СИСТЕМНИЙ АНАЛІЗ ТА НАУКА ПРО ДАНІ

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FLEET MANAGEMENT ALGORITHM FOR ENHANCING ENVIRONMENTAL FRIENDLINESS OF MARITIME DELIVERY

Background. Maritime cargo delivery accumulates over 80 % of international transport operations, providing a cost-effective method for global trade, particularly vital for developing countries. However, maritime transportation is heavily dependent on fossil fuels, which results in significant emissions of carbon dioxide CO_2 and creates environmental problems for water resources. To address these issues, this study proposes a solution to optimize maritime delivery route planning projects, and reduce fuel consumption and CO_2 emissions.
Objective. The objective is to develop an algorithm for planning delivery routes at optimal vessel speed, consisting of a genetic algorithm and a speed optimization step, to reduce fuel consumption and CO_2 emissions during maritime transportation. In addition, the results will be validated and the efficiency of the developed algorithm will be compared with a standard genetic algorithm without a speed optimization step.
Methods. This article proposes an implementation of an additional step of vessel speed optimization into the algorithm for calculating delivery routes, which can significantly reduce fuel consumption and CO_2 emissions without increasing the complexity of the algorithm itself. The route is computed by solving the vehicle routing problem.
Results. The study demonstrates that the application of the speed optimization step in the algorithm for planning delivery routes significantly reduces the volumes of fuel consumption and CO_2 emissions. Comparison of the experimental results showed that the genetic algorithm with a speed optimization step outperforms the standard genetic algorithm in terms of the volumes of fuel used and CO_2 emissions. Detailed analysis of various combinations of fleet composition emphasizes the need to balance the capacity of vessels to achieve maximum efficiency of cargo delivery. While adding more feeders initially reduces overall fuel consumption, overloading the fleet with underutilized vessels can lead to inefficiencies and increased operational costs. The study also considers alternative approaches such as increasing capacity and reallocating vessels among routes, highlighting their impact on fuel consumption and CO_2 emissions.
Conclusions. The study proposes an improved algorithm for constructing maritime cargo delivery routes using a genetic algorithm with a speed optimization step. Such an algorithm ensures effective management of maritime delivery route planning projects, while significantly reducing fuel consumption and CO_2 emissions into the environment. Also, optimal control of the fleet composition ensures the reduction of CO_2 emissions due to the efficient use of each vessel.
Keywords: water transport; fleet management; optimal control; route planning; route optimization; project management; fuel consumption; CO_2 emissions; vessel speed optimization; genetic algorithm.

Introduction

Maritime cargo delivery accounts for the largest share of global goods transportation, making up more than 80 % of international transport. This percentage is even higher in most developing countries [1]. One of the key advantages of maritime cargo transportation is its low delivery cost [2]. However, this mode of transportation consumes a vast amount of fuel, leading to significant carbon dioxide CO_2 emissions, which have a detrimental impact on the environment [3]. Many carrier companies operate ageing fleets that rely almost exclusively on fossil fuels, having resulted in a 20% increase in greenhouse gas emissions over the last decade [4]. Efficient ways to reduce CO_2 emissions include using modern fuels and deploying modern ships that are less harmful to the environment. These options are interconnected, as it is not feasible to easily switch to modern fuel on older ships and vice versa. Therefore, implementing these emission reduction strategies will require significant investment – first to renew the fleet of ships and then to transition to less harmful fuels. Consequently, the cost of delivery is

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likely to increase substantially, potentially decreasing the share of maritime delivery in the global market. It is important to note that fleet modernization can only be implemented in the long term, allowing for a gradual phase-out of outdated ships and fuels.

An alternative way to reduce CO_2 emissions is to plan the shortest delivery routes for cargo. It may seem intuitive that shorter routes use less fuel, leading to lower CO_2 emissions. However, a crucial factor influencing CO_2 emissions is the speed of the ship. Fuel consumption has a non-linear relationship with vessel speed — as speed increases, fuel usage increases significantly. Consequently, CO_2 emissions into the atmosphere also rise with increased speed.

High delivery speeds are justified by the fact that container shipping companies aim to deliver goods as quickly and reliably as possible. As fuel consumption increases, so does the delivery cost. Carrier companies commit to delivering goods within specified time frames and failing to meet these deadlines results in penalties and reputational damage. Therefore, it is crucial to plan delivery routes that allow cargo to be delivered on time while enabling ships to travel at the minimum acceptable speed to fulfil contractual agreements. Additionally, the lower speeds can lead to a reevaluation or reduction in delivery costs [5].

Article [6] considers the multiple travelling salesmen problem (mTSP) for constructing optimal routes, incorporating additional constraints such as feeder capacity, cargo accumulation intensity at the port, and maximum route duration or time windows. These constraints effectively expand the mTSP into the vehicle routing problem (VRP). The classic VRP extends the mTSP by including different service requirements at each node and varying capacities for vessels in the fleet management. The objective of these problems is to minimize the total cost or distance across all routes [7].

This article proposes an additional route optimization step that can significantly reduce costs and emissions without increasing the complexity of the route calculation algorithm. The route is computed using a genetic algorithm, which belongs to heuristic algorithms, providing approximate solutions that save computational resources — equivalent to time and budget [8, 9]. The genetic algorithm stands out as one of the best heuristics for finding delivery routes with lengths practically approaching the possible minimum [10, 11]. In some cases, the heuristic solution matches the exact solution's route length.

Various methods exist to enhance the performance of a genetic algorithm. A study on the selection mechanism and the elimination of invalid routes is discussed in [12]. The impact of a random number generator on population creation and mutation processes is explored in [13]. The fundamental mutation operation in genetic algorithms is the crossover operation, commonly known as two-point crossover. An alternative version of the algorithm featuring a modified three-point crossover is detailed in [14].

This paper proposes a solution that calculates the optimal speed of vessels along routes, identified using a genetic algorithm with enhanced constraints [6]. In maritime cargo delivery, the vehicle routing problem addresses the routing of optimal feeder tours. The determination of speed follows the identification of the optimal feeder route for cargo delivery. Opting for reduced-speed delivery routes allows ships to travel slowly enough to ensure timely cargo delivery while minimizing fuel consumption and thereby reducing CO_2 emissions.

Problem statement

The goal is to describe, implement, and justify the importance of using an algorithm, consisting of a genetic algorithm and a speed optimization step, to achieve reductions in fuel consumption and CO_2 emissions in maritime shipping. Moreover, comparisons with the algorithm without an additional optimization step will be demonstrated. To achieve the goal, the following four tasks are to be fulfilled:

1. To substantiate the inclusion of the speed optimization step after an initial route is produced by the genetic algorithm.

2. To show the advantage of the algorithm using the speed optimization step compared to the algorithm, which does not consider the speed of feeders.

3 To discuss the significance and practical applicability of the suggested improvements in the algorithm of maritime delivery route planning and project management.

4. To make an unbiased conclusion on the contribution to the field of algorithms used, in particular, to optimize maritime cargo delivery planning. An outlook of how the research should be extended and advanced is to be made as well.

GA with speed optimization

Route planning is a crucial aspect of maritime cargo delivery and project management, aimed at solving the traveling salesman problem. This classic problem involves constructing the shortest route that visits all points on a map exactly once before returning to the starting point. However, in practical maritime operations, companies manage large fleets of ships, and merely solving the classic travelling salesman problem is not sufficient to ensure optimal and profitable delivery of goods. As a result, the mTSP has emerged, focusing on finding the shortest routes for several salesmen simultaneously. Solving the mTSP requires an enhanced algorithm based on the classic TSP framework. Despite the complexity introduced by multiple salesmen, the ultimate goal remains the same: to identify the shortest possible routes, which are deemed optimal for efficient cargo delivery.

Constructing a route solely based on minimum length may not suffice for efficient maritime cargo delivery. Carrier companies must navigate numerous additional constraints crucial to planning delivery routes effectively. Key among these are feeder capacity, cargo accumulation intensity at ports, and maximum route duration, reflecting real-world processes in maritime cargo operations. Integrating these factors into algorithms enables the development of delivery routes that accommodate the complexities and specificities of maritime logistics [6]. Incorporating these constraints expands the mTSP into the VRP. The primary goal of these problems is to minimize the total cost or distance covered across all feeder tours.

Expanding the problem to include the VRP complicates the algorithmic logic required to find optimal routes, necessitating consideration of implemented restrictions. This challenge can be formulated as a mathematical optimization problem and solved using various algorithms, including metaheuristics or exact methods [15]. As previously mentioned, a proposed solution to address this transportation challenge involves the utilization of a genetic algorithm. Genetic algorithms leverage principles of natural selection to solve optimization problems efficiently [10].

The genetic algorithm iteratively modifies a population of individual solutions. In each iteration, the algorithm selects individuals from the current population to act as parents, generating offspring for the next generation. Through successive generations, the population evolves towards an optimal solution. During the generation of a new population, mutations occur. The algorithm used in this study incorporates mutations such as flip, swap, slide, and crossover. These mutations can also be combined, enabling the creation of complex mutations. Each of these operations modifies the individual in unique ways, contributing to a near-optimal solution.

Following the completion of all mutations across the population, the genetic algorithm proceeds with evaluation and selection steps. Each generated solution undergoes evaluation using a fitness function, which assesses its proximity to the optimal solution of the problem and verifies compliance with specified constraints. Solutions that violate any defined constraints are penalized and rendered infeasible, thereby excluding them from further mutations. Conversely, solutions that incur fewer penalties or remain penalty-free are deemed feasible and retained for subsequent mutation processes.

In our previous studies [6, 12, 13, 14], a genetic algorithm is utilized to find the shortest delivery routes while imposing a maximum route length constraint. The fitness function evaluated each feeder route's length, imposing penalties if it exceeded the defined constraint. This constraint aimed to enable uninterrupted cargo delivery routes without the need for refuelling, thereby reducing fuel costs and avoiding additional refuelling time. In this article, a new set of constraints is introduced and the algorithm's input data is expanded. Notably, the maximum route length restriction is omitted, as refuelling costs are now considered permissible during the cargo delivery process.

Expanding the problem to solve the VRP complicates the search for the optimal route. For instance, in the case of using a genetic algorithm, the population size must be sufficiently large to accommodate all constraints, such as capacity and speed of movement. If speed variations are not initially considered in the algorithm for solving mTSP, addressing the VRP requires multiplying the population size by the range of permissible vessel speeds. Consequently, this increases the time required to compute the optimal route.

This research proposes a solution to the cargo delivery problem using a genetic algorithm that considers route length, feeder capacity, and cargo accumulation at ports to compute the minimum route satisfying these conditions. Following the calculation of the feeder route, a speed optimization step is proposed to gradually reduce the speed of each feeder along the route. This speed reduction significantly decreases fuel consumption and CO_2 emissions. Integrating this speed optimization step leverages the existing genetic algorithm to find the optimal route without initially factoring in feeder speeds, thereby avoiding an increase in computation time. The speed reduction step requires minimal additional calculation time compared to the main route calculation. Thus, a hybrid approach is suggested for planning sea routes for cargo delivery, combining a genetic algorithm with an additional speed optimization step.

Maritime cargo delivery model

In this section, the mathematical model underlying the genetic algorithm for maritime route planning is presented. The model aims to optimize cargo delivery routes while considering various constraints, such as feeder capacity, port cargo accumulation, and route duration. By formulating this problem as a variant of the mTSP in order to achieve efficient and sustainable maritime logistics advanced optimization techniques can be leveraged. The primary objective of the model is to minimize the total cost, which includes fuel consumption and CO_2 emissions while ensuring that all delivery constraints are met. This involves not only finding the shortest possible routes but also optimizing feeder speeds and capacities. The genetic algorithm incorporates various mutations and crossover operations to explore a wide range of potential solutions, ultimately converging on an optimal or near-optimal route configuration.

The following variables are used in a simplified maritime cargo delivery model [6]: $N$the number of ports, p_{k1} and p_{k2} are the horizontal and vertical components of the position of the port k, and $M_{\max}$ the number of feeders available to accomplish the delivery. Every feeder m starts its tour off port 1 and ends up returning to that port. We denote the current number of feeders by M.

In our previous work, we considered a model in which the feeder had a limitation feeder m capacity C_m, accumulation intensity A_{nm} of cargo at port n visited by the feeder m, and maximum route duration $D_{\max}$. The minimization goal is to find such a set of flags X^*, at which

$$d_\Sigma(N, M, X^*) = \min_X d_\Sigma(N, M, X) \qquad (1)$$

under feeder capacity and cargo accumulation constraints.

This article discusses an approach to reducing fuel consumption during maritime delivery. Fuel consumption for a feeder vessel is primarily dependent on the vessel's speed and can be expressed as a cubic relationship. This means that fuel consumption increases exponentially with speed. At the same time, it depends on the specific characteristics of the vessel, including its engine efficiency and hull resistance.

To accurately calculate fuel consumption, it is essential to refer to the fuel consumption values at the vessel's maximum speed as specified in the technical documentation. Using this data, fuel consumption at lower speeds can be approximately estimated. Also, it can be adjusted with additional empirical data or specific operational considerations for the vessel.

In this work, the objective function is to minimize fuel consumption when delivering cargo by sea. So, the task is to find X^*, at which

$$d_\Sigma(R_m, v_m, X^*) = \min_X \sum_{m=1}^{N} F(R_m, v_m, X) \qquad (2)$$

where N is the number of routes, R_m is the route of the m feeder, and v is the speed of the m feeder. The restrictions from [6] must also be taken into account when searching for optimal routes and speeds.

Maritime shipping is a significant contributor to global CO_2 emissions, which play a major role in climate change and ocean acidification. By minimizing these emissions, we can help protect marine ecosystems and the environment. Additionally, compliance with increasingly stringent international regulations, such as those set by the International Maritime Organization (IMO), is essential to avoid penalties and ensure the sustainability of maritime operations. Lowering CO_2 emissions also has public health benefits, as it reduces the release of harmful pollutants, thereby improving air quality and reducing health risks for communities near ports and along shipping routes. Air pollutants from the ship operations using heavy fuel oil are shown in Table 1 [16]. The table displays the amount of pollution in grams produced per gram of fuel burned.

Testing

In the testing section, the algorithm's operation for constructing maritime cargo delivery routes with a speed optimization step is analysed. A comparison with the algorithm without this additional optimization step is conducted. Experiments are performed to evaluate the impact of the speed optimization step on algorithm performance. Henceforth in this article, the algorithm with the optimization step will be denoted as *GA_S*, while the algorithm without it will be referred to as *GA*. Each experiment is conducted under identical conditions, using the same port map and a predetermined number of feeders.

***Table* 1.** Emissions produced by heavy fuel oil

Pollutant	CO_2	CH_4	N_2O	NO_x	NMVOC	CO	PM_{10}	SO_2
EF HFO	3,114	0,000 06	0,000 15	0,0903	0,003 08	0,002 77	0,002 78	0,025

Table 2 presents the results of experiments comparing fuel consumption and carbon dioxide emissions between *GA* and *GA_S*. These experiments are conducted across varying numbers of ports, reflecting the need to establish sea delivery routes for both small-scale scenarios (e.g., the Sea of Azov or the Marmara Sea) and larger-scale scenarios encompassing several dozen ports (e.g., the Black Sea or the Mediterranean Sea) [17].

Table 2 demonstrates that the algorithm with an additional optimization step yields promising results in reducing fuel consumption and CO_2 emissions. This suggests that the speed reduction step can effectively contribute to planning optimal maritime delivery routes. Importantly, this approach allows for calculating the minimum permissible speed without introducing complexity to the existing algorithm. The additional step gradually reduces the speed of each feeder until it conforms to all specified delivery constraints, including the total fleet capacity necessary to manage accumulated cargo at ports within specified timeframes.

Considering an alternative approach to solving the VRP using a genetic algorithm without an additional optimization step, it becomes evident that incorporating speed selection into population generation and selection processes is crucial. Introducing a population with varied speeds inevitably increases its size compared to one without speed considerations. The larger population size in a genetic algorithm impacts the time required to reach an optimal solution. To compare the performance of algorithms with an additional speed optimization step and an algorithm featuring an expanded population, tests are conducted, and the results are presented in Table 3.

As shown in Table 3, the basic genetic algorithm (*GA)* finds a route faster than other algorithms. The genetic algorithm with a speed optimization step (*GA_S*) slightly increases the time required to obtain a route but has the advantage of reducing fuel consumption. This increase in time can be considered quite acceptable. A basic genetic algorithm (*GA*) is also run with an increased population (from 24 to 32 individuals) to simulate the operation of an algorithm that would evaluate all possible speeds. The time to find the optimal route using an algorithm with an increased population (*GA_IP*) is significantly longer than that of an algorithm with a speed optimization step. Thus, it follows that *GA_S* is more preferable for obtaining a route with the minimum permissible speeds if considering the speed of obtaining the result. On the other hand, *GA_IP* searches for solutions among a larger number of initial routes, which can help obtain a more preferable route, which requires more computational time.

Next, specific examples of constructing maritime delivery routes for the same set of ports are examined. Both algorithms – those with and without an additional speed optimization step – are tested. These experiments utilized the same port map to ensure objective evaluation of algorithm performance. Each test resulted in a map displaying constructed routes for every feeder involved in cargo delivery. Additionally, a table is constructed presenting key characteristics and properties of the calculated routes: feeder capacities, route lengths, tour durations, vessel speeds, cargo accumulation at ports, fuel consumption, and carbon dioxide emissions. Furthermore, tables presenting results from the algorithm with an additional speed optimization step illustrate differences in fuel consumption and CO_2 emissions.

In the initial test, the delivery routes for five feeders are computed using the algorithm without an additional optimization step. For the tests, the "Wes Janine" feeder vessel is chosen. It has a capacity of 1000 TEU, a top speed of 16 knots, and an approximate fuel consumption of 24 tons per day. The routes are illustrated in Fig. 1, while fuel consumption and CO_2 emissions are detailed in Table 4.

***Table* 2.** Comparison of *GA_S* and *GA* on fuel consumption and CO_2 emissions

		GA		*GA_S*		*GA* − *GA_S*	
		fuel	CO_2	fuel	CO_2	fuel	CO_2
N	10	356,23	1109,31	153,39	477,66	202,84	631,65
	15	536,47	1670,56	192,06	598,08	344,41	1072,48
	20	601,41	1872,79	222,99	694,41	378,42	1178,38
	25	803,76	2502,92	309,66	964,29	494,1	1538,63
	30	945,88	2945,47	318,97	993,29	626,91	1952,18
	35	1031,52	3212,18	373,99	1164,62	567,53	2047,56
	40	1230,11	3830,58	445,84	1388,35	784,27	2442,23
	45	1358,58	4230,64	466,16	1451,62	892,42	2779,02
	50	1473,41	4588,2	546,34	1701,31	927,07	2886,89

In the tables describing the characteristics of the tour, abbreviations are used: Acc — accumulation, Cons — consumption and d — difference.

***Table* 3.** Comparison of *GA*, *GA_S* and *GA* with increased population (*GA_IP*) on performance.

		GA	*GA_S*	*GA_IP*
N	10	0,072 413 961	0,072 851 451	0,103 959 863
	15	0,518 522 275	0,518 782 627	1,585 358 039
	20	1,249 203 49	1,249 525 882	2,045 274 353
	25	1,907 294 725	1,907 693 686	3,174 980 137
	30	3,648 222 176	3,648 680 647	4,429 585 902
	35	4,730 179 745	4,730 695 49	6,475 466 02
	40	5,993 691 235	5,994 274 039	8,846 539 392
	45	7,198 098 902	7,198 742 863	9,660 162 451
	50	8,419 610 608	8,420 315 353	11,584 472 2

Fig. 1 displays highly optimal routes that facilitate the delivery of goods without breaching specified restrictions on feeder timing and capacity. It's important to note that the algorithm used to generate these routes does not account for feeder speed, thus all feeders default to a speed of 16 knots. This relatively high speed enables efficient port service along the routes. Upon analyzing the constructed route, it's evident that the feeders handle cargo delivery with a margin of safety, as indicated by accumulated cargo and tour durations. With a maximum route duration set at 10 days and the longest route lasting 6 days, it can be inferred that reducing speed would not violate these restrictions. Furthermore, reducing speed would also lead to decreased fuel consumption.

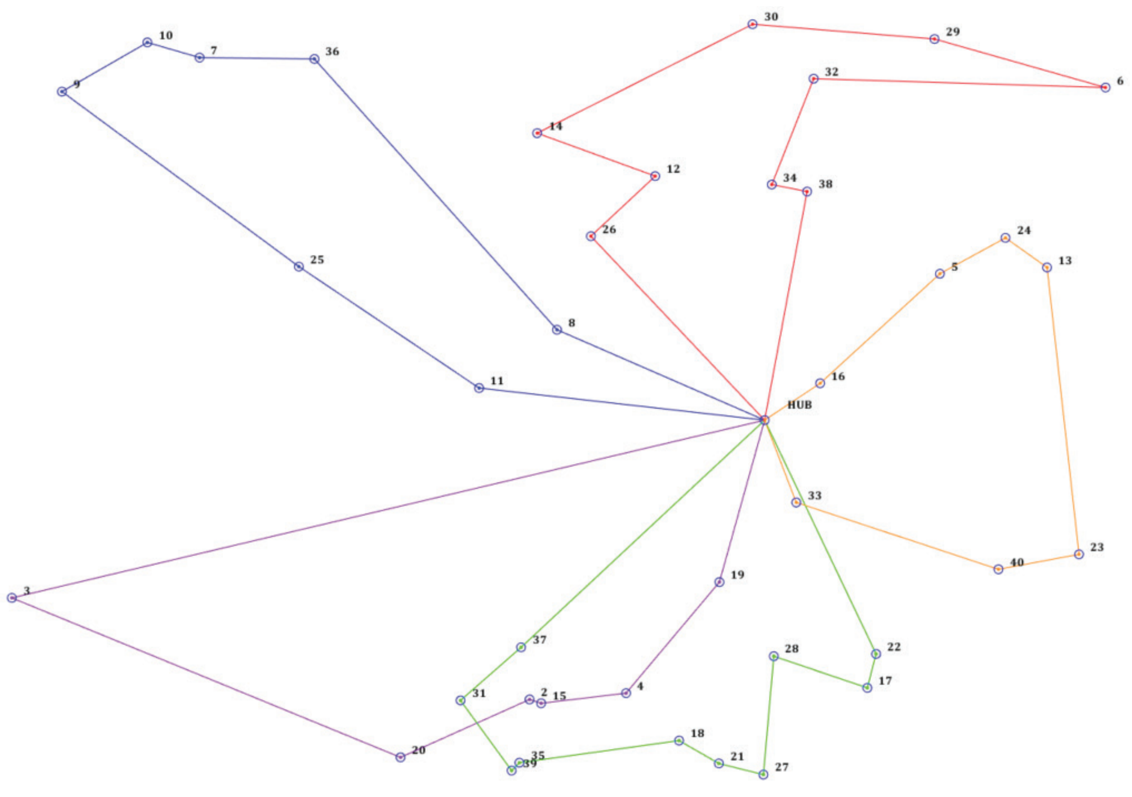

Fig. 1. Route of 5 feeders with a total consumption of 648 tons of fuel built by *GA*

***Table* 4.** Route of 5 feeders built by *GA*

	Feeder 1	Feeder 2	Feeder 3	Feeder 4	Feeder 5
Capacity	1000	1000	1000	1000	1000
Distance	88,82	82,68	84,8	69,57	55,81
Days_*GA*	6	6	6	5	4
Speed_*GA*	16	16	16	16	16
Acc_*GA*	990	600	720	800	380
Cons_*GA*	144	144	144	120	96
CO_2_*GA*	448,41	448,41	448,41	373,68	298,94

Fig. 2 depicts feeder routes similar to those in Fig. 1, but incorporating an additional optimization step. In this updated calculation considering optimal speeds, the trajectories of the routes have been adjusted. The width of each route line on the graph varies depending on the feeder speed – routes with higher feeder speeds are represented by wider lines.

By reducing feeder speeds, updates have been made to accumulation, duration, speed, fuel consumption, and CO_2 emissions. The algorithm's output data are presented in Table 5. The significant differences in fuel consumption and CO_2 emissions underscore the importance of employing the additional step to optimize feeder speeds.

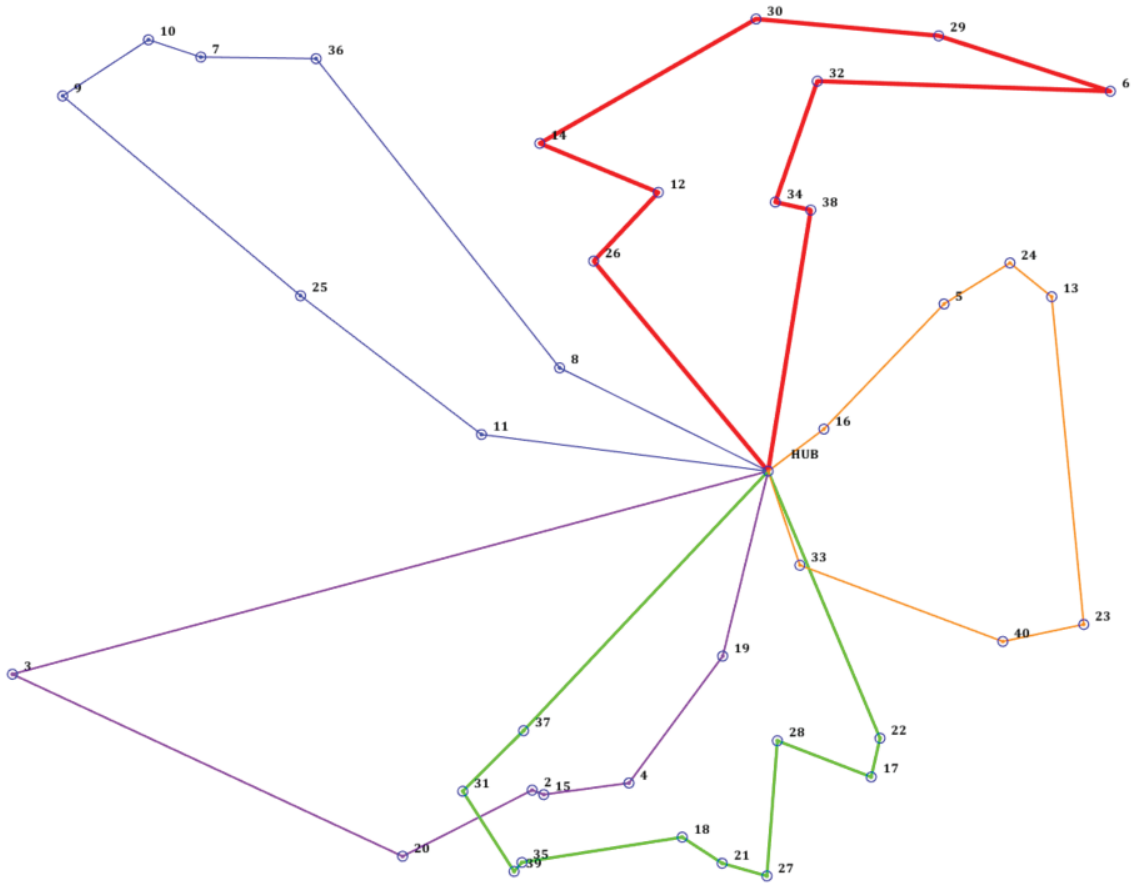

Fig. 2. Route of 5 feeders with a total consumption of 315,52 tons of fuel built by *GA_S*

***Table* 5.** Route of 5 feeders built by *GA_S*

	Feeder 1	Feeder 2	Feeder 3	Feeder 4	Feeder 5
Capacity	1000	1000	1000	1000	1000
Distance	88,82	82,68	84,8	69,57	55,81
Days_*GA*	6	6	6	5	4
Acc_*GA*	990	600	720	800	380
Cons_*GA*	144	144	144	120	96
Days_*GA_S*	6	9	8	6	7
Speed_*GA_S*	15	10	11	12	8
Acc_*GA_S*	990	900	960	960	665
Cons_*GA_S*	118,65	52,73	62,39	60,75	21
Cons_d	25,34	91,26	81,6	59,25	75
CO_2_d	78,93	284,2	254,13	184,5	233,55

Table 5 highlights that feeders 1 and 4 operate at speeds of 15 and 12 knots, respectively, indicating they are not operating at the lowest possible speed and thus consume more fuel. One approach to further reduce overall feeder speed and fuel consumption is to augment the fleet with additional feeders to distribute the workload. To explore this, an algorithm is deployed to construct delivery routes involving two additional feeders. The delivery trajectories are displayed in Fig. 3.

The addition of extra feeders to the fleet resulted in a reduction of both the overall average feeder speed and fuel consumption (Table 6). This reduction is attributed to the cubic relationship between fuel consumption and speed. Despite the inclusion of additional feeders, overall fuel consumption and CO_2 emissions are effectively lowered.

The involvement of additional feeders (Fig. 4) does not consistently result in reduced fuel con-

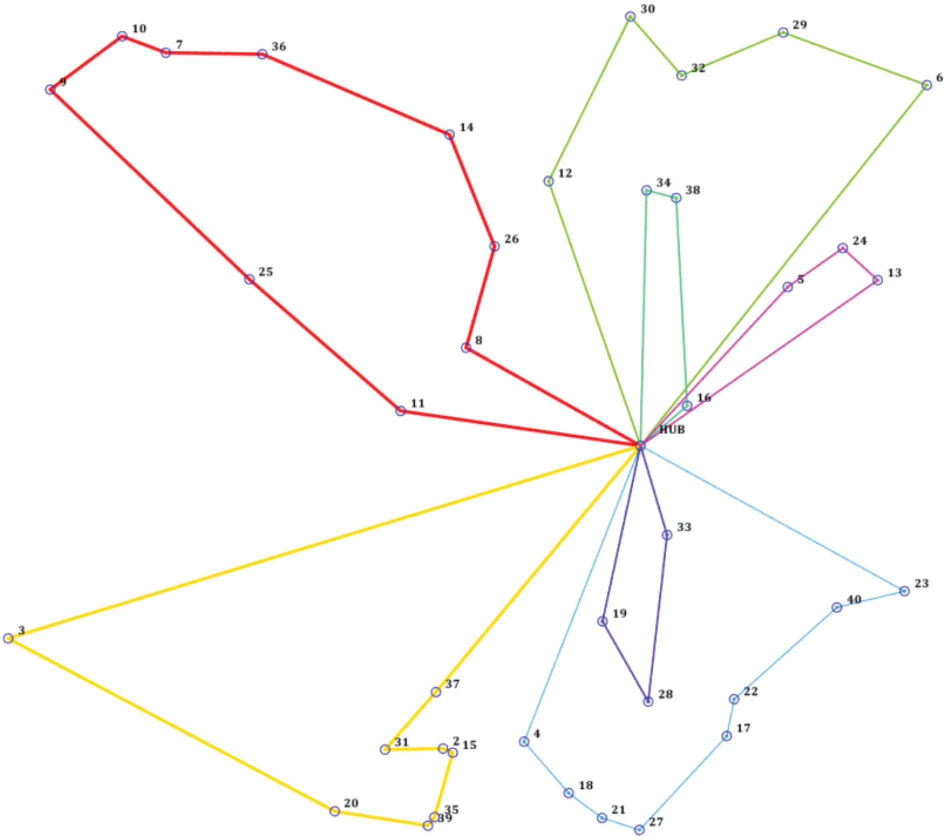

Fig. 3. Route of 7 feeders with a total consumption of 290,23 tons of fuel built by *GA_S*

***Table* 6.** Route of 7 feeders built by *GA_S*

	Feeder 1	Feeder 2	Feeder 3	Feeder 4	Feeder 5	Feeder 6	Feeder 7
Capacity	1000	1000	1000	1000	1000	1000	1000
Distance	86,4	90,38	71,33	32,3	63,61	31,12	34,23
Days_*GA*	6	6	5	3	4	2	3
Acc_*GA*	750	810	500	180	540	100	105
Cons_*GA*	144	144	120	72	96	48	72
Speed_*GA_S*	13	13	8	8	10	8	8
Days_*GA_S*	7	7	9	5	7	4	5
Acc_*GA_S*	875	945	900	300	945	200	175
Cons_*GA_S*	90,11	90,11	27	15	41,01	12	15
Cons_d	53,88	53,88	93	57	54,98	36	57
CO_2_d	167,8	167,8	289,6	177,49	171,22	112,1	177,49

sumption or its optimal control. Firstly, maintaining a larger fleet necessitates ongoing maintenance and the employment of crew members for each feeder. Secondly, despite the reduction in overall average feeder speed, Table 7 indicates that 4 out of the 8 feeders are loaded at only 12 %. This inefficient use of the fleet incurs high costs, both in terms of fuel consumption and feeder maintenance.

Another alternative option considered for constructing optimal delivery routes involves increasing the capacity of vessels. In the following experiment, 4 feeders are used, each with a larger capacity than those in previous experiments (Fig. 5). If a carrier company possesses a sufficiently diverse fleet of feeders, redistributing them between routes becomes more feasible. Larger feeders facilitate transporting more goods between ports without breaching delivery time constraints. Selecting the optimal fleet composition represents a distinct, complex optimization problem that can be addressed through various

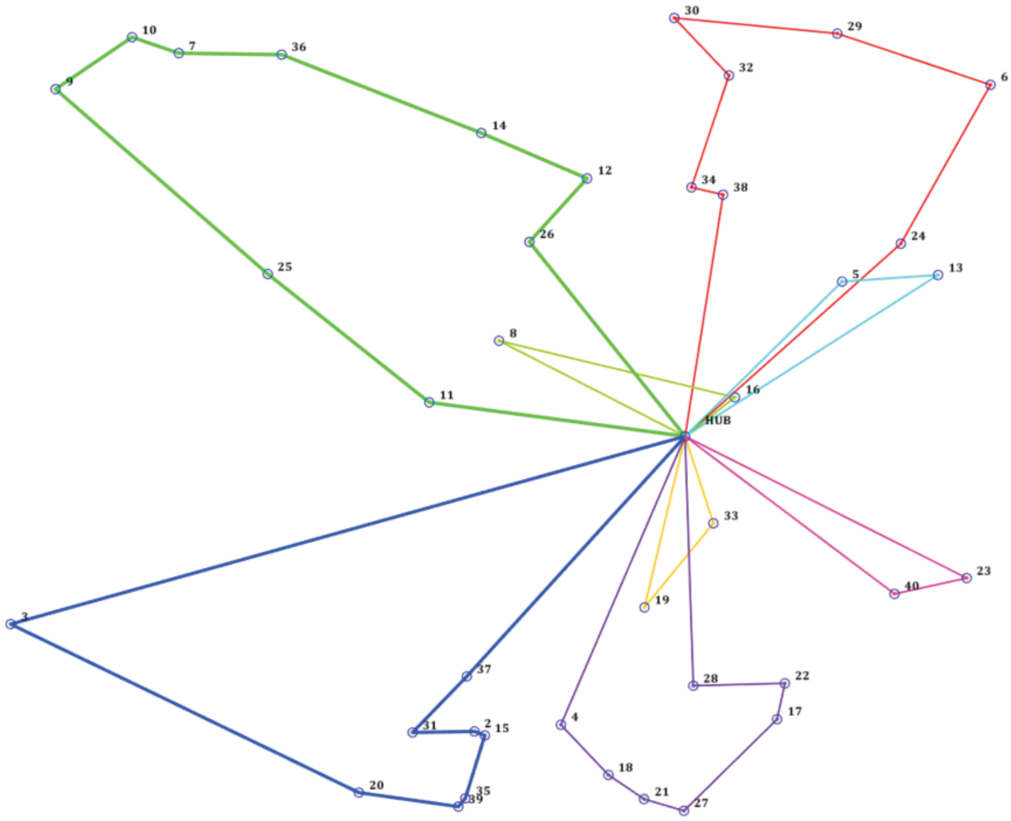

Fig. 4. Route of 8 feeders with a total consumption of 306,81 tons of fuel built by *GA_S*

***Table* 7.** Route of 8 feeders built by *GA_S*

	Feeder 1	Feeder 2	Feeder 3	Feeder 4	Feeder 5	Feeder 6	Feeder 7	Feeder 8
Capacity	1000	1000	1000	1000	1000	1000	1000	1000
Distance	70,23	22,06	26,28	87.1	32,65	90,38	55,6	33,97
Days_GA	5	2	2	6	3	6	4	3
Acc_*GA*	625	80	60	840	75	810	480	75
Cons_*GA*	120	48	48	144	72	144	96	72
Speed_*GA_S*	11	8	8	13	8	13	8	8
Days_*GA_S*	7	3	4	7	5	7	7	5
Acc_*GA_S*	875	120	120	980	125	945	840	125
Cons_*GA_S*	54,59	9	12	90,11	15	90,11	21	15
Cons_d	65,4	39	36	53,88	57	53,88	75	57
CO_2_d	203,68	121,44	112,1	167,8	177,49	167,8	233,55	177,49

methods — ranging from brute force searches to heuristic approaches like genetic algorithms.

As shown in Table 8, feeders with larger capacities effectively deliver goods within the designated 10-day limit, all while maintaining a minimum speed of 9 knots, resulting in the lowest fuel consumption and CO_2 emissions. Optimal utilization of feeder capacity is evident with four feeders operating at 90 % to 93 % capacity, which is highly efficient. This fleet composition does not require further adjustments, as it effectively handles the delivery of goods. Altering the set of feeders would necessitate redistributing ports, which could increase the average speed of all ships and, consequently, fuel consumption.

Selecting the optimal fleet composition is crucial to meet delivery obligations while minimizing delivery costs. Introducing additional feeders on the route can reduce costs up to a certain threshold, beyond which feeders may operate at minimum speed and with low loads.

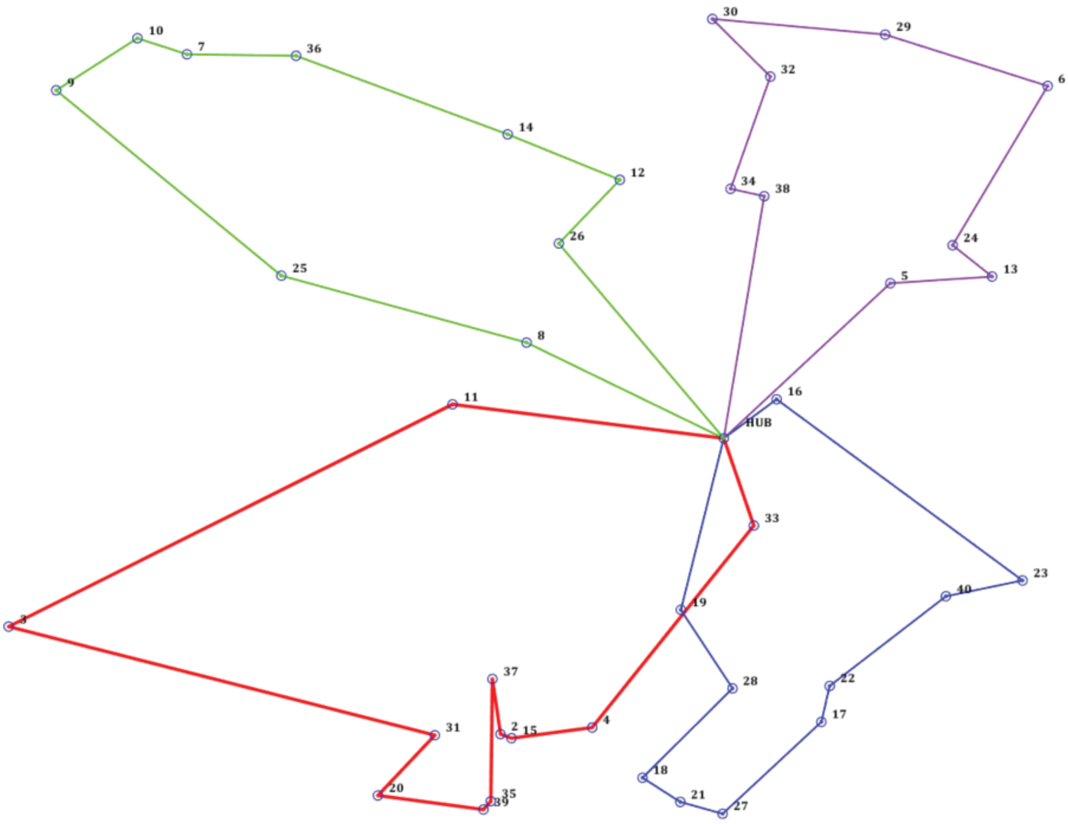

Fig. 5. Route of 4 increased capacity feeders with a total consumption of 303,35 tons of fuel built by *GA_S*

Table 8. Route of 4 increased capacity feeders built by *GA_S*

	Feeder 1	Feeder 2	Feeder 3	Feeder 4
Capacity	1500	1500	1500	1500
Distance	102,95	66,87	73,97	86,14
Days_*GA*	7	4	5	6
Acc_*GA*	1225	700	750	840
Cons_*GA*	280	160	200	240
Speed_*GA_S*	13	9	9	9
Days_*GA_S*	8	8	9	10
Acc_*GA_S*	1400	1400	1350	1400
Cons_*GA_S*	143,09	47,48	53,41	59,35
Cons_d	136,9	112,51	146,58	180,64
CO_2_d	426,31	350,38	456,45	562,53

Conclusions

The introduction of a speed optimization step within the genetic algorithm framework has proven instrumental in reducing fuel consumption and CO_2 emissions. Comparative analyses indicate that the genetic algorithm with speed optimization consistently achieves superior environmental friendliness performance compared to the standard genetic algorithm, without adding complexity to the algorithm. This finding underscores the viability of incorporating speed optimization in route planning to achieve substantial environmental benefits. By integrating feeder capacity, port cargo accumulation, and maximum route duration, the genetic algorithm's capabilities have been significantly expanded beyond merely finding the shortest route. However, it is important not to dismiss the simplified algorithm without these additional constraints entirely, as there are scenarios where route planning and project management for a single feeder or a few feeders without strict cargo flow or timing restrictions may suffice.

The contribution of this work to the development of algorithms for maritime cargo delivery is evident. Compared to other studies on this topic, such as improvements in 2-point crossovers, tour constraint penalties, and the influence of pseudorandom number generators, this research introduces another effective method for enhancing the practical performance of genetic algorithms, specifically for mTSP.

Furthermore, the study's examination of fleet composition reveals the critical importance of balancing feeder capacities to optimize delivery efficiency and cost-effectiveness. While adding more feeders can initially reduce costs, an excessive number of underutilized feeders can lead to inefficiencies and increased operational expenses. This highlights the necessity of careful project management and strategic planning in fleet composition to prevent such drawbacks.

The research also explores alternative approaches, such as increasing feeder capacities and redistributing feeders across routes. These methods demonstrate the potential to minimize fuel consumption and emissions but require meticulous optimization to ensure overall fleet efficiency. The study's findings suggest that selecting an optimal fleet composition and implementing advanced algorithms can significantly enhance sustainable maritime logistics.

Looking ahead, the integration of advanced technological solutions presents promising opportunities for achieving greener maritime cargo delivery. Future research should focus on refining these algorithms, exploring dynamic adaptations, and further optimizing fleet compositions to adapt to varying operational and environmental conditions. Such efforts will be crucial in aligning economic interests with environmental stewardship, and fostering sustainable practices in the maritime industry.

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АЛГОРИТМ УПРАВЛІННЯ ФЛОТОМ ДЛЯ ПОКРАЩЕННЯ ЕКОЛОГІЧНОСТІ МОРСЬКИХ ПЕРЕВЕЗЕНЬ

Проблематика. Морські вантажні перевезення становлять понад 80 % міжнародних транспортних операцій, забезпечуючи економічно ефективний спосіб ведення глобальної торгівлі, особливо важливий для країн, що розвиваються. Утім, морські перевезення сильно залежать від викопного палива, що призводить до значних викидів вуглекислого газу (CO_2) і створює екологічні проблеми для водних ресурсів. Для вирішення цих проблем у цьому дослідженні пропонується рішення для оптимізації проєктів планування морських маршрутів доставки, зменшення споживання палива і викидів CO_2.

Мета. Метою є розроблення алгоритму планування маршрутів доставки за оптимальної швидкості руху суден, що складається з генетичного алгоритму і кроку оптимізації швидкості, для скорочення споживання палива й викидів CO_2 під час морського транспортування. Крім того, буде проведено валідацію отриманих результатів і порівняння ефективності розробленого алгоритму зі стандартним генетичним алгоритмом без кроку оптимізації швидкості.

Методика реалізації. У статті пропонується впровадження додаткового кроку оптимізації швидкості руху суден в алгоритм розрахунку маршрутів доставки, що може значно зменшити витрати палива й викидів CO_2 без збільшення складності самого алгоритму. Маршрут обчислюють через розв’язання задачі маршрутизації транспортних засобів.

Результати. Дослідження показує, що застосування кроку оптимізації швидкості в алгоритмі планування маршрутів доставки суттєво зменшує об’єми споживання палива і викидів CO_2. Порівняння результатів експериментів показало, що генетичний алгоритм із кроком оптимізації швидкості перевершує стандартний генетичний алгоритм за об’ємами використаного пального і викидів CO_2. Детальний аналіз різних комбінацій складу флоту підкреслює необхідність балансування місткості суден для досягнення максимальної ефективності доставки вантажів. Хоча залучення більшої кількості суден спочатку знижує загальне споживання палива, надмірне використання флоту з недовантаженими суднами може призвести до зростання експлуатаційних витрат. У дослідженні також розглядаються альтернативні підходи, такі як збільшення місткості й перерозподіл суден між маршрутами, що також впливає на споживання палива і викиди CO_2.

Висновки. Дослідження пропонує удосконалений алгоритм побудови маршрутів морських вантажних перевезень, що використовує генетичний алгоритм із кроком оптимізації швидкості. Алгоритм забезпечує ефективне управління проєктами доставки, при цьому значно зменшуючи витрати палива і викиди CO_2 у навколишнє середовище. Також оптимальне керування складом флоту забезпечує скорочення викидів CO_2 за рахунок ефективного використання кожного судна.

Ключові слова: морський транспорт; управління флотом; оптимальне керування; планування маршрутів; оптимізація маршрутів; управління проєктами; споживання палива; викиди CO_2; оптимізація швидкості суден; генетичний алгоритм.

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