

The Optimization of Cassava Transportation to Reduce Carbon Emission

Thitinun Pongnam¹ Paramust Juntarakod^{2*} Banlu Phaichin¹ and Khanitta Chaibundit³

¹Faculty of Technical Education, Rajamangala University of Technology Isan, Khon Kaen Campus

²Faculty of Engineering, Rajamangala University of Technology Isan, Khon Kaen Campus

³Faculty of Engineering and Technology, Rajamangala University of Technology Isan

^{1,2}150 Srichan Road, Nai Mueang Subdistrict, Mueang Khon Kaen District, Khon Kaen, 40000

³744 Suranarai Road, Nai Mueang Subdistrict, Mueang Nakhon Ratchasima District, Nakhon Ratchasima, 30000

Received 7 January 2026; Revised 2 April 2026; Accepted 11 June 2026

Abstract

This research utilized Genetic Algorithm (GA) to optimize cassava transportation routes from cultivation fields to nearby collection yards, with the objective of minimizing CO₂ emissions based on optimized distances. Data collected included plot coordinates, plot size, vehicle type, vehicle weight, and payload capacity for each vehicle type to collection yard A, as well as coordinates of two alternative nearby collection yards, B and C. Four vehicle types, including tractor, farm tractor, 6-wheel truck, and pickup truck, were analyzed in transporting cassava from 20 surrounding plots to collection yard A, with each delivering different volumes of cassava. The GA-based optimization of routing grouped the 20 plots into efficient collection routes servicing three different yards (A, B, and C), achieving a total of 18 optimized trips, which the results section that the workload was equally distributed, with each yard (A, B, and C) receiving 6 trips to ensure operational consistency across all route and payload identified a required vehicle capacity of 17,000 kg to satisfy the minimum theoretical trip demand. When CO₂ emissions were calculated along the optimized route, the observed emissions from actual operations were substantially higher than the GA-derived values. Total CO₂ emissions GA were decreased carbon emissions by up to 67.2 – 68.1 % compared to using Tractors and Farm tractors, 54.6 % when using 4-wheel pickup trucks and 0.09 % for the 6-wheel trucks. The results demonstrate that GA driven optimization significantly enhances agricultural logistics by reducing transportation time, costs, and environmental impact through the strategic selection of collection yards and vehicle types

Keywords : Genetic algorithm; Greenhouse gas; Cassava; Carbon emission; Optimization

* Corresponding Author. Tel.: +668 6354 8683, E-mail Address: paramust.ju@rmuti.ac.th

1. Introduction

Cassava is a vital crop in many tropical countries, serving as a critical source of carbohydrates for both human and animal consumption [1]- [2]. It also holds substantial industrial value as a raw material for renewable energy production, particularly ethanol. Its utilization, however, varies sharply by region: Africa primarily uses cassava for direct consumption, while the Americas focus on commercial cultivation for industrial supply. In Asia, cassava is predominantly utilized by the downstream industry rather than for direct consumption. Globally, production is concentrated in Africa, followed by Asia, the Americas, and Oceania. As of 2022, Thailand ranked as the third-largest cassava producer in the world, after Nigeria and Congo [3]. Thailand is a major exporter of cassava products, supplying markets such as China, Japan, Indonesia, Taiwan, and Malaysia, with cassava product exports valued at approximately 3,133.4 million USD [4]. Cassava cultivation is widespread across all regions of Thailand, with the Northeast accounting for the largest share at 54.5%, followed by the Central (25.6%) and Northern (19.9%) regions, totaling to approximately 7.9 million Rai (1.26 million hectares). The Northeast alone yields about 15.39 million tons per year [5]. For the 2025-2026 period, cassava output is projected to increase, driven by an expansion of harvested area in response to rising demand from the energy and animal feed industries, as well as the need for product stock to ensure food and energy security [6]. This growth is expected to

intensify activity across the entire cassava supply chain, from cultivation to processing. An analysis of the cassava starch supply chain identified three major contributors to the product's carbon footprint (CF): cultivation, root transport, and starch processing. Cultivation is the dominant factor, accounting for 52% of the total CF, while cassava root transport contributes 8% [7]. Globally, the largest source of greenhouse gas (GHG) emissions from human activities stems from burning fossil fuels for electricity, heat, and transportation. In the United States in 2022, total GHG emissions by economic sector were distributed as follows: transportation (28%), electric power (25%), industry (23%), commercial and residential (13%), and agriculture (10%) [8].

In the transport sector, there is a global drive toward promoting the use of renewable energy, particularly electric power, to reduce GHG emissions. The global goal is to achieve Net Zero Emissions by 2050, while Thailand has set its target for 2065. Within this framework, the Thai transport sector aims to reduce its GHG emissions by 20% by 2030 [9]- [10]. This objective remains challenging, despite supportive policies such as import tax reductions for electric vehicles and investments in public transport system. Within the agricultural supply chain, farmers typically use small trucks (like "E-taen" vehicles) and six-wheel trucks to transport produce from their farms to factories or purchasing points. Motorcycles are also used for small-volume transportation to middlemen or collection yards. Most farmers sell their

produce to nearby buyers or processors, with only a minority engaging in long-distance or inter-provincial markets [11].

The reliance on internal combustion engine (ICE) vehicles for transporting agricultural goods exacerbates traffic congestion, overweight loading, particulate matter (PM) dust pollution, and GHG emissions in line with rising industrial demand [12]- [13]. Existing studies on cassava transport logistics primarily focus on movement from middlemen to industrial factories, which typically involves only a few trips by large trucks. This is because large-scale operators actively manage transport operations to minimize costs and product damage. However, the initial transport stage, from the farmer's field to the collection yard (**Fig. 1**) or middleman, has received far less attention. Farmers typically bring fresh cassava roots directly to the yards or factories, often choosing the destination based on listed prices, familiarity, or proximity to their farms. Transport planning at this stage is largely informal and habit-driven, with limited consideration of costs, trip frequency, or travel distance.



Fig. 1 Cassava collection yard.

A lack transport consolidation among farmers increases the number of trips, exacerbating traffic issues, overloading problems (**Fig. 2**), and environmental pollution. Optimizing transport routes from cultivation fields to suitable collection yards or buyers, considering factors such as distance, price, and emission reduction (especially greenhouse gases), would help alleviate transportation challenges. Such optimization would support both farmers and the government in achieving the Net Zero Emission targets for the transport sector.



Fig. 2 Cassava transport with overloaded vehicle.

The genetic algorithm (GA) is widely recognized as a powerful optimization tool for solving transportation problems, capable of producing superior solutions within reasonable computational times [14]- [15]. Recent research has demonstrated that GA can provide upper bounds on objective function values, yielding a computationally efficient and statistically robust solution for vehicle routing problems involving perishable products [16]. Furthermore, GA can be applied to solve vehicle routing problems to reduce carbon emissions and promote sustainable development in the transportation sector. For instance, GA has been applied to analyze the impact of environmental self-regulation on the

Vehicle Routing Problem (VRP), considering carbon emissions from fuel combustion, which are determined by distance, fuel carbon content, fuel consumption, and driver category. These studies demonstrate that GA is a promising approach for addressing these challenges [17].

Therefore, this study proposes using GA to determine optimal transport routes for cassava from cultivation fields to nearby collection yards. The GA optimized model is compared against actual transportation data from an observation yard, where current practices involve various informal methods, typically using one truck per plot based on conventional practice, which the inefficient transportation methods lead to increased air pollution. The analysis focuses on minimizing carbon dioxide emissions by optimizing both transport routes and vehicle load capacity. This framework provides a systematic approach for identifying optimal transport paths, aiding in carbon emission reduction, and offering guidance for future policy formulation on the transport of other economic crops, balancing agricultural income with carbon emissions.

2. Research Methodology

2.1 Data Collection

1. Data were collected on the types and number of vehicles used to transport cassava to local purchasing yards in Khon Kaen Province, Thailand. The survey identified four categories of vehicles utilized for this transport: tractor, farm tractor (e-taen thai tractors), 6-wheel truck, and pickup truck (**Fig. 3 a – d**). This

research considered only diesel-fueled vehicles, as diesel engines offer higher efficiency and simpler engine design, making them the preferred choice for heavy transport compared to gasoline-powered alternatives [18].

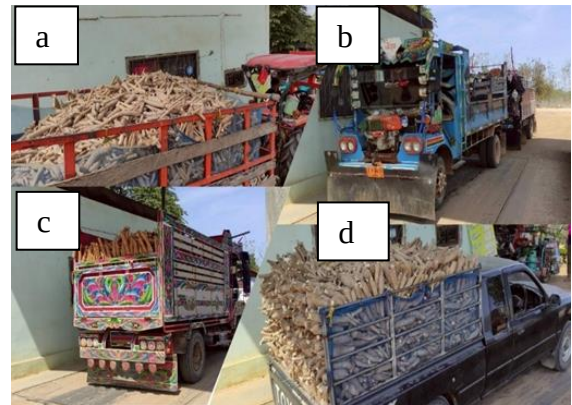


Fig. 3 Vehicle types used for cassava transport: (a) Tractor, (b) Farm tractor, (c) 6-wheel truck, and (d) Pickup truck.

2. Initial data were collected at Purchasing Yard A to determine the vehicle types used by farmers, the average payload (loading weight), the average vehicle weight (tare weight) (**Table 1**) (**Fig. 4**). Subsequently, two nearby purchasing yards, Yard B and Yard C, were selected based on their coordinates obtained from Google Earth Pro.

Table 1 Average payload and tare weight of vehicles used for cassava transport.

Truck	Payload avg (kg)	Tare weight avg (kg)
Pickup	2453	1663
6-wheel	4052	3266
Tractor	3354	2620
Farm tractor	3800	2165



Fig. 4 Weight measurement of cassava transport trucks.

3. The payload weight factor was determined according to the standard used for calculating CO₂ emissions, following the Thai National LCI Database, TIIS-MTEC-NSTDA (with TGO electricity data for 2016-2018). For truck transportations, loading conditions were categorized into two groups: 100% and 0% [19].

4. The commuting distance between the farms and yards was calculated using the coordinates (longitude and latitude) of farm and yard locations obtained from Google Earth Pro and QGIS (**Fig. 5**).

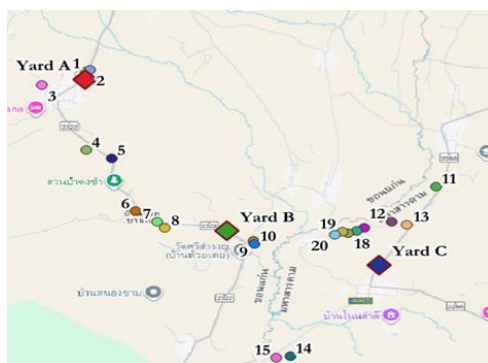


Fig. 5 Locations of 20 cassava plots and three purchasing yards (A, B, and C).

2.2. Optimization of the routes using GA

2.2.1 Optimization of the routes.

GA searches for optimal solutions by mimicking natural selection and evolutionary processes [20]- [21]. It iteratively generates, tests, and refines a population of candidate solutions (routes) until a highly optimized result is obtained. In the cassava transportation problem, GA importance lies in its ability to simultaneously determine key parameters, including:

1. Problem Formulation

The logistics problem involves collecting cassava from $n = 20$ distinct customer nodes (cassava plots). These nodes were geographically defined by their GPS coordinates (longitude and latitude). The objective is to minimize the total distance traveled by the vehicle fleet, which is used as an established proxy for reducing operational costs and associated emissions.

2. Key Parameters and Constraints

2.1. Customer demand: Each of the 20 cassava plots had a different demand, resulting in a total aggregate demand of 286,200 kg. This total demand was calculated based on the plantation area, as shown in **Fig. 6**., where the estimated yield was 2,700 kilograms [22] of cassava per 1,600 m² harvested.

2.2. Vehicle fleet and cassava plots:

The operation employed a fleet of $m = 3$ vehicles, which must originate and terminate their routes at one of the $k = 3$ distinct cassava plot locations.

2.3. Capacity constraint: The primary constraint is the maximum vehicle loading capacity. The model considered a range of truck capacity values (5,000 kg to 32,000 kg). The maximum value of 32,000 kg aligns with the TGO standard for large transport vehicles [19]), with particular focus on operationally relevant values between 7,000 kg and 32,000 kg. These capacity levels align with transportation guidelines [19] and the empirical data summarized in Table 1, where the lowest observed weight was about 5,000 kg. For all routes, the total load on any vehicle must not exceed the specified capacity limit.

2.2.2. Trip Requirement Analysis

In the post-processing stage, the logistical efficiency of the optimized solution was quantified:

1. Theoretical minimum trips: This value represented the lower bound on the number of trips, calculated by dividing the total demand by the single vehicle capacity.

2. Total optimized trips: The actual number of required trips was determined by analyzing the route structure, specifically by counting the segments where the route returned to a depot for unloading, indicated by a sequence breaks. This value was equal to or slightly higher than the theoretical minimum, reflecting the added inefficiencies imposed by geographic clustering of cassava plots. Given the fundamental constraint that total optimized trips must be greater than or equal to the theoretical minimum, to the study examined the impact of varying vehicle capacity. To ensure robust and applicable results, the

system was analyzed across a range of plausible truck capacity values, from 5,000 to 32,000 kg. This experimental approach ensured that the calculated total optimized trips respected capacity constraints and remained greater than or equal to the corresponding theoretical minimum.

3. Fleet allocation: The final step estimated the trip workload distribution across the three available trucks (Truck 1-3), assuming GA achieved a balanced assignment to maximize fleet utilization.

2.3. Analysis of CO₂ emissions from cassava transport compared with GA optimized routes.

Following optimization of cassava transport routes using GA, the resulting optimal distance was used to calculate the CO₂ emissions according to equation (1) [23]. Calculations were performed for all four vehicle types over the investigated capacity range (5,000 to 32,000 kg), assuming a 100% payload for each trip.

$$\text{Emissions} = \text{Activity} \times \text{Emission factor} \quad (1)$$

When

$$\text{Activity} = \text{Distance (km)}$$

$$\text{Emission factor (EF)} = \text{GHG emissions per unit (kgCO}_2\text{eq/kg)}.$$

3. Results and Discussion

3.1. Optimization of cassava transportation routes using GA

The optimization of cassava transportation routes using GA was conducted for vehicle capacities ranging

from 5,000 to 32,000 kg. The estimated cassava yield for plots 1–20 (**Fig. 5**) was 2,700 kg per 1,600 m². The resulting optimized routes and associated metrics are presented in **Fig. 7** and **Fig. 8**.

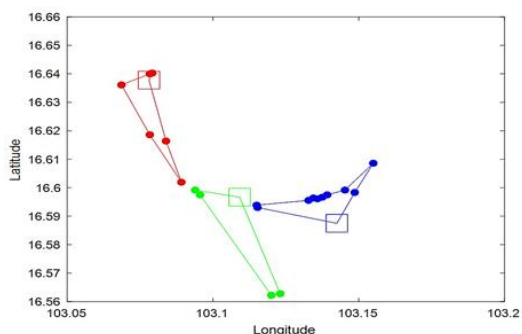


Fig. 7 Optimized cassava transportation routes generated by the Genetic Algorithm (GA)

Fig. 7. The Optimized routes of GA across a range of vehicle payloads, specifically from 5,000 kg to 32,000 kg. The results showed that, the minimum value required to achieve a total of 18 trips (**Fig. 8**) was a vehicle capacity of 17,000 kg, according to the TGO standard for 10-wheel transport vehicles [19] and above were required for the cassava transport routes to satisfy the minimum theoretical trip requirement.

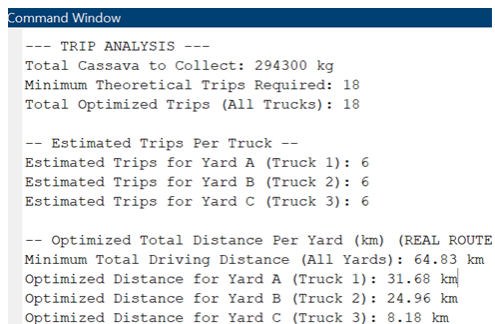


Fig. 8 The trip analysis and optimized travel distance for GA-based cassava transport.

Fig. 8. The GA was applied to optimize routes and payloads which the overall trip analysis, confirming high logistical efficiency. The total amount of cassava collected was 294,300 kg, and the minimum theoretical number of trips was 18. The GA-optimized solution achieved this lower bound, yielding a total of 18 optimized trips across all trucks. This result fully satisfies the condition that the realized number of trips must be greater than or equal to the corresponding theoretical minimum.

Furthermore, the estimated trips per truck, as determined by GA, indicate a near equal distribution of workload among the three collection yards: Yard A, Yard B, and Yard C each required 6 trips to complete the transportation task.

3.2 Carbon dioxide emissions per kilometer based on GA-determined truck weight

Used the optimized cassava transportation routes determined by the GA, the optimization is performed, which follows an iterative evolutionary process (1) initial population of potential routing sequences, (2) fitness evaluation based on route, load and round, (3) selection of the most efficient routes, (4) crossover to combine optimal route segments, and (5) mutation to prevent local optima. This process continues until the algorithm identifies the optimal. This process continues until the algorithm identifies the global optimum for the logistics network, which the CO₂ emissions were calculated along these routes. The analysis considered vehicle mass constraints, with the minimum

cassava payload set at 17,000 kg as determined by the GA optimization, in accordance with the standard specifications for 10-wheel trucks outlined by the Thailand Greenhouse Gas Management Organization [19]. The truck’s empty (tare) weight was approximately 13,500 kg [24], resulting in a gross vehicle weight (GVW) of 30,500 kg at full load. This approach ensures that the environmental impact assessment reflects both optimized routing and realistic vehicle operating conditions.

Table 2 Optimized cassava transportation routes determined by GA.

Yard	Plot				Trips	Dist. (km)	Google Dist. (km)	Error (%)
A	2	1	3	4	6	33.63	28.56	18
	6	5						
B	7	8	15	14	6	24.96	49.15	49
C	10	9	20		6	8.18	46.28	82
	19	18	17					
	16	12	11					
	13							
Total						66.77	124.00	46

As presented in **Table 2**, a subsequent validation of the optimized routes against real-world driving distances using Google Earth Pro revealed a significant discrepancy: the total distance estimated by GA deviated by 46% from the actual georeferenced routes. This considerable variance is attributed to the GA reliance on the straight-line distances based on GPS coordinates for its fitness function, which does not account for road networks and topographic barriers.

Consequently, to ensure the validity and accuracy of the environmental impact assessment, CO₂

emissions were calculated using the validated real driving distances obtained from the Google Earth Pro analysis rather than the initial GA estimated values. However, the calculations continued to follow the transportation routes determined by GA.

3.3 A Comparative CO₂ Emission Analysis: Scenario Using Observational Data

The results presented in **Table 3** detail a comparative analysis of CO₂ emissions based on observational data collected specifically from Yard A. The simulation incorporated four distinct truck types (as specified in **Tables 1** and **2**) and employed distances derived from Google Earth Pro for the yard-to-plot routes. While the GA-generated transportation routes were based on grouping to optimize collection, the actual operations involved a single vehicle servicing each plot, carrying as much as possible per trip and making multiple trips until all cassava was harvested. The number of transport trips was fixed at the theoretical minimum required to service the total demand. Emission calculations accounted for load factors on the two-way journey: the 0 % load emission factor was applied to the outbound leg (from the receiving yard to the cassava plot), and the 100 % load emission factor was applied to the inbound leg (from the cassava plot back to the yard) All trips were assumed to start and end at a designated yard. The total CO₂ emissions (kgCO₂eq) are summarized in **Table 3**.

Table 3 Total CO₂ emissions (kgCO₂eq) calculated from observational data compared with emissions estimated using GA determined routes.

	Yard	Pickup	6-wheel	Tractor	Farm tractor	GA
	A	69.32	27.85	91.17	83.43	30.84
	B	106	48.40	144.94	160.22	44.02
	C	100.36	49.09	145.53	148.94	50.40
	Total	275.67	125.37	381.65	392.59	125.26
SD	A	12.97	5.67	15.57	17.56	2.31
	B	20.79	9.35	29.03	30.89	4.32
	C	5.14	2.48	7.26	7.24	2.16
Max	A	30.20	12.25	36.06	39.13	7.93
	B	56.29	25.70	78.64	83.81	12.20
	C	19.72	9.64	28.10	27.72	6.73
Min	A	0.61	0.18	1.02	0.42	0.11
	B	1.18	0.81	2.00	2.37	0.36
	C	1.63	1.12	2.77	3.27	0.11

The comparative analysis **Table 3** demonstrates a significant disparity, with observed CO₂ emissions exceeding those estimated by GA optimization. A small standard deviation indicates high consistency and minimal variability in the observational data, which represent the environmental impact boundaries for each scenario. In contrast, the GA Optimization significantly narrows CO₂ emissions gap between maximum and minimum values by balancing workloads and optimizing routes.

Moreover, the GA model at Yard A exhibited an R² value of 0.51, suggesting that the independent variables explain approximately 51% of the variability observed in the dependent variable, as shown in **Fig. 9**.

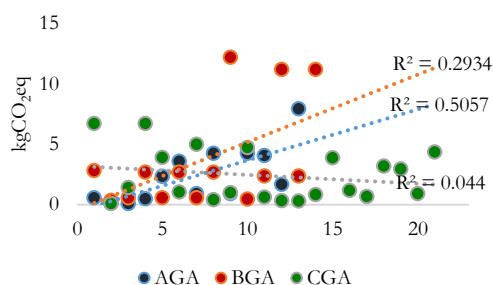


Fig. 9 CO₂ emissions from cassava transportation to yards A, B, and C as optimized by GA.

Fig. 9. The lower R² values for BGA and CGA compared to AGA are attributed to the higher variability in plot sizes and distribution within the yard group. While GA optimizes for a target payload of 17,000 kg, the actual harvest totals from the farms often result in residual loads, which results in more trip frequencies that do not scale linearly with distance. Consequently, the payload weight becomes an important factor in emission variance, leading to the observed data dispersion in the regression analysis.

This substantial divergence can be primarily attributed to two key operational factors: the lower effective capacity of the vehicles used in the observational data and the resulting increased number of necessary transport trips. The suboptimal utilization of vehicle capacity in real-world practice necessitates more trips to satisfy the total demand, directly leading to greater fuel consumption and CO₂ emissions.

4. Conclusion

The optimization of cassava transportation using GA proved highly effective for agricultural logistics management, enabling the rapid generation of optimal transport plans to both farmers and receiving centers. This study demonstrated that implementing a tailored logistics strategy significantly reduces time, cost, and environmental pollution compared to conventional methods, primarily through the optimized selection of receiving yards and vehicle types. Although the GA successfully addressed both capacity and routing, a notable limit was a 46% error in the estimated total distance compared to actual travel distances. After adjusting to real driving distances by Google earth pro, the GA optimized transport strategy utilizing 10 - wheel trucks with a payload of at least 17,000 kg and a grouped collection approach can decreased carbon emissions by up to 67.2-68.1% compared to using Tractors and Farm tractors, 54.6 % when using 4 - wheel pickup trucks and 0.09 % for the 6 - wheel trucks, although 10-wheel trucks have difficulty to access farmland, the result was a policy alternative through farmer groups to enable the use of larger, more efficient vehicles. Furthermore, although payload and carbon emissions are directly proportional, the GA optimization demonstrates that the significant reduction in the total number of trips outweighs the increased per-trip emissions. By consolidating the total Cassava 294,300 kg into the theoretical minimum of 18 trips using a 17,000 kg capacity which

was decreased overall carbon emissions compared to multiple trips by smaller, less efficient vehicles. In particular, it supports strategies such as minimizing partially loaded trucks and empty vehicle runs, selecting appropriate vehicle sizes, and establishing farmer cooperatives (or groups) to achieve cost savings [11]. Route optimization remains a fundamental efficiency strategy, as it directly reduces operating costs and is already widely recognized and exploited in practice [18].

5. Acknowledgement

The authors gratefully acknowledge the Faculty of Industrial Education and the Faculty of Engineering, Rajamangala University of Technology Isan, for providing the facilities and support that enabled this research.

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