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Article

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Transborder logistics network design for agricultural product transportation in the Greater Mekong Subregion[☆]



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ABSTRACT

This research aimed to design a transportation model for the international trade of agricultural products between Thailand, Laos, and Cambodia, known as the Great Mekong Subregion (GMS). Agricultural products are transported from a farmers' cooperative to a foreign end market. The mathematical models GA, DE, and VaNSAS were developed to determine the optimal mode of transportation. The objectives of the proposed methods are to (1) maximize the total profit for the entire agricultural chain and (2) minimize the makespan or the arrival time of the containers to the end market in order to maintain the freshness of the agricultural product. The computational result shows that VaNSAS produces a 100 % optimal solution for small-size problem instances, while DE and GA produce a 63.63 % and 72.72 % optimal solution, respectively. For large-size problem instances, VaNSAS shows a profit that is higher than that of DE and GA by 10.53 % and 8.96 %, respectively, while it shows a makespan that is lower by 9.57 % and 7.20 %, respectively.

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1. Introduction

The Greater Mekong Subregion (GMS) is an economic cooperation program that was developed from the Mekong committee in 1952 under the assistance of the Asian Development Bank (ADB). The GMS members consisted of six countries along the Mekong River's bank: Cambodia, the People's Republic of China (PRC), the Lao People's Democratic Republic (Lao PDR), Myanmar, Thailand, and Vietnam. More than 350 million people live in the GMS member countries, which thus play an important role in the regional economic system, with an intra-GMS trade value of around 490 billion USD (Dul & Limmeechokchai, 2021; Kengpol et al., 2012; Komchornrit, 2017; Le et al., 2020).

Road transportation is the principal mode of transport in the Greater Mekong Subregion. However, its management and operations still need to be harmonized and standardized. The challenge is that road infrastructure in Cambodia, Lao PDR, Myanmar, and Vietnam continues to lag behind that of Thailand and PRC. Multilane divided highways only exist in Vietnam. Limited access highways are non-existent in Cambodia, Lao PDR, and Myanmar. Ring roads around major cities and toll roads only exist in Myanmar and Vietnam, where urban congestion has hindered the efficient flow of goods carried by trucks, especially during peak hours. This is also among the reasons behind the implementation of total or partial truck bans in the GMS, the only exception being Guangxi province (Banomyong, 2013).

The GMS transportation network, which is depicted in Fig. 1, aims to link all GMS nations together as well as with China and India. The Asian Development Bank (ADB) is funding this global endeavor. To encourage social and economic growth, ADB helps its members and partners by offering loans, grants, technical assistance, and equity investments. When the project is complete, it will make international trade between these regions and the rest of the world

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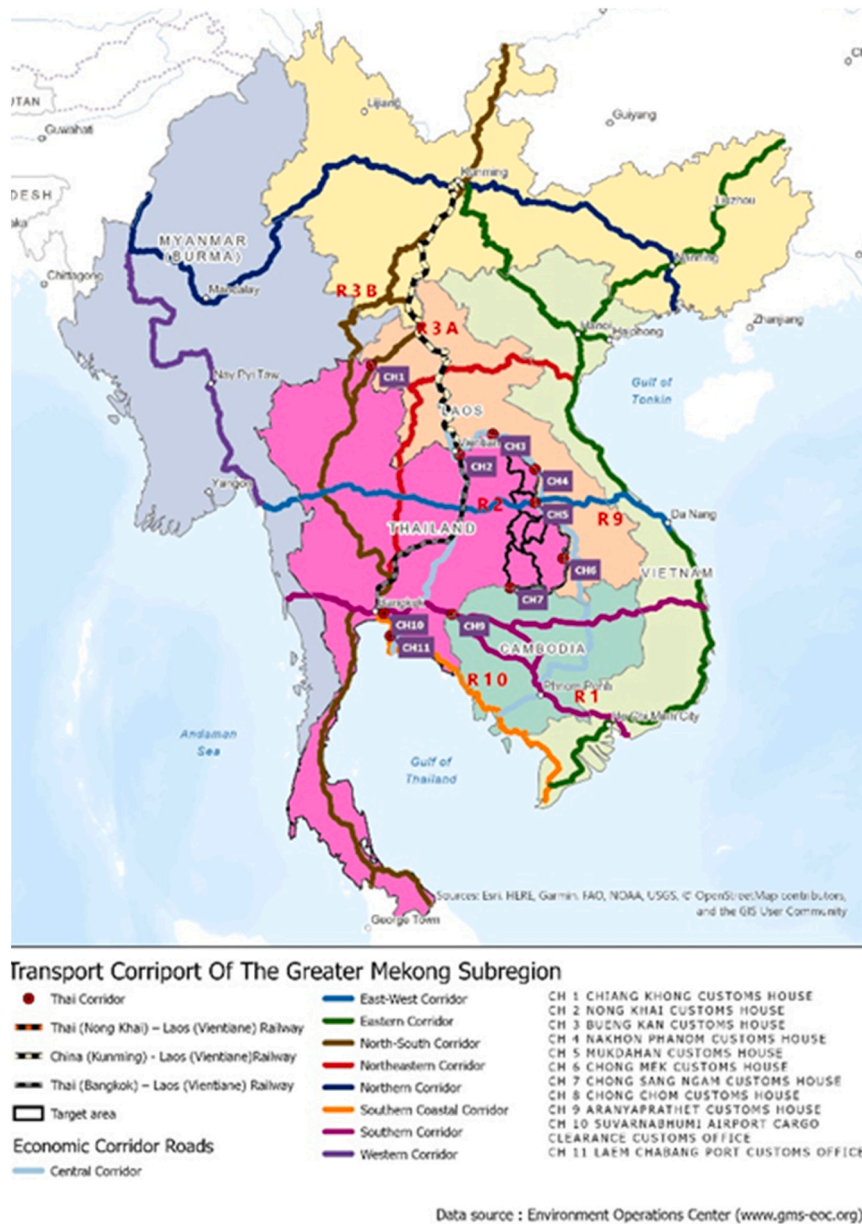


Fig. 1. Transport network in GMS.

easier. For the particular regions or locations that are not located immediately on the main economic corridor road, an efficient logistics network design is required to connect their transportation infrastructure to the main regional road. Additionally, one of the most things that travel through this area is agricultural product, a perishable good that degrades easily while in transportation. This makes the agricultural product-specific logistics network essential for maintaining the region's competitiveness in global trade.

Logistics network design is a crucial activity for enhancing the efficiency and effectiveness of the trading and transportation of goods (Ayvaz et al., 2015; Hatefi & Jolai, 2014; Li et al., 2021; Wang, Huang et al., 2021; Wang, Cheng et al., 2021). A better logistics network contributes to improved logistics and supply chain management in a region. Nguyen et al. (2021) considered the current situation and analyzed 21 cities' logistics freight volume and combined the characteristics of the hub-and-spoke network structure among ASEAN countries, which includes some GMS countries in the bloc. The results revealed that an ASEAN regional logistics network is

based on Singapore as a hub node center. The cities with the main radiating logistics demand of the Jakarta logistics development belt are Ho Chi Minh, Kuching, and Java; those of the Kuala Lumpur logistics development belt are East Kalimantan, Kuantan, and Da Nang; those of the Chon Buri logistics development belt are Phnom Penh and Riau; those of the Bangkok logistics development belt are Hanoi, Vientiane, and Yangon.

Transportation problems related to agricultural products have been widely studied (Akpınar, 2021; Hsu et al., 2007; Osvald & Stirn, 2008; Sethanan & Pitakaso, 2016; Seyyedhasani & Dvorak, 2018; Shahabi-Shahmiri et al., 2021; Tarantilis & Kiranoudis, 2002). Agricultural products are perishable and need intensive care during transportation to the destination. Distribution planning problems with stochastic and time-dependent travel times and time-varying temperatures have been modeled. Many authors (Baghizadeh et al., 2021; Derigs et al., 2011; Doerner et al., 2008; Hsu et al., 2007; Hwang & Yoon, 1981; Khan et al., 2020; Ma et al., 2017; Mendoza et al., 2011; Mercier et al., 2017; Reis & Leal, 2015; Wang et al., 2018;

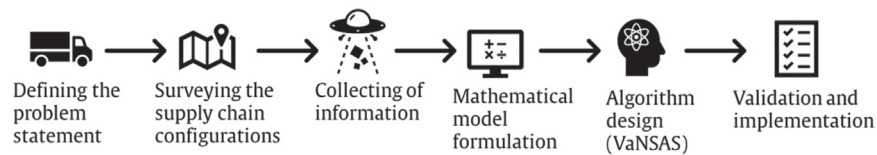


Fig. 2. Research logical process.

Zulvia et al., 2020) have proposed different shipping strategies, have identified a number of actors in the transportation chain, and have outlined the limitations of different transportation modes. Transported agricultural products pass through different actors in the supply chain; thus, it forms a transportation or service network. The service network design (SND) problem has been modeled and presented by Andersen et al. (2009a, 2009b), Andersen et al. (2011), Li et al. (2017), Moccia et al. (2011), Pedersen et al. (2009), and Thiongane et al. (2015). We were unable to discover any research that designed the agricultural logistics network in these regions, despite the fact that we have reviewed the research pertaining to the logistics network design and transportation in GMS regions.

The purpose of this research was to design a logistics network for the border trade of agricultural products between Thailand, Laos, and Cambodia. The area along the Thai-Loas border, which is not directly on the major road of the economic corridor, will be the focus of the investigation. These include the Thai provinces of Ubon Ratchathani, Srisaket, Amnatchareon, Mukdahan, and Nakornpanom. The farmers who produce the agricultural goods in this area are not accustomed to the activities associated with product export. Particularly in the custom process and while considering the providers of transportation logistics. In this situation, the container loading center (CLC) will be utilized as a tool to facilitate the import and export of agricultural products in this region so that the farmers can readily access the import and export mode. The CLC will be utilized as the venue to collect agricultural products from the farmers, handle customs, and ship the goods to the final consumer, who is located in a country other than Thailand. The ideal position for the CLC, which will be where farmers' commodities are collected, will open up the possibility of increasing the logistical system's profit. It must be situated in the proper areas so that farmers can reach it quickly, and it must be situated where it can access the region's main road as well.

One of the most important considerations for the logistical chain, according to Logistics (2020), is selecting a precise location for the warehouse or the hub for collecting containers. The effectiveness of the logistical network may be affected. The ideal site will provide every benefit for each supply chain participant. In the network of logistics for agricultural products in the studied region. From the farmers, the goods will be delivered to the designated container loading center (CLC). The goods will then be transported by truck to the final destination via the appropriate border checks (BC). However, the proper CLC sites and transportation methods are crucial to generating more or less profit along the entire agricultural product supply chain (Jiang et al., 2021; Jiang et al., 2020).

In our study, the transportation time, the time taken to travel from an origin to a destination, needs to be within a certain range. Products need to be transported via a border checkpoint where inter-trade documents are checked, and this can delay transportation time. We have selected borders as candidates for shipping routes based on which borders are convenient for international trade shipping.

The method that we will use to solve the proposed problem is referred to as Variable Neighborhood Strategies Adaptive Search (VaNSAS) (Pitakaso et al., 2020). VaNSAS comprises four steps: (1) generate an initial set of tracks (solution); (2) perform a track touring process; (3) update the heuristics information; (4) repeat

Steps 2 and 3 until the termination condition is achieved. The basic concept of VaNSAS is that the quality of the current solution improves if many types of heuristics are used. These heuristics include metaheuristics, simple heuristics, or the well-known local search procedure. Generally, three to four heuristics are designed to be used in VaNSAS. The track has the freedom to select the heuristics in black box optimization. A suitable improvement procedure (IP) is selected with different probabilities. The probability of selecting an IP is iteratively updated depending on the average solution quality of tracks that previously used that IP. VaNSAS has been successfully used to solve various problems, such as the location routing problem, the assembly line balancing problem (Jirasirilerd et al., 2020; Pitakaso et al., 2021; Worasan et al., 2020), and the scheduling and routing problem (Worasan et al., 2020).

However, we can draw the following conclusions about our suggested problem and approach to solving it.

- (1) The logistics network for agricultural products in the GMS regions is being designed in this article for the first time.
- (2) This article is the first to consider the duration of the container to arrive at the end customer as one of the objective functions in order to maintain the product's freshness, which is the most crucial quality for agricultural products, when the product is given to the final consumers.
- (3) This article is the first to discuss and design the logistics network link between the regional major road (the "economics corridor") and the local road, specifically for the logistics network for agricultural products.
- (4) It is the first time that the VaNSAS has been used to designed the logistical network design.
- (5) The container loading center (CLC) is a crucial component of the link between farmers and the export system for agricultural products. As a result, the advantage of having CLC serve as the goods collection center will be revealed.

This paper is structured as follows so that you can find all of the article's commitment contributions. In Section 2, the mathematical model that represents the network design will be presented. Sections 3 and 4 show the proposed methods and computational results, and the last section, Section 5, presents the conclusions and outlook of this research. The logical process of the conducted research is shown in Fig. 2.

2. Problem statement and mathematical model

2.1. Problem statement

Fresh agricultural products are transported from farmers to center markets (collecting centers). The collecting center (CC) packs the agricultural product in containers according to the demand of the end market. The containers are transported to the borders and then, at the border, after customs clearance at Thai and neighbor countries (NC), are attached to a truck trailer (NC law) and transported to the end market. The objective function is to (1) maximize profit for the entire agricultural chain and (2) minimize the arrival time of the container to end customers. A framework of the proposed problem is shown in Fig. 3.

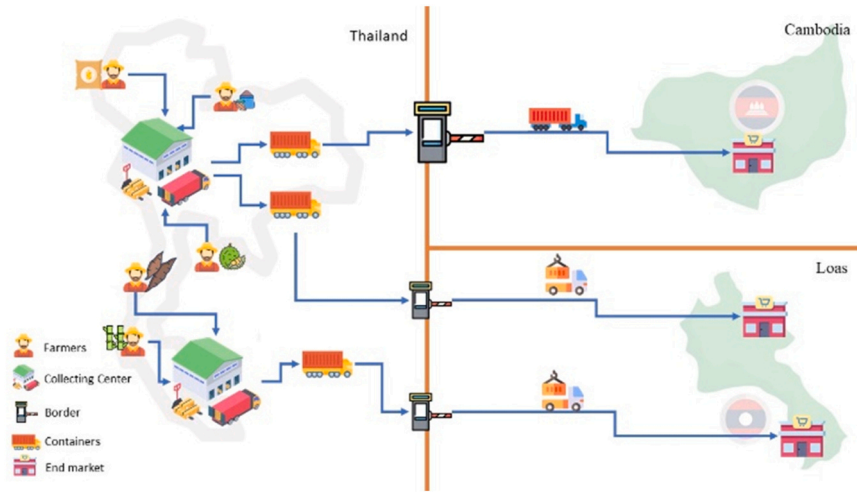


Fig. 3. Proposed problem definition.

2.2. Mathematical model

In this section, the mathematical model of the logistics network design for agricultural products is introduced.

Sets:

- G: Set of containers $g; g \in G$.
- I: Set of container loading centers (CLC) $i; i \in I$.
- J: Set of farmers $j; j \in J$.
- K: Set of borders $k; k \in K$.
- L: Set of end markets $l; l \in L$.
- V: Set of vegetable types $v; v \in V$.

Indices:

- g: Container number ($g=1, 2, 3, \dots, G$).
- i: Container loading center ($i=1, 2, 3, \dots, I$).
- j: Farmer ($j=1, 2, 3, \dots, J$).
- k: Border ($k=1, 2, 3, \dots, K$).
- l: End market ($l=1, 2, 3, \dots, L$).
- v: Vegetable type ($v=1, 2, 3, \dots, V$).

Parameters:

- A: Traveling speed (minute per kilometer).
- B_k^1 : Time taken to change trailer head at border k (minute).
- B_{gi}^2 : $\begin{cases} 1 & \text{if container } g \text{ is located at CLC } i \\ 0 & \text{otherwise} \end{cases}$
- B_{vk}^3 : Required space to load a ton of vegetable k (m^2/ton).
- B_{vg}^4 : Cost of loading vegetable v to container g (Baht).
- B_{gi}^5 : Time at which container g starts loading at CLC i (minutes start counting from 6 AM).
- B_{jk}^6 : Trailer head changing time (minute per k).
- B_{gl}^7 : Target time at which container g must arrive at end market l (minutes counting from 6 AM of that day).
- D_{ji} : Distance from farmer j to CLC i .
- E_{ik} : Distance from CLC i to border k .
- G^g : Great number set to 50,000.
- H_{kl} : $\begin{cases} 1 & \text{if end market } l \text{ is allowed to travel from border } k \\ 0 & \text{otherwise} \end{cases}$
- M_{vl} : Demand of vegetable v from end market l (ton).
- N_{kl} : Distance from CLC i to border k (km).
- O_{vj}^1 : Available vegetable v at farmer j .
- O_{vjgi}^2 : Number of vegetables v delivered to container g located at CLC, delivered from farmer j .
- O_{vg}^3 : Number of vegetables v packed in container g .
- P_{g}^1 : Capacity of container g (m^2).
- P_k^2 : Operating time at border k per container.
- S_{vl} : Selling price of vegetable v at end market l (Baht).

T: Transportation fuel cost (Baht/km).

Decision variables:

B_{gl}^8 : Actual arrival time at which container g arrives at end market l (minutes counting from 6 AM of that day).

- X_{jgi} : $\begin{cases} 1 & \text{if farmer } j \text{ deliver goods to container } g \text{ located at CLC } i \\ 0 & \text{otherwise} \end{cases}$
- Z_{gikl} : $\begin{cases} 1 & \text{if container } g \text{ is delivered from } i \text{ through } k \text{ to } l \\ 0 & \text{otherwise} \end{cases}$

Objective functions:

$$\begin{aligned} \text{Max } Z &= \sum_{v \in V} \sum_{g \in G} \sum_{i \in I} \sum_{k \in K} \sum_{l \in L} S_{vl} Z_{gikl} O_{vg}^3 - \sum_{g \in G} \sum_{i \in I} \sum_{k \in K} \sum_{l \in L} T Z_{gikl} (E_{ik} + N_{kl}) - \\ &\sum_{g \in G} \sum_{i \in I} \sum_{k \in K} \sum_{l \in L} Z_{gikl} B_k^1 - \sum_{j \in J} \sum_{g \in G} \sum_{i \in I} T X_{jgi} D_{ji} - \sum_{v \in V} \sum_{g \in G} B_{vg}^4 O_{vg}^3 \end{aligned} \tag{1.1}$$

$$\text{Min } Z = \max_{g,l} B_{gl}^8 \tag{1.2}$$

subject to:

$$\sum_{k \in K} \sum_{l \in L} Z_{gikl} \leq B_{gi}^2, \forall g \in G; i \in I \tag{2}$$

$$Z_{gikl} \leq H_{kl}, \forall g \in G; i \in I; k \in K; l \in L \tag{3}$$

$$O_{vjgi}^2 \leq X_{jgi} G^g, \forall v \in V; g \in G; i \in I; j \in J \tag{4}$$

$$\sum_{j \in J} X_{jgi} \leq B_{gi}^2, \forall g \in G; i \in I \tag{5}$$

$$\sum_{g \in G} \sum_{i \in I} O_{vjgi}^2 \leq O_{vj}^1, \forall v \in V; j \in J \tag{6}$$

$$O_{vg}^3 = \sum_{j \in J} \sum_{i \in I} O_{vjgi}^2, \forall v \in V; j \in J \tag{7}$$

$$\sum_{g \in G} \sum_{i \in I} \sum_{k \in K} Z_{gikl} O_{vg}^3 \leq M_{vl}, \forall v \in V; l \in L \tag{8}$$

$$\sum_{v \in V} B_{vg}^4 O_{vg}^3 \leq P_g^1, \forall g \in G \tag{9}$$

$$A D_{ji} X_{jgi} \leq B_{gi}^5, \forall g \in G; j \in J; i \in I \tag{10}$$

$$Z_{gikl} (P_k^2 + E_{ik} + N_{kl} + B_{gk}^6) \leq B_{gl}^7, \forall g \in G; i \in I; k \in K; l \in L \tag{11}$$

$$B_{gl}^8 \leq B_{gl}^7, \forall g \in G; l \in L \tag{12}$$

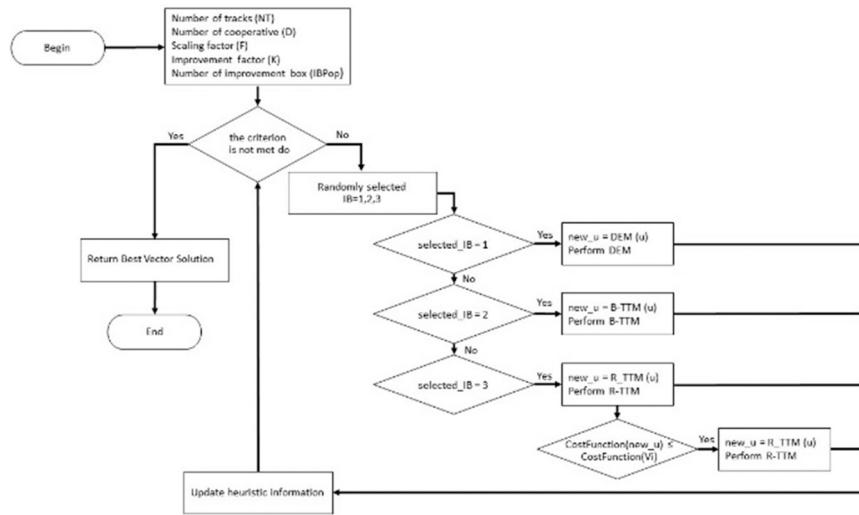


Fig. 4. Algorithm of VaNSAS.

There are two objective functions of the proposed problem: Eq. (1.1) and Eq. (1.2). Eq. (1.1) tries to maximize the total profit in the system. It is composed of five terms: 1) income from selling vegetable v at end market l ; 2) total transportation cost of container g from CLC i to border k and from border k to end market l ; 3) the trailer head changing cost at border k ; 4) the transportation cost of vegetable v from farmer j to CLC i ; 5) the loading cost of vegetable v into container g . Eq. (1.2), which is the second objective function, tries to minimize the maximum makespan of the container or the maximum arrival time of the containers. Constraint (2) ensures that the container g located at CLC i will deliver to at most 1 pair of borders and end markets and only when container g is located at CLC i . Constraint (3) ensures that the container g will only deliver to the end market l only when the end market l is allowed to ship via border k . Constraint (4) ensures that vegetable v will be shipped from farmer j to container g located at CLC i only when farmers j delivers the goods to container g . Constraint (5) ensures that farmers can ship to container g located at CLC i only when container g is available at CLC i . Constraint (6) ensures that the vegetable v , which be shipped from farmer j , does not exceed its availability at farm j . Constraint (7) defines the amount of vegetable v packed in container g . Constraint (8) ensures that the amount of vegetable v shipped to market l will not exceed its demand. Constraint (9) ensures that container g does not exceed its capacity. Constraint (10) ensures that farmer j delivers container g located at CLC i before the loading start. Constraint (11) ensures that the arrival time of the container is earlier than its commitment time to market l , and Constraint (12) ensures that the arrival time of container g at market l is less than the commitment time.

The likelihood of a container shortage is reduced since the major objectives of this research are to optimize overall system profit and reduce overall time spent on the container system. There are five terms in the first objective term Eq. (1.1). The cost of transportation from one actor in the chain to other actors is mentioned in three of the five terms. The primary contributor to today's global carbon emissions is transportation. Due to the cumulative emissions from the millions of vehicles on the road, the sector of goods transportation and the private car are the two major polluters. People can switch to more ecologically friendly forms of transportation like public transportation, biking, and walking to lower greenhouse gas emissions. Unfortunately, the export system cannot use zero-emission vehicles since the exporters' ability to choose a vehicle is always constrained by the volume of cargo to be transported. On average, the truck uses 9.25 gallons of fuel every 100 kilometers (Webfleet,

2020). The truck emits 185 pounds of CO2 per 100 kilometers (C2ES, n.d.). Therefore, when we strive to lower the transportation costs associated with the agricultural supply chain, we can also aim to lower the overall amount of CO2 produced in the system, which helps to mitigate the global warming effect. The system's overall daily transportation distance, according to preliminary computer results, is above 15,000 km. This indicates that the system as a whole releases more than 27,759 pounds of CO2 every day. According to the computational results, we may cut the overall transportation distance by 30–40%, which will lower the total amount of CO2 released from 27,759 pounds to 16,655 pounds. Reduce the overall cost, and it may follow that the amount of CO2 released into the system is likewise under control.

3. Methodology

3.1. Variable neighborhood strategy adaptive search (VaNSAS)

The Variable Neighborhood Strategy Adaptive Search (VaNSAS) is used to solve the proposed problem. VaNSAS is composed of four steps: 1) generate an initial set of tracks, 2) perform a track touring process, 3) update heuristics information, and 4) re-do Steps 2 and 3 until the termination condition is met. VaNSAS shown in Fig. 4, and can be explained stepwise as follows.

3.1.1. Generate the initial solution

The set of initial tracks is randomly generated. A track is decoded to represent the solution for the proposed problem. The encoding and decoding method are as follows.

3.1.2. Generate the set of initial tracks (encoding method)

Integer encoding is used to represent the proposed problem. Table 1 shows an example of an initial set of tracks (X_{ijr}). Each track has 6 positions (D) when D is the number of agricultural

Table 1
Example of initial tracks.

Track	Cooperative					
	1	2	3	4	5	6
1	874	588	724	405	652	939
2	131	765	527	806	457	110
3	864	754	148	867	434	657

Table 2
Meaning of digits in the track's value.

Container Loading Center (CLC)		Border		End-market (EM)	
Value of digit	Meaning	Value of digit	Meaning	Value of digit	Meaning
0–1	CC no. 1	0–2	Border no. 1	0–3	EM no. 1
2–3	CC no. 2	3–4	Border no. 2	4–6	EM no. 2
3–4	CC no. 3	4–6	Border no. 2	7–9	EM no. 3
5–6	CC no. 3	7–9	Border no. 2		
7–9	CC no. 3				

cooperatives. However, a track has dimensions of $1 \times D$, while X_{ijt} is the track number i at position j at iteration t .

3.1.3. Decode the initial track

The value in Position 4 of Vector 3, which is 867, means that the solution is for the Cooperative 4 to deliver goods to Wholesaler 8, who will deliver the product to Border 6 and End-Market 7. The number of actors affects the number of digits of the value in position. In case it has more than 10 wholesalers (or so), the digit represents the wholesaler who needs to have two digits, such as 12XX. Conversely, if there are fewer than 10 wholesalers (or so), in this example, there are 5 wholesalers (collecting center: CC), 4 borders, and 3 end markets. The code represented in Table 2 can be interpreted as the meaning shown in Table 2.

The number to represent the solution must be in range. If the value of position is 867, Farmer 4 will transport the product to CC 5, which will transport to Border 2, which will transport to EM 3. The forming of the network chain needs to maintain (1) the capacity of the wholesalers, (2) the capacity of the border, (3) the maximum demand of the end market, and (4) the limitation of trade regulation between countries (some end markets cannot receive deliveries from some checkpoints). An example of the result of the decoding method is shown in Table 3.

The shipping plan, shown in Table 3, generates profit from selling all products and subtracting the administrative cost from the wholesaler, and border checkpoint is 444,000 USD. Suppose the total traveling cost is calculated by multiplying the total traveling distance by the traveling cost per kilometer, which is \$0.20 per kilometer. If this plan has a total distance of 5500 km, then it has a traveling cost of \$1100. Therefore, the total profit generated from this plan is \$442,940. The transportation time of the container is calculated

Table 3
Result of the volume transported within the chain.

Detail					
	CLC				
	1	2	3	4	5
Cap	5000	5500	4500	4000	4000
Cost	2.5	2.6	2.4	2.5	2.8
Total agri. prod. shift to CC			2600	2900	2500
	Border				
	1	2	3	4	
Cap	5000	5500	6000	5000	
Cost	3.4	3.6	3.6	3.4	
Total agri. prod. shift to BD		1100 + 2900			
		4000 (From CC-4 and CC-3)	(From CC-5)	(From CC-3)	
	End market				
	1	2	3		
Cap	1	2	3		
Price	5000	4500	4000		
Shipped from border	50	60	55		
Total agri. prod. shift	–	1	3.4		

Remark: * Actors have zero products shipped because the previous actors in the chain delivered all products to other actors.

from the CLC to the end market. If we restrict this using the information given in Table 3, the result of the transportation time is shown in Table 4.

Based on the data given in Table 4, the makespan of the solution is 248, and the average arrival time is 213.75 min. The proposed method will try to minimize these two objectives, which are (1) the total profit generated in the agricultural chain and (2) the makespan of the container. The next step of VaNSAS is applied to obtain a promising solution, and it can be explained stepwise as follows.

3.1.4. Track touring process

The tracks iteratively tour in the improvement box(es). In our research, three improvement boxes were designed. These methods are (1) the differential equation method (DEM), (2) the best track transition method (B-TTM), and (3) the random track transition method (R-TTM). We used a roulette wheel selection for the track to select the preferred improvement box. The probability of selecting an improvement box was controlled by Eq. (13) (Pitakaso et al., 2020)

$$P_{bt} = \frac{FN_{bt-1} + (1 - F)A_{bt-1} + KI_{bt-1}}{\sum_{b=1}^B FN_{bt-1} + (1 - F)A_{bt-1} + KI_{bt-1}} \tag{13}$$

P_{bt} is the probability to select the improvement box b in iteration t ; N_{bt-1} is the number of tracks that select an improvement box b in the previous iteration; A_{bt-1} is the average objective value of all tracks that selected improvement box b in the previous iteration; I_{bt-1} is a reward value, which increases by 1 if improvement box b finds an optimal solution in the last iteration but is 0 otherwise; IB is the total number of improvement boxes; F is the scaling factor ($F = 2$); K is the improvement factor ($K = 1$).

3.1.5. Differential equation method (DEM)

To perform all improvement boxes methods, three sets of tracks need to be initiated. These sets of tracks are (1) the initial set of tracks, (2) the best set of tracks (X_{ijt}^{best}), and (3) a random set of tracks (X_{ijt}^{rand}). All the sets of tracks are composed of NT tracks, and each track has the size D , where D is the number of agricultural cooperatives. An example of the initial set of tracks is shown in Table 1, and it is obtained by randomly selecting the integer number for the positions of a track. The best set of parameters consists of the NT best tracks, which provides the best solution from Iteration 1 to the current iteration. The tracks will be updated when it has the best new solution, which has a better objective function than the tracks that are in the best set of tracks. The best new track will replace the worse tracks in the best set of tracks. An example of the best set of tracks is shown in Table 5.

As shown in Table 5, the best objective found since the first iteration is \$504,462. The update will be performed whenever it has the best new solution that has a higher profit than that of \$469,493, and Track 3 in the best set of tracks will be deleted and replaced by the best new track. The random track is simply a random NT number of tracks, which has dimension D (similar to the example shown in Table 1). The differential equation method is the method that randomly selects the tracks from the best set of tracks and then uses Eq. (14), (15) to generate new tracks.

$$V_{ijt} = X_{r1jt} + F(X_{r2jt}^{rand} - X_{r3jt}^{best}) \tag{14}$$

$$V_{ijt}^A = \begin{cases} V^{Min} & \text{if } V_{ijt} \leq V^{Min} \\ V_{ijt} & \text{if } V^{Min} < V_{ijt} \leq V^{max} \\ V^{max} & \text{otherwise} \end{cases} \tag{15}$$

The product of Eq. (14) and Eq. (15) are called D -track (V_{ijt}). V_{ijt} is the position value of D -track i , position j , iteration t . F is the scaling factor, which is set to 2. $R1$ is the label of the vector that selects the DEM as the improvement box. $R2$ is the track that is randomly

Table 4
Makespan of the container shipped using the plan given in Table 3.

	CLC	Border	Transportation time (minutes)	Border	EM	Transportation time (minutes)	Total transportation time (minutes)
Cont.1	5	3	80	3	3	114	194
Cont.2	4	1	110	1	2	138	248
Cont.3	3	4	103	4	3	113	216
Cont.4	3	1	95	1	2	102	197

Table 5
Example of Best set of tracks (X_{ijt}^{best}): NT = 7).

Track	Cooperative						Objective function
	1	2	3	4	5	6	
1	124	558	695	619	691	505	504,462
2	732	733	584	407	340	583	471,777
3	760	761	868	199	602	863	469,493

selected from the best set of tracks, and R3 is the track that is randomly selected from the random set of tracks. V^{Min} is the minimum value of the track allowed, and V^{max} is the maximum value of the track allowed. In this research, it is set to be 000 and 999, respectively. The DEM will perform iteratively until a predefined iteration is met (in this study, the maximum number of iterations of DEM is set to 100).

3.1.6. Best-track transition method (B-TTM)

The track will randomly select one track out of the NT best set of tracks (X_{r3jt}^{best}), and Eq. (16) is used to generate the B-TTM's track (V_{ijt}). This IB is used so that the track converts faster to the optimal result from the guideline of the best solution found.

$$V_{ijt} = \begin{cases} X_{r1jt} & \text{if } rand_j \leq CR \\ X_{r3jt}^{best} & \text{otherwise} \end{cases} \quad (16)$$

When CR is the predefined parameter, which is set to 0.8, $rand_j$ is a random number [0,1] of position j. X_{r1jt} is the track that selects B-TTM to be the improvement box.

3.1.7. Random-track transition method (R-TTM)

This method will use a random track instead of using the best set of tracks (B-TTM). The track will randomly select one track out of the NT random set of tracks (X_{r2jt}^{rand}), and Eq. (17) is used to generate the R-TTM's track (V_{ijt}). This IB is used so that the current solution escapes from the local optimal.

$$V_{ijt} = \begin{cases} X_{r1jt} & \text{if } rand_j \leq CR \\ X_{r2jt}^{rand} & \text{otherwise} \end{cases} \quad (17)$$

When CR is the predefined parameter, which is set to be 0.8, $rand_j$ is a random number [0,1] of position j. X_{r1jt} is the track that selects R-TTM to be the improvement box.

3.1.8. Update the heuristics information

Some heuristic information needs to be updated in order to use it for the next iterations. The rule for updating is shown in Table 6.

The proposed problem is a multi-objective problem, so the best objective will be formed in terms of a Pareto front. The Pareto front will be used to maintain a non-dominated solution. Let $f^1(e_r)$ and $f^2(e_r)$ be the objective function of Objective 1 and 2 of track r, respectively. Let \mathfrak{R} be a set of feasible solutions, $e = (e_1, e_2, \dots, e_i)$ is the set of decision vectors, and $f^v(e) = (f^1(e), f^2(e), \dots, f^V(e))$ is the set of objective functions of vector e. e will dominate e' if and only if $f^v(e) \leq f^v(e')$ for all $v = 1, 2, 3, \dots, V$.

After the Bi-VaNSAS has been executed until the termination condition is met, and the Pareto front has been collected, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), see (Hwang & Yoon, 1981), will be used to reveal the promising set of parameters and start to construct a normal decision matrix, which will transform various attributes into non-dimensional attributes by Eqs. (18) - (24).

$$\eta_{lv} = \frac{x_{lv}}{\sqrt{\sum_{l=1}^L (X_{lv})^2}} \quad (18)$$

$$U_{lv} = w_v \eta_{lv} \quad (19)$$

$$U_v^* = \{ \max_L U_{lv} \text{ if } v \in V; \min_L U_{lv} \text{ if } v \in V^* \} \quad (20)$$

$$U'_v = \{ \min_L U_{lv} \text{ if } v \in V; \max_L U_{lv} \text{ if } v \in V^* \} \quad (21)$$

$$S_l^* = \sqrt{\sum_{v=1}^V (U_v^* - U_{lv})^2} \quad (22)$$

$$S'_l = \sqrt{\sum_{v=1}^V (U'_v - U_{lv})^2} \quad (23)$$

$$C_l^* = \frac{S'_l}{S_l^* + S'_l} \quad (24)$$

Table 6
Updating the role of the heuristics information.

Variable	Update procedure
N_{bt}	Total number of tracks that select improvement box b from iteration 1 to iteration t
A_{bt}	Average profit value generates from improvement box b from iteration 1 to iteration t
I_{bt}	$I_{bt} = I_{bt-1} + G$ When $G = \begin{cases} 1 & \text{if black box b contain global best solution in iteration t} \\ 0 & \text{otherwise} \end{cases}$
X_{ijt}^{best}	Update best set of tracks if there are better solution.
X_{ijt}^{rand}	Randomly select the value in position of all tracks, all positions

Algorithm 1: Variable Neighborhood Strategy Adaptive Search

input: Number of tracks (NT), Number of cooperative (D), Scaling factor (F), Improvement factor (K), Number of improvement box (IBPop)
output: Best_Track_Solution

```

begin
  Population = Initialize Population (NT, D)
  IBPop = Initialize Information IB(NIB)
  encode Population to WP
  while the stopping criterion is not met do
    for i=1: NT
      // selected improvement box by RouletteWheelSelection
      selected_IB = RouletteWheelSelection(IBPop)
      If (selected_IB = 1) Then
        new_u = DEM (u)
        Perform DEM
      Else if (selected_IB = 2)
        new_u = B-TTM (u)
        Perform B-TTM
      Else if (selected_IB = 3)
        new_u = R-TTM (u)
        Perform R-TTM
        IF(CostFunction(new_u) ≤ CostFunction(Vi)) Then
          Vi = new_u
        End For Loop//end update heuristics information
      End For Loop
    End For Loop
  End
  Return Best_Vector_Solution
End

```

Fig. 5. Pseudo code of VaNSAS.

where x_{lv} is the value of the objective function of the point l objective v , L is the number of points in the Pareto front, V^* is a set of positive objective functions, and V' is a set of negative objective functions. w_v is a predefined parameter, which is the weight of each objective function. $U^* (U^* = \{U_1^*, U_2^*, \dots, U_n^*\})$ and $U' (U' = \{U'_1, U'_2, \dots, U'_n\})$ are positive and negative ideal solutions, respectively. S_p^* and S'_l are the separation measures for each alternative from both the positive and negative ideal solutions, which will be used to calculate the relative closeness to the ideal solution. (C_l^*). The set of parameters that has the C_l^* value closest to 1 will be selected as the most promising solution.

3.1.9. Repeat the track touring process and the heuristic information updating

The track touring process and the heuristic information update will be repeated until the predefined iteration is met. In conclusion, the VaNSAS will use three methods to improve the current solution. At each iteration, the track will independently select its improvement box from the previous selection. The pseudo code of VaNSAS is shown in Fig. 5.

The cost function used in the algorithm and the comparing of the objective function used to update the heuristics information. Eq.1.1 and Eq.1.1 will be weighted. w_1 and w_2 are the weight of Objective 1 and 2 respectively. w_1 will be uniformly random from 0.01 to 0.99 and w_2 is $(1- w_1)$.

3.1.10. The compared methods

We compared two heuristics with VaNSAS: (1) a genetic algorithm (GA) and (2) a differential evolution algorithm. The GA algorithm used in this research was adopted from Mitchell (1998), while

the DE was adopted from (Sethanan & Pitakaso, 2016). GA and DE will use a Pareto front and TOPSIS as tools to evaluate and compare.

4. Computational results and framework

We coded the mathematical model in Lingo V.11 and coded the VaNSAS, DE, and GA with C++, executing them using a PC Intel® Core™ i5–2467 M CPU 1.6 GHz. (Table 7) Twenty-one randomly generated datasets and one case study were tested to compare the performance of the proposed methods. Each had a different number of vegetables, farmers, container loading centers, borders, and end markets. Details of the test instances are shown in Table 8. The problem instances are divided into two groups: (1) small-size test instances (S-group) and (2) large-size test instances (L-group). The small-size test instances find an optimal solution within 24 h, and large-size test instances using Lingo V.11 find a lower bound and the best solution in 240 h.

Instance S-1 to L-10 represent randomly generated datasets, while L-11 is the case study in GMSG. The details of the data generated are shown in Table 8.

We executed the first experiment on the small-size test instances. All 11 test instances tested optimality using an equal weight of two objectives in VaNSAS, DE, and GA using Lingo V.11. The computational result of the optimal solution and the computational time taken for Lingo v.11 to find the optimal solution are shown in Table 10. VaNSAS, DE, and GA were programmed and run 5 times. Each instance required 15 min of computational time. The best objectives out of five runs were extracted as the method's representative solution.

Table 7
Details of the test instances.

No of instances	# of vegetable	# of famers	# of CLS	# of border	# of end-market	# of container	No of instances	# of vegetable	# of famers	# of CLS	# of border	# of end-market	# of container
S-1	3	11	4	3	4	10	L-1	4	100	4	5	6	25
S-2	3	15	4	4	4	10	L-2	4	120	4	5	7	25
S-3	4	15	5	4	5	10	L-3	4	130	4	4	7	30
S-4	4	15	6	4	6	10	L-4	4	130	5	4	7	30
S-5	4	20	5	3	6	12	L-5	4	150	5	4	8	30
S-6	3	20	5	4	5	12	L-6	4	150	6	4	8	40
S-7	4	20	7	3	6	12	L-7	5	150	6	4	8	40
S-8	4	20	6	4	5	12	L-8	6	180	6	4	8	40
S-9	4	23	7	3	6	12	L-9	5	180	7	5	10	50
S-10	4	23	6	4	5	13	L-10	5	198	8	5	10	50
S-11	4	24	4	4	6	13	L-11	6	198	8	5	10	50

Table 8
Range of data randomly generated for each problem instances.

Parameters	Value
D_{ji} (km)	U[15,350]
T (Baht/Km)	U[4,6]
M_{vl} (ton)	U[500,1500]
O_{vj}^1 (ton)	U[1,20]
B_{vg}^4 (Baht/ton)	U[5,10]
B_{gk}^6 (minute per k)	U[15,25]
P_g (m ²)	U[50,60,80,100]
E_{ik} (km)	U[80,300]
S_{vl} (Baht/ton)	U[1200,2000]
N_{kl} (km)	U[60,350]
P_k (minute)	U[15,35]
B_k^1 (minute)	U[15,25]
B_g^3 (m ² /ton)	U[0.3,1.5]
B_{gl}^7 (minute)	U[300,600]

From Table 9, we can see that VaNSAS finds a 100 % optimal solution, while DE and GA can only find a 63.63 % and 72.72 % optimal solution, respectively. VaNSAS uses less computational time than that of Lingo (97.05 %), while obtaining the same computational result. Lingo uses an average of 508.75 min, while other proposed methods use 15 min for all test instances. Table 10 shows the computational time of GA, DE, and VaNSAS taken to find the optimal solution. Seven test instances are selected to compare the methods. These seven instances are the instances where all methods find an optimal solution. We execute this experiment.

five times for seven test instances and stopped the algorithms (DE, GA, and VaNSAS) when it found the optimal solution. The best time out of five runs is shown in Table 10.

Table 11 shows that VaNSAS uses 29.52 % and 27.93 % less computational time than that of DE and GA to find the same optimal solution. Therefore, we can conclude that VaNSAS outperformed the other methods in finding the optimal solution in terms of quality of the solution and computational time. The next experiment will show how VaNSAS finds the best solution. We performed it on the largest test instances (L-11). We run the algorithm for 1500 iterations and collected the best solution found. All three methods, GA, DE, and VaNSAS, found a solution. Fig. 6, shows the best solution found during the simulation of all three methods.

Fig. 6, shows that VaNSAS has the following attribute comparing with GA and DE. VaNSAS finds the best solution more often than the other methods. Fig. 4, shows that VaNSAS finds the best solution 67 times while GA and DE find it 31 and 36 times, respectively. Thus, VaNSAS can escape the local optimal better than the other methods. This means VaNSAS finds the best solution. We next used VaNSAS with 1, 2, and 3 improvement boxes. VaNSAS-1 used DEM as the improvement box, VaNSAS-2 used DEM and B-TTM as the improvement box, while VaNSAS-3 used DEM, B-TTM, and R-TTM as the improvement box. They all executed 1500 iterations, and the best solution found during the simulation is shown in Fig. 7.

Fig. 7, shows that VaNSAS-1 found the best new solution less often than the two other methods, and when it did, it did not improve much by comparison. VaNSAS-2 found a better solution than VaNSAS-1 because it found a better solution faster, but when it led to a good solution, it was trapped in that place for a long time (the number of times that it changed solution was lower than that of VaNSAS-3). VaNSAS-3 is VaNSAS-2 + R-TTM, so the algorithm could escape from the local optimal better than the other methods, and it could even help VaNSAS-2 escape from the local optimal by finding the best new solution more often. We can conclude that VaNSAS-1 could search within a small area, and VaNSAS-2 could convert to the search area faster and had a better solution (faster than VaNSAS-1),

Table 9
Objective functions of small-size test instances.

	Lingo			DE		GA		VaNSAS	
	Profit (Baht)	Makespan (Min)	Comp.time (Minute)	Profit (Baht)	Makespan (Min)	Profit (Baht)	Makespan (Min)	Profit (Baht)	Makespan (Min)
S-1	1,134,871	266	129.5	1,134,871	266	1,134,871	266	1,134,871	266
S-2	1,274,842	277	138.9	1,274,842	277	1,274,842	277	1,274,842	277
S-3	1,394,449	281	214.3	1,394,449	281	1,394,449	281	1,394,449	281
S-4	1,648,926	314	259.5	1,648,926	314	1,648,926	314	1,648,926	314
S-5	2,181,642	312	253.1	2,181,642	312	2,181,642	312	2,181,642	312
S-6	1,951,887	326	278.8	1,951,887	326	1,951,887	326	1,951,887	326
S-7	2,200,174	300	348.1	2,200,174	300	2,200,174	300	2,200,174	300
S-8	2,179,740	343	514.7	2,169,882	359	2,162,835	355	2,179,740	343
S-9	2,138,845	338	1047.7	2,119,924	358	2,138,845	338	2,138,845	338
S-10	2,097,651	350	982.5	1,987,293	361	2,049,371	359	2,097,651	350
S-11	2,269,147	337	1429.2	2,198,277	358	2,174,348	351	2,269,147	337

Table 10
Computational time each method takes to find the optimal solution.

	Computational time (minutes)		
	DE	GA	VaNSAS
S-1	10.15	10.69	8.48
S-2	10.83	10.41	8.24
S-3	11.48	10.98	8.58
S-4	12.91	13.43	9.42
S-5	13.01	12.87	10.34
S-6	14.37	12.39	10.76
S-7	13.08	14.01	10.45
Average	12.26	12.11	9.47

but it was then trapped in the local optimal. VaNSAS-3 can help the proposed method to escape from the local optimal.

The next experiment was performed with large-size test instances. Each heuristic was executed 5 times. The Pareto front of all methods was collected. TOPSIS was used to pull the most promising solution among all Pareto points. w_1 and w_2 used in TOPSIS were set to (0.8,0.2), (0.5,0.5) and (0.2,0.8) respectively. The solution is shown in Table 11. The stopping criterion was computational time, set to 45 min for all instances. Table 12 shows the statistical test of the information given in Table 9 using the Wilcoxon Sign Rank test.

From Tables 11 and 12, we can conclude that, comparing within the same heuristic, the weight of w_1 and w_2 plays a significant role in increasing or reducing the profit of the supply chain or the makespan of the containers. By comparing between heuristics, we can conclude that all heuristics perform significantly differently. Figs. 8 and 9, show the level of the value obtained from all proposed methods.

From Figs. 8 and 9, we can see that, a high value of w_1 (a low value of w_2) leads to a higher profit, because if the value of w_1 increases, the algorithm will find more profit when comparing the minimization of the makespan. We can conclude that, if we want to obtain a better profit, w_1 needs to be high; if we want a low makespan, w_1 needs to be low. Figs. 10 and 11, compare the profit generated and the makespan using different methods.

From Figs. 10 and 11, we can conclude that VaNSAS generates a higher average profit and a lower makespan compared with the other methods. VaNSAS finds a profit higher than that of DE and GA by 10.53 % and 8.96 %, respectively, while it finds a lower makespan by 9.57 % and 7.20 %, respectively.

In general, the solution approaches are compared in multi-objective aspects: (1) the average of the Pareto-optimal solution (ANP) and (2) the average ratio of the Pareto-optimal solution (ARP). N is

the number of iterations in one experiment. n_1, n_2, \dots, n_k is the number of Pareto-optimal solutions found in the k th experiment, and K is the total number of experiments. ANP and ARP are calculated using Eqs. (25) and (26).

$$ANP = \frac{n_1 + n_2 + n_3 + \dots + n_k}{K} \tag{25}$$

$$ARP = \frac{\frac{n_1}{N} + \frac{n_2}{N} + \frac{n_3}{N} + \dots + \frac{n_k}{N}}{K} \tag{26}$$

We performed this experiment on the L-11 problem (case study). We varied the number of iterations from 300 to 1500, and the Pareto points are reported in Table 13.

From Table 13, we can conclude that VaNSAS outperformed all other methods, as it finds higher ARP and ANP ratios. It has an ARP ratio that is higher than DE and GA by 26.77 % and 21.44 %, respectively, while VaNSAS finds an ANP ratio that is higher by 22.58 % and 17.26 %, respectively.

In the next experiment, all methods were used to solve L-11 problem instances. The Pareto solution was collected for 1000 iterations. The Pareto front of all methods is shown in Figs. 12a–c.

Figs. 12a–c show that VaNSAS fills the gap of each Pareto front more so than the two other methods. GA and DE have more distance between Pareto points more often than VaNSAS, which means the mechanism of VaNSAS can discover more Pareto solutions.

The next experiment was the result of the L-11, or the case study. The case study is composed of six types of goods, 198 farmers, eight containers, a loading center, five borders, and ten end markets. The result is shown in Table 14.

Based on Table 14, 198 farmers delivered their goods to 8 CLCs. CLC-1 to CLC-8 had to receive the different goods from different farmers. They had to receive goods from 30, 22, 28, 28, 27, 22, 21, and 20 farmers, respectively. The total profit of the system was 5539,212.00 Baht, the average profit per container was 110,784.24 Baht, the average profit per farmer was 27,975.82 Baht, and the average profit per ton of vegetables was 9201.1 Bath/ton (total goods shipped was 602 tons/day). The maximum makespan for all containers was 534.7 min, while the average makespan for all containers was 503.2 min. Example of the logistics network design of the GMS is shown in Figs. 13–14.

Fig. 13, shows a small logistics network of three agricultural products, including rice, rubber, and cassava. The network flow started from the farmers of each agricultural product in Thailand, connected to the agricultural center markets, moved to the Nakhon Phanom border, and finally transported to the Bolikhamsai market and the Nongchab market in Lao PDR.

Table 11
Computational result of large-size test instances.

W1/ W2 weight	GA										VaNSAS									
	(0.8,0.2)		(0.5,0.5)		(0.2,0.8)		(0.8,0.2)		(0.5,0.5)		(0.2,0.8)		(0.8,0.2)		(0.5,0.5)		(0.2,0.8)			
	Profit (Million Baht)	Makespan (minutes)	Profit (Million Baht)	Makespan (minutes)	Profit (Million Baht)	Makespan (minutes)	Profit (Million Baht)	Makespan (minutes)	Profit (Million Baht)	Makespan (minutes)	Profit (Million Baht)	Makespan (minutes)	Profit (Million Baht)	Makespan (minutes)	Profit (Million Baht)	Makespan (minutes)	Profit (Million Baht)	Makespan (minutes)	Profit (Million Baht)	Makespan (minutes)
L-1	3.189	410.2	3.089	401.4	3.014	389.7	3.378	407.5	3.271	392.4	3.209	392.4	3.681	357.1	3.638	347.6	3.589	331.6	3.589	331.6
L-2	3.378	427.8	3.219	418.9	3.198	407.8	3.487	421.6	3.412	416.7	3.318	416.7	3.879	367.8	3.767	357.2	3.678	347.8	3.678	347.8
L-3	3.859	476.6	3.809	467.8	3.749	458.2	3.923	471.3	3.849	447.0	3.713	420.3	3.879	398.3	4.209	387.9	4.167	376.2	4.167	376.2
L-4	3.928	487.9	3.814	476.4	3.741	469.7	3.981	468.8	3.879	451.9	3.789	424.8	4.387	402.8	4.261	401.3	4.138	385.9	4.138	385.9
L-5	3.987	498.5	3.871	482.7	3.779	471.4	4.018	458.1	4.008	442.8	3.898	414.1	4.419	411.8	4.278	402.8	4.192	387.3	4.192	387.3
L-6	4.072	510.2	4.025	504.2	3.998	499.7	4.091	507.4	4.068	502.8	4.024	488.2	4.781	481.5	4.547	467.0	4.487	448.9	4.487	448.9
L-7	4.238	526.7	4.173	517.0	4.107	471.9	4.256	522.8	4.214	513.2	4.169	502.8	5.008	502.1	4.756	498.2	4.568	463.6	4.568	463.6
L-8	4.683	545.2	4.582	532.5	4.527	487.3	4.712	543.8	4.691	522.4	4.483	475.2	5.027	512.8	4.992	507.2	4.878	456.9	4.878	456.9
L-9	5.037	574.6	4.990	525.2	4.755	499.2	5.045	569.4	5.037	523.9	4.815	483.6	5.501	544.7	5.447	512.6	5.267	464.1	5.267	464.1
L-10	5.057	579.8	5.020	534.3	4.821	517.4	5.096	571.1	5.071	525.6	4.881	491.4	5.543	568.1	5.490	515.4	5.397	478.4	5.397	478.4
L-11	5.110	596.7	5.057	556.4	4.829	521.3	5.141	588.4	5.123	542.1	4.975	518.7	5.582	581.1	5.506	534.7	5.429	488.8	5.429	488.8

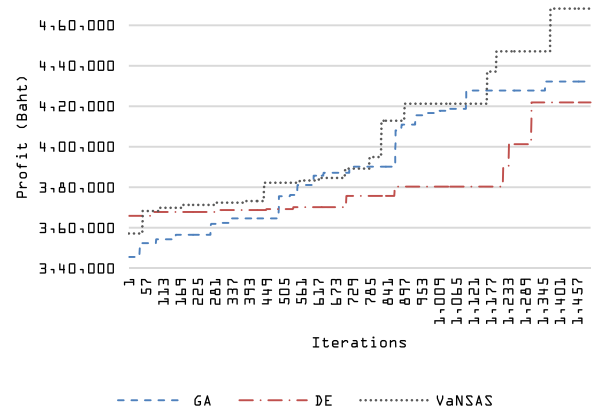


Fig. 6. Solution development of the proposed methods.

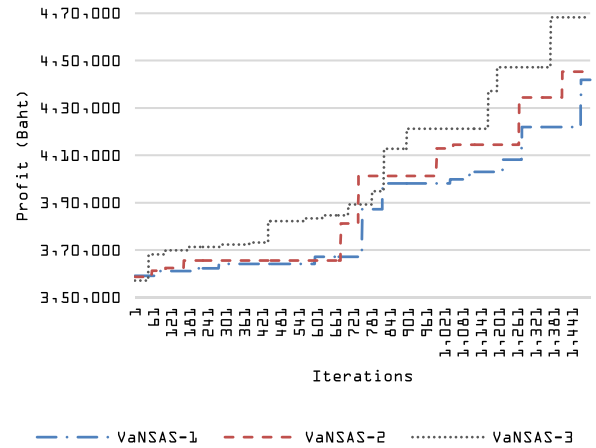


Fig. 7. Profit generated from VaNSAS-1 to VaNSAS-3.

Fig. 14, shows an example of a large GMS logistics network. There are three types of agricultural products, including rice, rubber, and cassava, which are transported across the border to Lao PDR and Cambodia. Each farmer was assigned to an appropriate CLC, and the CLCs were then also assigned to the optimal borders, after which the agricultural products were optimally distributed to the end markets in Lao PDR and Cambodia with minimum cost and makespan.

Figs. 13 and 14, depict the transportation network design example using our recommended methods, VaNSAS. There is no center for container loading in the existing exportation system that is used to export agricultural products. In the export system, a containment loading facility, often referred to as a dry port or inland port, is essential because it enables small and medium-sized exporters to enter the market more quickly. The simulation results of the current exporting system for agricultural products with and without container loading centers are compared in Table 15.

We can observe from the data in Table 15 that when using the CLC in the export system, all methods—GA, DE, and VaNSAS—provide improved results. Locating the CLC in the system utilizing GA, DE, and VaNSAS as the logistics network design approach provides higher profits than when the CLC is not employed by 6.14 %, 13.44 %, and 10.09 %, respectively. VaNSAS blatantly provides more profit than alternative methods. The choice to include CLC in the network system for the export of agricultural products can therefore be advantageous for other regions of Thailand that export agricultural goods across land borders to other GMS nations, such as those that export from Laos to Vietnam and China, Cambodia to Laos, Vietnam, and China, and Myanmar to India, China, and Vietnam (as shown in

Table 12
P-value of the Wilcoxon sign rank test of information given in Table 1.

	DE					GA					VaNSAS				
	Profit		Makespan			Profit		Makespan			Profit		Makespan		
DE	0.8	0.5	0.2	0.5	0.2	0.8	0.5	0.2	0.5	0.2	0.8	0.5	0.2	0.5	0.2
	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	0.5					0.5					0.5				
	Profit		Makespan			Profit		Makespan			Profit		Makespan		
DE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GA															

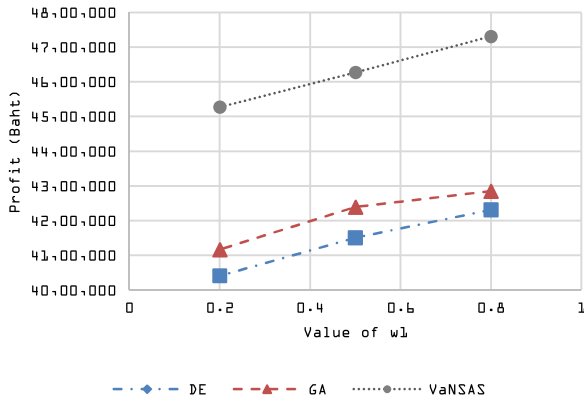


Fig. 8. Profit obtained Using different values of w1 and different solving methods.

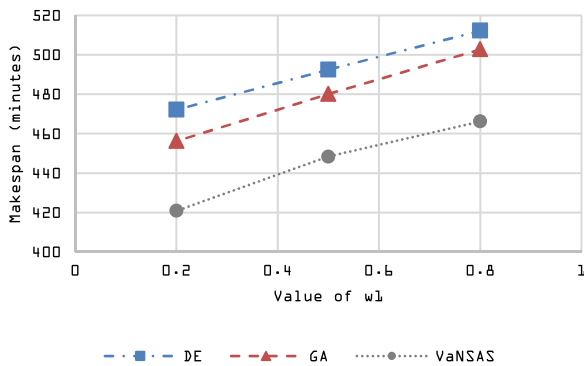


Fig. 9. MakeSpan obtained Using different values of w1 and different solving methods.

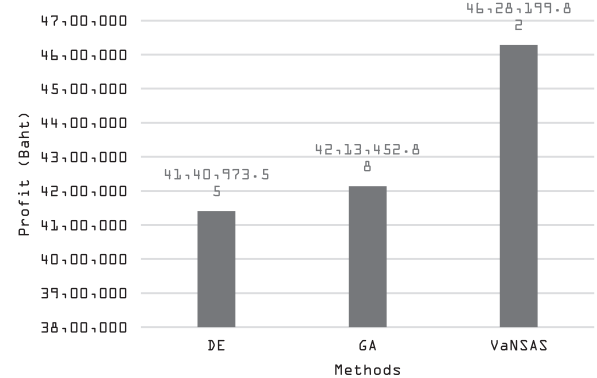


Fig. 10. Profit generated using different methods to find the optimal solution.

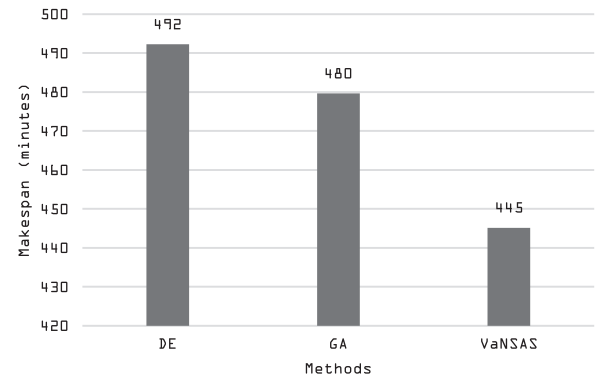


Fig. 11. Makespan generated using different solution approaches.

Fig. 1). The rice-producing regions of the GMS nations are depicted in Fig. 15. We can see that the CLC and our suggested approach, VaNSAS, may be used to apply for the rice export system, which should increase the effectiveness of the rice exportation system in all GMS nations.

5. Discussion

With this study, we hope to construct an efficient agricultural logistics network (ALN) for cross-border commerce in GMS regions. To construct ALN for GMS, we created the Variable Neighborhood Strategies Adaptive Search (VaNSAS). The computational outcome of the experiment presented in session 4 demonstrates that VaNSAS outperforms the currently used heuristics, such as DE and GA. This finding that VaNSAS provides a better solution than Genetic Algorithm (GA) and the Differential Evolution algorithm (DE) is

Table 13
ANP and ARP of all proposed methods.

#iterations	DE		GA		VaNSAS	
	#Pareto Points	Ratio	#Pareto Points	Ratio	#Pareto Points	Ratio
1	300	0.85	94	0.28	124	0.41
2	300	0.89	91	0.30	148	0.49
3	500	0.118	126	0.24	179	0.36
4	500	0.120	130	0.26	183	0.37
5	700	0.195	201	0.28	228	0.33
6	700	0.189	214	0.27	240	0.34
7	1000	0.212	242	0.21	280	0.28
8	1000	0.218	238	0.22	294	0.29
9	1500	0.349	360	0.23	389	0.26
10	1500	0.331	341	0.22	397	0.26
ARP		0.25		0.27		0.34
ANP		0.24		0.25		0.31

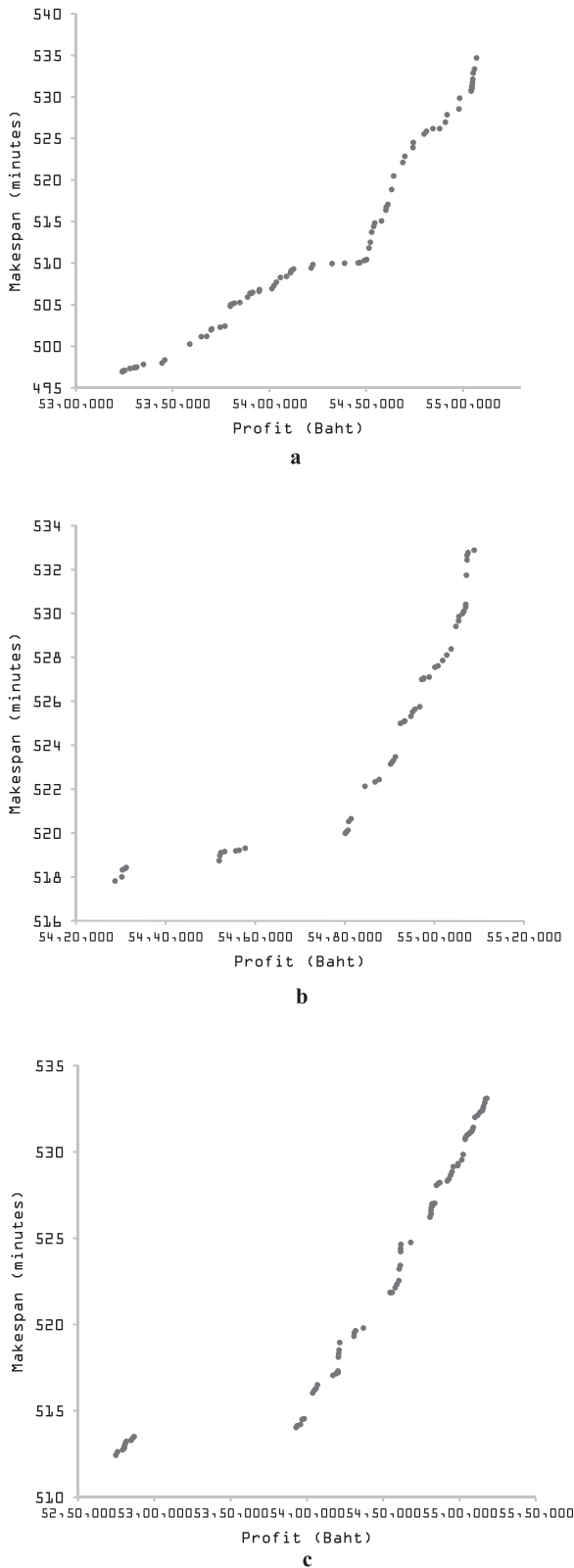


Fig. 12. a. Pareto front of VaNSAS. b. Pareto front of DE. c. Pareto front of GA.

supported by Worasan et al. (2020), and Theeraviriya et al. (2019). This is as a result of VaNSAS using a variety of strategies for improvement in comparison to GA and DE. In contrast to the current heuristics, VaNSAS's improvement processes are able to elude the local optimal more successfully. The results shown in Figs. 10a–c,

Table 14 Computational result of the problem instances of L-11 (case study in GMS).

	Farmer	Vegetable types	Border	End-Market	#Container used	Profit (Baht)	MakeSpan (minutes)
C1C-1	2,5,15,28,29,30,31,32,33,34,46,47,48,111,112,113,114,115,140,141,142,143,186,187,188,189,190,191,193,194	1,2,3	1,4,5	10,5,7,3	8	824,587	524.8
C1C-2	11,13,14,35,71,72,73,79,80,81,82,83,84,85,116,117,118,119,144,145,146,192	2,4	2,3,4	9,2,1	5	587,912	534.7
C1C-3	6,16,17,36,37,74,75,76,77,78,120,121,122,123,133,134,135,136,137,138,139,177,178,179,180,195,196,197	5,6,1	1,2,3	4,3,5,1	8	874,177	478.9
C1C-4	1,3,23,24,25,26,27,49,50,51,52,53,54,67,68,69,70,124,125,126,127,128,129,181,182,183,184,185	4,5	2,5	8,7,6,5	8	837,569	531.2
C1C-5	12,21,22,61,62,63,64,65,66,105,106,107,108,109,110,130,131,132,169,170,171,172,173,174,175,176,198	3,2	3,4	2,4,7,8	8	868,136	504.6
C1C-6	9,10,38,55,56,57,58,59,60,86,87,88,89,104,147,148,149,150,164,165,166,167	2,3,4	1,2,3	1,3,5,7	4	480,052	515.2
C1C-7	4,20,39,40,41,90,91,92,93,94,95,96,151,152,153,154,155,156,157,158,168	1,3	1,5	2,8,9	4	494,917	417.9
C1C-8	7,8,18,19,42,43,44,45,97,98,99,100,101,102,103,159,160,161,162,163	1,5	4,5	8,9,10	5	571,862	518.5
Total					5,539,212.00		4025.8
Max					874,177.00		534.7
Average					692,401.50		503.2

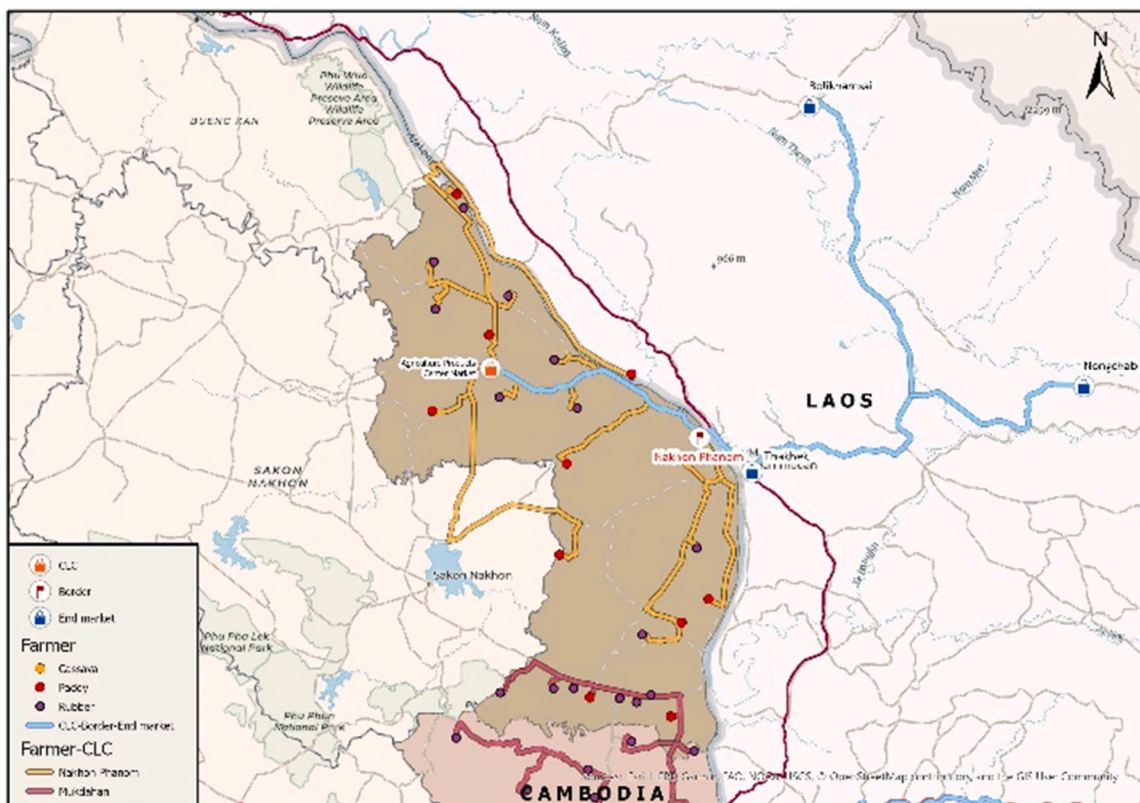


Fig. 13. An example of a small transportation network.

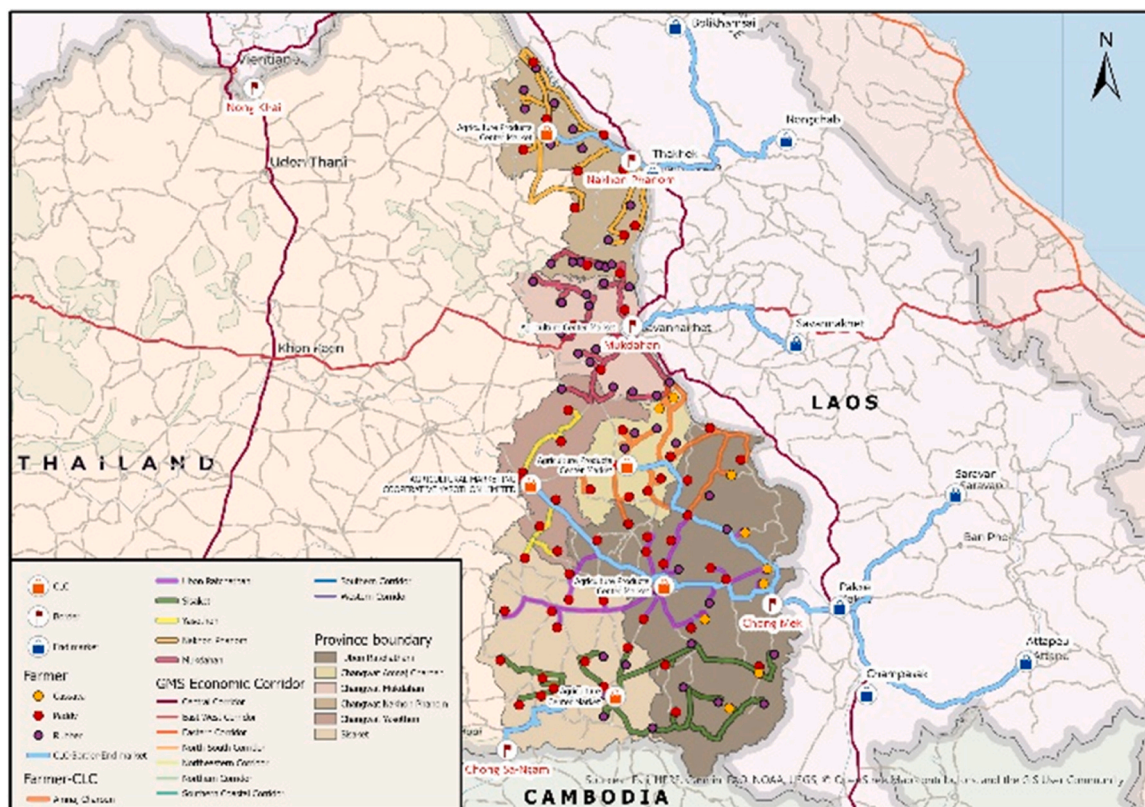


Fig. 14. An example of a large transportation network.

Table 15
Comparing total profit generated of the case study with and without container loading center (CLC).

	Profit (Baht)		
	GA	DE	VaNSAS
With CLC	5,123,745	5,057,312	5,539,212
Without CLC	4,827,199	4,458,248	5,031,471
Reduced cost(%)	6.14	13.44	10.09

which clearly show that VaNSAS's Pareto points are distributed along the front line continuously while GA and DE's have a larger gap between them, can be used to support this conclusion. This can indicate that GA and DE are more stuck on the local optimal than VaNSAS is. This conclusion is supported by the outcome from Chainarong et al. (2021).

The result of the designed agricultural network design of the case study (Table 15) shown that when the container loading center (CLC) has been integrated in the logistics network it can enhance the capability of the farmers to arrive at the CLC faster and when they have to ship the goods to logistics providers directly. The small and medium size of farmers can reach the exportation system earlier than without the CLC has been integrated in the model. This idea can be supported by the similar idea of proposing the inland port or dry port in Fazi et al. (2020). In order

to ensure on-time delivery and adhere to capacity constraints, Fazi et al. (2020) proposed the process for determining the appropriate distribution of containers to barges. The computational result demonstrates that the proper site allocation of the containers benefits the transportation system. The model and suggested strategy aim to increase barge utilization and traveling distance. Numerous studies have examined the operational and strategic advantages of using land ports and dry ports, and the conclusions from these studies support the findings in Table 15 of our study. Examples include Fazi et al. (2015), Maraš et al. (2013), Braekers et al. (2013), An et al. (2015) and Fazi (2019).

The fundamental concept of the CLC incorporated into the model is backed not only by the dry port/inland port but also by the theory of the location-allocation problem. According to Wang, Huang et al. (2021); Wang, Cheng et al. (2021) the proper site for the CLC's establishment and the proper distribution of farmers to the new location can lower the logistics system's overall operating costs. [In order to solve the location-allocation problem, Wang, Huang et al. (2021); Wang, Cheng et al. (2021) proposed a method for determining the best location for the agricultural product transportation network's hub, and they came to the conclusion that it is important for increasing the transportation efficiency and guaranteeing the freshness of agricultural products. This idea can be supported by various research such as Feng et al. (2022), Blad et al. (2022), Petersen et al. (2019) and Enbel-Yan and Leonard (2012) which revealed that establishing the collecting center in the right location enhance the efficiency of allocation the right farmers or customers to

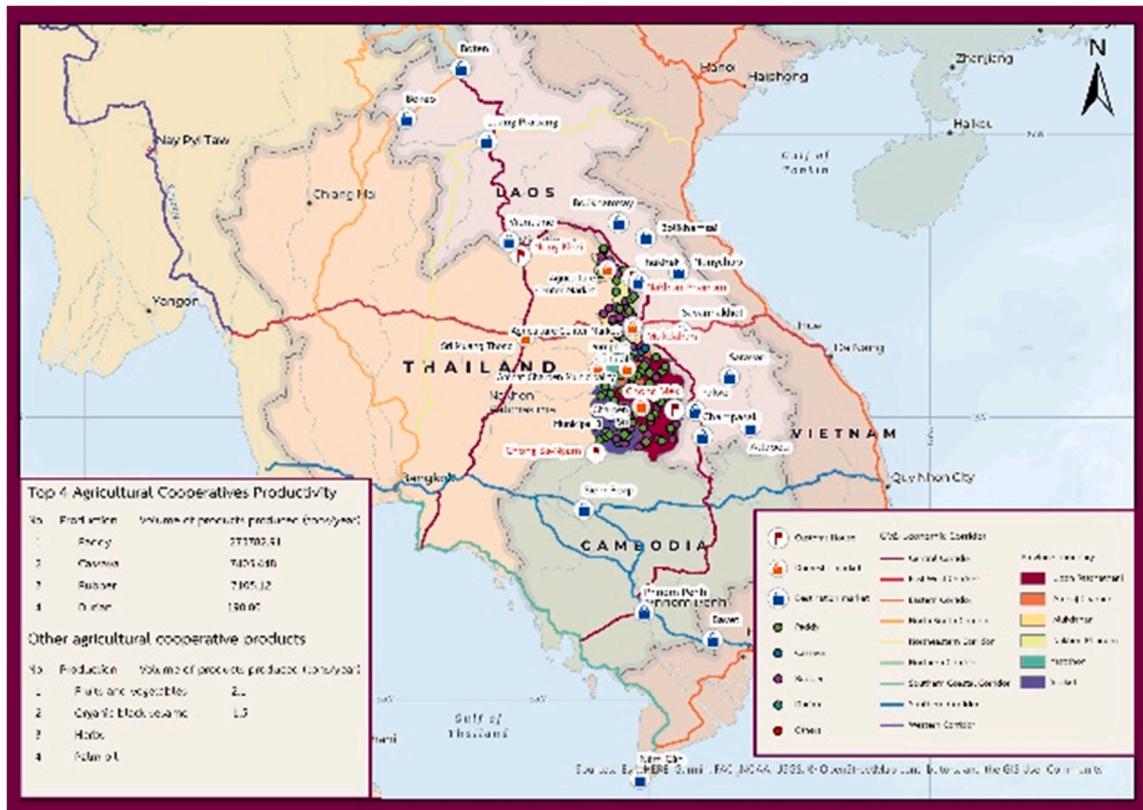


Fig. 15. Rice Production Area in GMS.

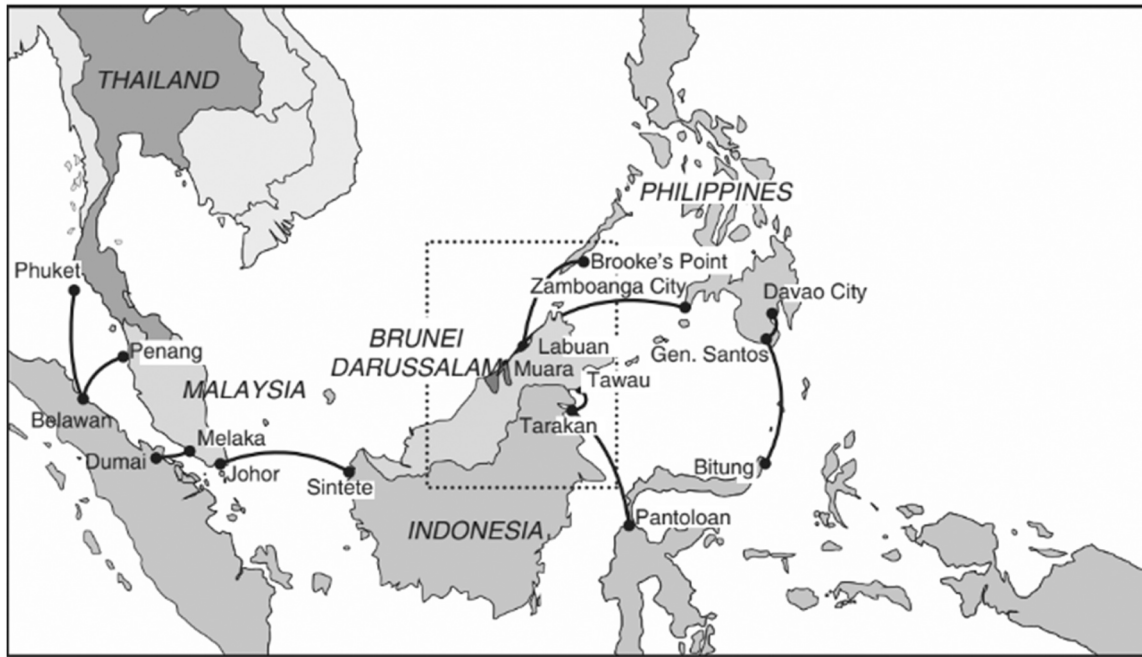


Fig. 16. Short Sea Shipping mode in ASEAN.

that location will lead to generate the low cost and high profit to the logistical system.

6. Conclusion and future outlook

This session will be broken up into four distinct sessions: (1) a summary of the study in the academic aspect; (2) a summary of the research in the social component; (3) future work and perspective; and (4) research limitations.

6.1. Research summary in academic aspect

This research aimed to design a transportation model for international trade of agricultural products between Thailand, Laos, and Cambodia. The agricultural products are transported from a farmers' cooperative to a foreign end market. The mathematical models GA, DE, and VaNSAS have been developed to determine the optimal mode of transportation. The objectives of the proposed methods are to (1) maximize the total profit for the entire agricultural chain and (2) minimize the makespan or arrival time of the containers to the end market in order to maintain the freshness of the agricultural product.

For small problem instances, the computational result shows that the proposed method, VaNSAS, finds a 100 % optimal solution, while DE and GA find only 63.63 % and 72.72 % optimal solutions, respectively. It uses lower computational time than that of Lingo (97.05 %). Comparing the speed of VaNSAS with DE and GA, we found that VaNSAS uses 29.52 % and 27.93 % less computational time than that of DE and GA to find the same optimal solution. For larger-size test instances, VaNSAS finds a profit higher than that of DE and GA by 10.53 % and 8.96 %, respectively, while it finds a lower makespan by 9.57 % and 7.20 %, respectively. Comparing the performance to solve multiple objectives, VaNSAS can find a higher ARP and ANP ratios. It has an ARP ratio that is higher than DE and GA by 26.77 % and 21.44 %, respectively, and can find a ANP ratio that is higher by 22.58 % and 17.26 %, respectively. Therefore, we can conclude that VaNSAS outperformed other methods.

6.2. Summary of the research in the social component

In terms of the social component, this study methodology and its findings can be applied to create a strategy plan for the import/export of agricultural products in various regions and across various nations. The region under studied is located in Thailand's northeast, close to the Mekong River. We learn from the model that is being used that the containers loading center (CLC) can be used as a tool for farmers to access the import/export system more easily in order to export agricultural products from small and medium farmers or producers. The CLC in our model performs tasks similar to or identical to those of a dry port or inland port; however, since road transportation is more common in this region than sea or train transportation, choosing the right location for the CLC and the best route from the farmers' local road to the main economic corridor that will connect producers to the end consumers is the key to the success of this type of agricultural logistics.

The network in Fig. 3, can therefore be employed in other places, but the appropriate agricultural network architecture will differ depending on the state of the local road, the CLC's capacity, the demand for the product from end users, and the capacity of the farmers and producers. As a result, the designed network may be helpful for policy makers who must design the logistical network in the region where there are many small and medium-sized agricultural producers who find it difficult to access the export/import system, thereby enhancing their capacity and raising the GDP of the entire nation.

6.3. Future work and perspective

In future research, in regard to the performance of VaNSAS, more improvement boxes that can intensify and diversify searches can be used and to determine their efficiency when used with VaNSAS. Extension of the area of the case study would also be interesting for this research, since the transportation network would be more complicated than the current one, and this may affect the efficiency of VaNSAS, which is indeed a challenge. Road transportation is one of the modes of transportation that contributes the most CO2 to global pollution, hence it is important to identify alternative modes so that

global pollution can be reduced. Even the GMS regions, only some part that are connected to the sea but the short sea shipping can be used as the part of the agricultural logistics network. According to Crew (2021), short-sea shipping has significant economic and environmental advantages, and as shipping companies are now exploring the potential of short-sea shipping, less pollution and less money is spent on transportation. Short sea shipping is efficient for connecting Indonesia, the Philippines, Brunei, Malaysia, and a few regions of Thailand, including Bangkok and Phuket, according to Arof and Zakaria (2020). By linking the aforementioned cities with some cities in Vietnam, Thailand, and Cambodia, such as Nam Can, Vung Tau, and Da nung, Sihannoukville, Re Ambei, Sattahip, Chonburi, and Prachuap Khiri Khan, short sea shipping (SSS) capabilities in the GMS regions can be strengthened. The relationship between road transportation and SSS as a mode of transportation for the GMS region should be expanded in the upcoming research as it relates to sustainable transportation (as shown in Fig. 16.).

6.4. Research limitations

Due to the fact that this research was conducted for the specific region of GMS, the transportation network in other regions may be completely different. Based on the type of agricultural products, local roads, border checkpoints, and end-user demand, particularly in GMS regions, the agricultural network design result presented in this study was established. If we use the same model and methods in another area, the simulation's outcome could be completely different. Nevertheless, the model can still be used to plan a transportation network in another location with a little modification to the parameter values and the existing state of the network.

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