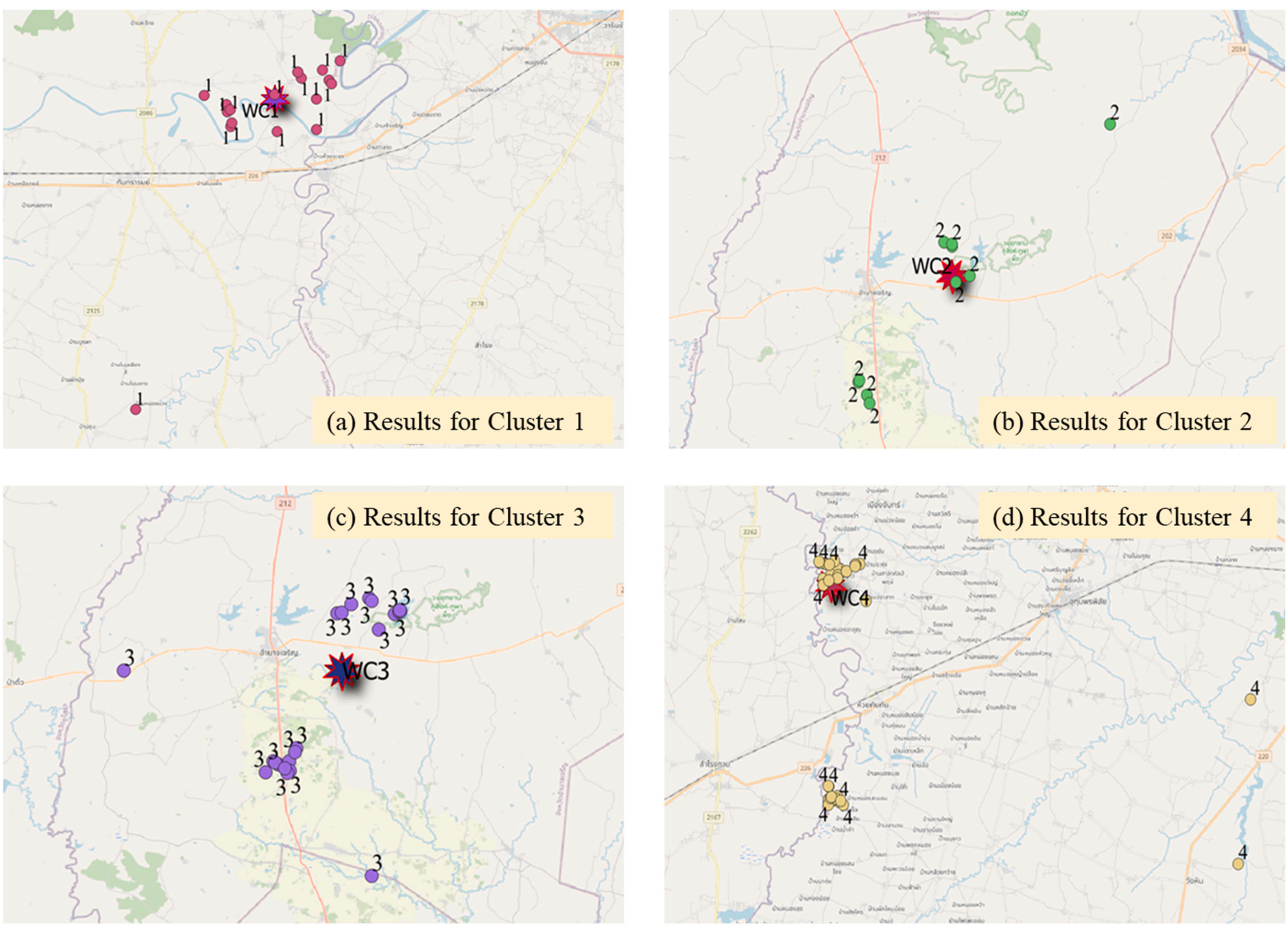

Fig. 8. Wood processing site for farmers in (a) Cluster 1, (b) Cluster 2, (c) Cluster 3, and d) Cluster 4.

$$W_{i,k} - S_{i,k} = t_i^{ra} \sum_{(i,j) \in A;\, i \neq j} X_{i,j,k};\ \forall\ i = 1, .., n,\quad k \in V \tag{15}$$

$$W_{i,k} \leq t_i^{rb} \sum_{(i,j) \in A;\, i \neq j} X_{i,j,k};\ \forall\ i = 1, .., n,\quad k \in V \tag{16}$$

$$t^{beg} \leq W_{i,k} \leq t^{end};\ \forall\ i = 1, .., n,\quad k \in V \tag{17}$$

Finally, variable-type constraints relevant to dimensions of decision variables, which are inclusive of binary and continuous-types for the proposed mixed integer linear programming model are shown in Equations (18) – (22).

$$X_{i,j,k} \in \{0, 1\};\ \forall\ (i, j) \in A,\quad k \in V \tag{18}$$

$$Y_{i,j} \geq 0;\ \forall\ (i, j) \in A \tag{19}$$

Table 3
Locational, quantity, and time relevant data of the case study.

Location	Latitude	Longitude	Pickup quantity (kilograms)	Time window (agreed earliest time)	Time window (agreed latest time)
Wood supply site (WC1)	13.5793359	100.7617415		N/A	N/A
Node 1 (W27)	15.1615522	104.6905147	57	9:00	17:00
Node 2 (W31)	15.1344963	104.6327180	679	9:30	10:20
Node 3 (W38)	15.1526875	104.6168721	396	9:00	17:00
Node 4 (W41)	15.1366762	104.6333192	849	10:00	11:01
Node 5 (W42)	15.1472667	104.6299594	113	9:00	17:00
Node 6 (W43)	15.1430998	104.6305810	396	10:30	11:49
Node 7 (W44)	15.1430998	104.6324031	226	9:00	17:00
Node 8 (W45)	15.1533872	104.6584877	566	11:00	12:02
Node 9 (W46)	15.1593389	104.6918025	396	9:00	17:00
Node 10 (W47)	15.1673784	104.6866989	566	11:30	12:57
Node 11 (W48)	15.1315736	104.6599839	113	9:00	17:00
Node 12 (W49)	15.1664174	104.6721321	226	12:00	13:16
Node 13 (W64)	15.1327825	104.6830828	283	9:00	17:00
Node 14 (W68)	14.9700875	104.5766218	283	12:30	13:40
Node 15 (W71)	15.1627767	104.6740553	170	9:00	17:00
Node 16 (W74)	15.1664174	104.6721321	226	13:00	13:55
Node 17 (W79)	15.1728261	104.6970240	566	9:00	17:00
Node 18 (W84)	15.1505027	104.6829633	283	13:30	14:52

$$W_{i,k} \geq 0; \forall\, i = 1, .,n, \quad k \in V \tag{20}$$

$$S_{i,j} \geq 0; \forall\, (i,j) \in A \tag{21}$$

$$W^{max} \geq 0 \tag{22}$$

3.4. Analysis of multi-objective optimization model

3.4.1. Linear normalization (LN) tchnique

We next discuss the LN technique as shown in Equations (23) – (24) for a profit-type objective (i.e., the more criterion value, the better) and a cost-type objective (i.e., the lesser criterion value, the better), respectively (Ravindran, 2016; Ransikarbum et al., 2021a,2021b). This normalization technique converts data to be in a range between 0 and 1. Both the ideal/utopia (I) and anti-ideal/nadir (AI) solutions are employed, where the I and AI solutions are the best and the worst possible feasible solution from considering each objective j, respectively. In particular, the I_j notation represents the ideal solution based on the highest value (i.e., maximum) for profit-type objective function and the lowest value (i.e., minimum) for cost-type objective function. In contrast, the AI_j notation implies the anti-ideal solution based on minimum value for profit-type objective function and maximum value for cost-type objective function. We note that all the normalized values ($n_j(x)$) after performing the LN technique will be transformed to the profit-type objective function (i.e., maximum value is considered better).

$$n_j(x) = \frac{f_j(x) - AI_j}{I_j - AI_j} \quad ; \; Profit - type \tag{23}$$

$$n_j(x) = \frac{AI_j - f_j(x)}{AI_j - I_j} \quad ; \; Cost - type \tag{24}$$

3.4.2. Non-preemptive approach

We next discuss the non-preemptive approach, which can be used to transform the multi-objective optimization into a single-objective optimization problem by using a weighted sum of the objective functions under consideration. In particular, by implementing the LN technique introduced earlier, each objective function will be transferred to a profit-type objective function and in a range between 0 and 1. A range between 0 and 1 of each objective function helps to allow inter-criterion comparison with unitless. Next, the non-preemptive approach can be used to integrate various objective functions and combine into a single-objective optimization problem as shown in Equations (25) – (26).

$$Maximize \;\; Z^{NP} = \alpha_{Z1}\left(\frac{ai^{Z1} - Z_1}{ai^{Z1} - i^{Z1}}\right) + \alpha_{Z2}\left(\frac{ai^{Z2} - Z_2}{ai^{Z2} - i^{Z2}}\right) + \alpha_{Z3}\left(\frac{ai^{Z3} - Z_3}{ai^{Z3} - i^{Z3}}\right) \tag{25}$$

$$\alpha_{Z1} + \alpha_{Z2} + \alpha_{Z3} = 1 \tag{26}$$

4. Case study and results

4.1. Case study

We next discuss the case study and data collection for an analysis of the BFSC design in this study. Initially, we used the data obtained from the Information Center of the Royal Forest Department (2022), Ministry of Natural Resources and Environment (MNRE), Thailand. This case study focuses theNortheastern region of Thailand with 20 provinces. These provinces are governed and separated by four governmental districts. We used the data from four provinces (i.e., Ubon Ratchathani, Yasothon, Amnat Charoen, and Sisaket) for this study (Fig. 4). Next, data related to total utilized area and locational coordinates (i.e., latitude and longitude) are gathered from farmers participated in the RFD's project and from the GIS software to promote fast growing trees for renewable energy in the BSCN. Collected data show that there are 88 farmers with diverse areas participating in the project. The summary data relevant to the growing area in Rai (Squared meters (m^2)) are presented in Table 1. Moreover, data related to locational coordinates (i.e., latitude and longitude) of fast growing wood-biomass farm/nodes (i.e., N^W) are also collected and converted to a map format using Geographic Information System (GIS) platform as illustrated in Figure 5.

4.2. Analysis using K-means Algorithm

We next discuss the analysis using K-means algorithm to classify variables related to supply area and locational (i.e., latitude and longitude) data for all 88 farmers/suppliers. Initially, the Elbow method is coded in Python to evaluate the proper number of K (i.e., number of classified groups). In particular, the Elbow method implements a heuristic procedure to determine the number of clusters in a data set, which involves plotting the explained variation as a function of the number of clusters. Then, the elbow-like or linear-piecewise point of the curve can be chosen as the number of clusters to further implement in the K-means algorithm. In our analysis, the Elbow method suggests that

Table 4
Origin-Destination Matrix (OD Matrix) for distance of the wood farmers in Cluster 1.

	WC1	W27	W31	W38	W41	W42	W43	W44	W45	W46	W47
WC1	0.0	3.7	3.3	4.5	3.1	3.1	3.1	2.9	0.3	3.7	3.6
W27	3.7	0.0	6.9	8.0	6.7	6.7	6.8	6.5	3.6	0.3	0.8
W31	3.3	6.9	0.0	2.6	0.3	1.5	1.0	1.1	3.5	6.9	6.9
W38	4.5	8.0	2.6	0.0	2.5	1.5	1.8	1.9	4.5	8.1	7.7
W41	3.1	6.7	0.3	2.5	0.0	1.2	0.8	0.9	3.3	6.8	6.7
W42	3.1	6.7	1.5	1.5	1.2	0.0	0.5	0.4	3.1	6.8	6.5
W43	3.1	6.8	1.0	1.8	0.8	0.5	0.0	0.2	3.2	6.8	6.6
W44	2.9	6.5	1.1	1.9	0.9	0.4	0.2	0.0	3.0	6.6	6.4
W45	0.3	3.6	3.5	4.5	3.3	3.1	3.2	3.0	0.0	3.6	3.4
W46	3.7	0.3	6.9	8.1	6.8	6.8	6.8	6.6	3.6	0.0	1.0
W47	3.6	0.8	6.9	7.7	6.7	6.5	6.6	6.4	3.4	1.0	0.0
W48	2.1	4.7	2.9	5.2	2.9	3.7	3.4	3.3	2.4	4.6	4.9
W49	2.3	2.0	5.5	6.1	5.3	5.0	5.2	4.9	2.1	2.3	1.6
W64	3.3	3.3	5.4	7.4	5.4	5.9	5.8	5.6	3.5	3.1	3.9
W68	21.9	24.6	19.2	20.8	19.5	20.5	20.1	20.3	22.2	24.4	24.9
W71	2.2	1.8	5.4	6.2	5.2	5.0	5.2	4.9	2.0	1.9	1.5
W74	2.3	2.0	5.5	6.1	5.3	5.0	5.2	4.9	2.1	2.3	1.6
W79	4.8	1.4	8.1	8.9	7.9	7.7	7.9	7.6	4.7	1.6	1.3
W84	2.6	1.5	5.7	7.1	5.5	5.7	5.7	5.5	2.6	1.4	1.9

	W48	W49	W64	W68	W71	W74	W79	W84
WC1	2.1	2.3	3.3	21.9	2.2	2.3	4.8	2.6
W27	4.7	2.0	3.3	24.6	1.8	2.0	1.4	1.5
W31	2.9	5.5	5.4	19.2	5.4	5.5	8.1	5.7
W38	5.2	6.1	7.4	20.8	6.2	6.1	8.9	7.1
W41	2.9	5.3	5.4	19.5	5.2	5.3	7.9	5.5
W42	3.7	5.0	5.9	20.5	5.0	5.0	7.7	5.7
W43	3.4	5.2	5.8	20.1	5.2	5.2	7.9	5.7
W44	3.3	4.9	5.6	20.3	4.9	4.9	7.6	5.5
W45	2.4	2.1	3.5	22.2	2.0	2.1	4.7	2.6
W46	4.6	2.3	3.1	24.4	1.9	2.3	1.6	1.4
W47	4.9	1.6	3.9	24.9	1.5	1.6	1.3	1.9
W48	0.0	4.1	2.5	20.1	3.8	4.1	6.1	3.2
W49	4.1	0.0	3.9	24.1	0.5	0.0	2.8	2.1
W64	2.5	3.9	0.0	21.4	3.5	3.9	4.7	2.0
W68	20.1	24.1	21.4	0.0	23.8	24.1	26.0	23.1

(*continued on next page*)

Table 4 (*continued*)

	WC1	W27	W31	W38	W41	W42	W43	W44	W45	W46	W47
W71	3.8	0.5	3.5	23.8	0.0	0.5	2.7	1.7			
W74	4.1	0.0	3.9	24.1	0.5	0.0	2.8	2.1			
W79	6.1	2.8	4.7	26.0	2.7	2.8	0.0	2.9			
W84	3.2	2.1	2.0	23.1	1.7	2.1	2.9	0.0			

the above data set can be grouped to either 2 clusters or 4 clusters (i.e., the step of the stepwise linear curve) (Figure 6). The variance or the within clusters sum of squared errors (Y-axis) can be plotted against the number of clusters (X-axis). Next, given a discussion of the key stakeholders, four clusters are selected as a proper number of 'K' in our analysis to illustrate the selection of the wood collection/wood chip processing site.

Next, to examine how each farmer/supplier of wood biomass should be grouped in to a cluster among the four clusters, the K-means algorithm is applied. Three key associated variables for an analysis are supply area, latitude, and longitude, respectively. The algorithm, in particular, assesses each observation (i.e., farmer), and moves into the nearest cluster, which has the smallest Euclidean distance between the observation and the centroid of the respective cluster. Analyzed results are shown in Table 2. It can be seen that Cluster 4 has the least variability of the 4 clusters, followed by Cluster 1, 2, and 3, respectively. Additionally, to determine a central location for wood collection site to collect wood and produce wood chip for subsequent process of the BFSC, the rectilinear minisum location model is applied, where the rectilinear distance helps to better illustrate the structure of road network (Tompkins et al., 2010). The results for locational positions of suggested sites for wood collection /wood chip processing nodes are also presented in the table.

We further illustrate how farmers are grouped in each associated cluster using a GIS map as shown in Figure 7(a). Figure 7(b) further illustrates analyzed wood collection/woodchip processing locations. Additionally, we further present a wood collection/wood chip processing site with associated farmers in each cluster as shown in Figures 8(a) – 8(d), respectively. Clearly, both the distance/location and land area associated with each farmer are considered to determine a proper wood collection/ wood chip processing site.

4.3. Analysis using VRPFTW model

We next discuss the next results obtained from analyzing the pickup route from the associated wood collection sites to each farmer using the developed VRPFTW model. In our study, we demonstrate the pickup route of the first cluster (i.e., C1) in an analysis. We note however that other clusters can be similarly applied and interpreted. In our study, we model the proposed mathematical problem in AMPL software and solved on a computer with processor of Intel ® Core ™ i7–6500 U CPU with installed RAM of 8.00 GB. Given that the proposed model is a variant of VRP model, in which the complexity is known to be NP-hard problem, the maximum computation time to solve is used (Geetha et al., 2012). In this study, the computation time is limited to 3600 s for each problem instance.

Initially, data related to key parameters for the VRPFTW are collected and assessed as shown in Table 3. In particular, data relevant to locational node (i.e., latitude and longitude), estimated pickup quantity (in boxes), approximated time window for each node (i.e., agreed earliest and latest time to pickup) are obtained and presented. For example, in order to pick up wood supplies at node W45 with an estimated amount of 566 kg per day, there is a time requirement for a pickup time from 11:00 AM – 12:02 PM. The flexible time is also allowed after 11:00 AM, but there is a strict need to pick up by 12:02 PM. Other time slots of pickup are not allowed by the model and the farmers. We note that some nodes in our case study have no any restrictions for the required time windows (i.e., 'no requirement' in the table). For instance, in order to pick up wood supplies at node W27, an estimated amount of 57 kg per day is needed. There is no requirement for a pickup time implying that a driver can arrive at any time from 9:00 AM – 5:00 PM.

Next, based on the latitude and longitude data of each node in the network, we compute the distance in kilometers as illustrated in the Origin-Destination (O-D) matrix in Table 4. In addition, there are some assumptions associated with other parameter data that are worth

Table 5
Results from solving the VRPFTW with single- and multi-objective function of Cluster 1.

	Minimize Z_1	*Minimize* Z_2	*Minimize* Z_3	Non-Preemptive
Total cost (Baht)	5533	10,792	10,825	5625
Total lateness (minutes)	1738	35	289	150
W_max	16:00	14:55	13:55	13:55
Number of used vehicles	5	10	10	5
Computation time (s)	3600	495	3600	3600

Table 6
Results for operational planning using the non-preemptive case.

Vehicle	Route plan
V1	WC1 – N7 – N5 – N4 – N14 – WC1
V2	WC1 – N11 – N3 – N12 – N18 – WC1
V3	WC1 – N15 – N9 – N8 – WC1
V4	WC1 – N1 – N2 – N6 – N16 – WC1
V5	WC1 – N13 – N17 – N10 – WC1
Vehicle	Estimated Arriving time
V1	9:00 – 9:04 – 9:28 – 10:00 – 12:30 – 13:55
V2	9:00 – 9:05 – 9:36 – 12:00 – 13:30 – 13:55
V3	9:00 – 9:05 – 9:29 – 11:00 – 11:23
V4	9:00 – 9:04 – 9:37 – 10:30 – 13:00 – 13:55
V5	9:00 – 9:04 – 9:33 – 11:30 – 11:57
Vehicle	Cumulative pickup quantity
V1	WC1 – 226 kg. – 339 kg. – 1188 kg. – 1471 kg. – WC1
V2	WC1 – 566 kg. – 962 kg. – 1188 kg. – 1471 kg. – WC1
V3	WC1 – 170 kg. – 566 kg. – 1132 kg. – WC1
V4	WC1 – 57 kg. – 736 kg. – 1132 kg. – 1358 kg. – WC1
V5	WC1 – 368 kg. – 934 kg. – 1500 kg. – WC1

mentioning. That is, we assume that the available fleet of vehicles for the operational planning is at most 15 vehicles, in which the capacity of each vehicle is approximated for 1500 kg per planning trip. Additionally, the loading time and the time window of each node are obtained from the historical data and based on agreed approximation. In addition, we assume that the planning horizon is for 8 h starting from 9:00 AM – 5:00 PM inclusive of the lunch break. Next, the speed of the driver is assumed to be 60 kilometers per hour. Thus, given the distance in kilometers between a pair of nodes, the associated travel time in minutes can be computed and obtained. Clearly, these parameter data used in the model can be adjusted based on different policies and requirements of concerned stakeholders in the BFSC.

We next illustrate how our developed model works with data obtained from the case study. Initially, each objective function is solved as a single-objective optimization model to evaluate the ideal solution and anti-ideal solution of the case study data. Then, these acquired ideal and anti-ideal solutions are combined with the LN technique to find the multi-objective solution of the problem using the non-preemptive method. That is, the LN converts actual units of each objective function from solving the problem into a numeric value ranging between 0 and 1, where the highest value is considered the better. Then, the non-preemptive method converts the multi-objective optimization model into a weighted single objective function.

The results obtained are presented in Table 5 for both solving with each single objective function and with the non-preemptive approach. The results clearly suggest that there are trade-offs among each conflicting objective function, in which the results from the non-preemptive approach is found to be the compromising one. For example, solving the total cost objective shows that the total cost in Baht is the minimum one with 5533 Baht and only 5 vehicles are used. However, there are trade-offs such that the total lateness and the latest time of the last stop at the worst case is at 16:00. In contrast, minimizing the total lateness shows that only 35 min are needed to account for the flexibility in driving. However, the total cost is found to be quite high with 10,792 Baht for 10 used vehicles. Similarly, optimizing the last objective of W_max shows that the worst case of the latest time for the last node is guaranteed to be by 13:55 with a trade-off in high total cost and lateness. Meanwhile, the results obtained from solving the multi-objective model using the non-preemptive approach show that by balancing the three objective functions, the latest time of the last node will be at 13:55 with the lateness of 150 min as well as the total cost of 5625 Baht for five vehicles. Additionally, the computation time is found to reach the allowed maximum time for all the cases except for the second objective function.

We further illustrate key results related to decision variables for the operational planning based on solving the non-preemptive case as shown in Table 6. Both a route plan for the pickup and estimated arrival time at each wood supply node are also presented. For example, the first vehicle starts from the wood collection site (i.e., WC1) at 9:00 and moves to N7 (i.e., W44) at 9:04 to pick up 226 kg of wood supply. Then the same vehicle moves to N5 (i.e., W42) at 9:28 to pick up 113 kg of wood supply. Thus, the used space for the amount of wood supply in the vehicle is now at 339 kg. Next, the vehicle moves to N4 (i.e., W41) at 10:00 to pick up wood supply for 849 kg and then moves to N14 (i.e., W68) at 12:30 to pick up 283 kg of wood supply at this node. The accumulative amount is now at 1471 kg, which is close to the capacity limit of the vehicle at 1500 kg. Thus, the vehicle returns to the wood collection/wood chip processing node at WC1. Additionally, the obtained results strongly suggest that this vehicle arrives at N7 at 9:04 and N5 at 9:28, in which the agreed earliest arrival time should be at 9:00. This is due to the time flexibility allowance of the model to allow that each driver can arrive at each node more or less than the agreed earliest time, but with the strict requirement for the agreed latest time for the time window slot of each wood supply node. We note that similar interpretation can be performed for other vehicles and routes. We further provide the illustrated results using GIS map as shown **in** Figure 9.

4.4. Discussion and Managerial Implication

Technology as well as open innovation can be seen as strategic policies and competitive advanatges because they not only can contribute to business performance and competitiveness, but also can be considered key and dynamic sources of value establishment and strategic differentiation. One of the key operations impacting business strategy and productivity pertains to logistics operation. The success in the overall business plan also lies in the integration among key stakeholders in the business supply chain. This is also the case for BFSC, in which operational success requires a great deal of integration among upstream, midstream, and downstream process. Thus, rather than considering decisions for locations of pre-processing facilities of wood chip processing sites and distribution channels in an isolate way, there is a need to integrate both problems as presented in this study. In particular, both the K-means algorithm and the VRPFTW models can be developed and used in an integrated way as illustrated in this study.

The implementation of K-means algorithm allows a decision maker in the BFSC to conveniently investigate clusters of farm and wood locations without the need for the complex training procedure of the algorithm. Additionally, the use of integrative non-preemptive approach and the LN technique also allows the complex multi-objective optimization programming to be assessed and examined. Additionally, the employed LN can also be further applied when decision makers involving in the BFSC need further sensitivity analysis. That is, various

Fig. 9. Pickup route for five vehicles for Cluster 1.

relative weight computation techniques can be further integrated to account for decision makers' preferences on diverse aspects of objective functions.

5. Conclusions and future research

Biofuels are considered renewable-type energy that are derived from biomass. In contrast to fossil fuels being non-renewables, biofuels are relatively less-flammable compared to fossil fuels and can support greenhouse gas reduction. Planning for biofuel logistics and supply chain has recently been one of the emerging research topics worldwide due to a complex structure and requirements comparing to traditional network. Both locational and distribution decisions in the biofuel sector are thus requiring attentions to make the chain sustainable eventually. In this research, the integrated K-Means algorithm and the multi-objective optimization model for biomass pickup route from the located wood collection site/wood chip processing node was proposed. In particular, the K-means algorithm is used together with the rectilinear minisum location model to evaluate the proper location of wood chip processing node, whereas the vehicle routing problem with flexible time window is proposed to tackle the pickup route planning. The multiple objectives are evaluated, which are in the realm of socio-economic perspective, inclusive of the total cost, the lateness, or allowance of flexible time, and the latest time to reach the last destination node of each route. We then verified and validated the model by demonstrating the model with a regional case study of wood type-biomass data in Thailand. We furthered assessed tradeoffs among conflicting objectives of interest in using the integrated linear normalization technique and the non-preemptive approach.

This paper offers a real-world case study for practitioners and supply chain designers in the context of biofuel supply chain. Limitations of the current study include the model complexity, the single type of wood biomass, the deterministic aspect for parameters, and the two echelons of the BFSC currently examined. Thus, future research directions include assessing algorithms to handle large-scale BFSC problem. As it is evident that larger data set relevant to biofuel sector can be expected in this globalization era, multi-objective metaheuristic approaches can be further examined in an effort to deliver practical solutions under efficient computation time. Next, fuzzy K-means and stochastic programming can be further analyzed and modeled to tackle uncertainty aspects. Besides, it is also interested to investigate not only other types of biomass to evaluate multicommodity aspect of the model, but also to evaluate other types of renewable energy sources in corresponding to sustainability goals.

Declaration of Competing Interest

The authors declare no conflict of interest.

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