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Optimising the Pioneer Shipping Route Considering Wave Variations

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Abstract

Pioneer shipping is a government-subsidised maritime services that connect remote areas in the Indonesian Archipelago. This paper applied a genetic algorithm variant to optimise pioneer shipping routes while accounting for variability in wave conditions. The algorithm is implemented on a real shipping network in East Java comprising two main routes, and several improvement scenarios are evaluated, including optimisation of existing routes, route fractioning, and route merging. The optimisation results show that route lengths can be reduced by up to 51% compared with existing operations. The fractioning scenario offers substantial reductions in travel distance but requires an additional vessel to serve the newly created route. In contrast, the merging scenario improves efficiency by reducing the number of vessels required, albeit at the cost of longer travel distances and travel times. Accounting for wave height variability, the simulation results indicate that wave fluctuations can increase travel time by up to 23%.

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INTRODUCTION

Indonesia is the world's largest archipelago, comprising thousands of islands from Sabang to Merauke. Inter-island connectivity and accessibility pose significant challenges in enhancing community welfare and fostering fair development. The government then proposed a mechanism known as the Pioneer Shipping Routes, which plays a crucial role in linking remote areas to developed regions, facilitating the distribution of goods, and fostering economic and social growth [1]. Pioneer shipping is a sea transportation service designed for remote, outermost, and border areas. Pioneer shipping serves regions with limited transportation infrastructure, low population density, and minimal commercial viability. Although pioneer shipping shares operational characteristics with short-sea shipping, the objectives are different. Short sea shipping primarily seeks to reduce environmental impacts and enhance economic efficiency [2–5], whereas pioneer shipping focuses on enhancing connectivity to underdeveloped and hard-to-access regions. While short-sea services typically employ Ro-Ro vessels, Pioneer Shipping relies on smaller general cargo vessels, typically in the range of 500–1,000 DWT. These routes are operated by the national shipping company and supported through government subsidies. Despite their strategic importance, pioneer shipping services face key challenges, including inefficient routing and limited integration with the broader maritime network [6].

There is also growing attention to routing optimisation within the vehicle routing problem (VRP) framework [7,8]. Building on this foundation, the literature has introduced the maritime vessel routing problem (mVRP), which adapts the VRP to maritime contexts by accounting for the distinct operational and environmental challenges of maritime

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logistics. A substantial body of research has developed within the VRP framework to address mVRP [2,9,10]. Building upon the classical concepts of the VRP[9] their work proposed a robust optimisation-simulation framework for offshore supply vessel planning. The resulting schedules are designed to absorb weather-induced delays while minimising fleet size and operational costs, demonstrating how the use of slack times and robustness parameters can proactively buffer schedules against uncertainty. In addition, the comprehensive review by Ksciuk et al. [11] highlights how uncertainty in travel time, port operations, demand, and environmental regulations increasingly necessitate the application of stochastic programming, robust optimisation, and hybrid simulation approaches across strategic, tactical, and operational planning levels. The review further emphasizes that the integration of robust planning techniques remains limited in many maritime applications and calls for more models that jointly account for stochastic dynamics and operational constraints.

In line with these developments, earlier work by Christiansen & Fagerholt [12] offers a robust scheduling model that introduces multiple time windows, arrival-dependent service times, and penalty costs for risky port arrivals (particularly near weekend closures). Their model utilises set partitioning and dynamic programming to generate and optimise feasible ship schedules, while explicitly accounting for port operating constraints and ensuring scheduling robustness. Further extensions of robust scheduling were presented in [13]. They developed a chance-constrained mixed-integer nonlinear programming model that determines optimal departure times, sailing speeds, and port-specific service levels. By allowing different vessels to operate at varying speeds and service standards - depending on their fuel efficiency and port importance - they demonstrated that adaptive, variable service-level allocation yields substantial fuel-cost savings relative to fixed service-level policies. Subsequently, Christiansen et al. [14] extended their work by providing a comprehensive review of Liner Shipping Network Design (LSNDP). Their work concentrated on high-level route design and vessel assignment within cost and time constraints. The review highlighted the increasing need to incorporate operational uncertainties, such as transit time variability, transhipment complexity, and environmental regulations, into long-term planning models. More recently, deterministic mVRP formulations have been extended to explicitly address uncertainties [13] arising from route conditions [4,14] or port operations [15,16]. Building on the above literature, this paper addresses the design of the pioneer shipping route using the mVRP framework, accounting for wave uncertainty [17]. A genetic algorithm is applied to a real-world shipping network in East Java, consisting of two main routes.

The remainder of this paper is organised as follows. The mathematical modelling framework is described in Methods section and then a case study is presented in Section Numerical Experiment, followed by the Conclusion.

METHODS

This paper aims to determine the optimal routing for pioneer shipping by minimising the total voyage time. As inferred by Equation (1), the travel time is also a function of wave height, w, which can influence the speed of the vessel. Given $\mathbb{D}$ as a set of ports, where $\mathbb{D} = \{1, 2, \dots, d, \dots, D\}$, and $\mathbb{R}$ as a set of routes, namely $\mathbb{R} = \{1, 2, \dots, r, \dots, R\}$. The destination ports are then assigned to route-r, namely $\mathbb{D}^r = \{1, 2, \dots, i, \dots, D^r\}$.

$$\sum_{r \in \mathbb{R}} \sum_{i \in D^r} \sum_{j \in D^r} x_{ij}^r \, t_{ij}^r \,(w) \tag{1}$$

Equation (2) shows that each port is visited exactly once by a single vessel and allocated to a specific route. Equation (3) ensures that each vessel that visits a port must also depart from that port. Equation (4) states that a vessel that visits a port within a specific route must also depart from that node within the same route. If it does not visit the port, it must not depart from it.

$$\sum_{r \in \mathbb{R}} \sum_{i \in \mathbb{D}^r} x_{ij}^r \leq 1, \forall j \in \mathbb{D}^r \tag{2}$$

$$\sum_{r \in \mathbb{R}} \sum_{i \in \mathbb{D}^r} x_{ij}^r = \sum_{r \in \mathbb{R}} \sum_{i \in \mathbb{D}^r} x_{ji}^r \,, \forall j \in \mathbb{D}^r \tag{3}$$

$$\sum_{i \in \mathbb{D}^r} x_{ij}^r = \sum_{i \in \mathbb{D}^r} x_{ji}^r \,, \forall j \in \mathbb{D}^r \,, r \in \mathbb{R} \tag{4}$$

These constraints are tightened by Equation (5) which ensure that no seaport in one route may be visited by a vessel assigned to a different route, Equation (6) which ensures that no vessel is allowed to travel from one seaport directly back to the same seaport.

$$\sum_{k\in\mathbb{K}}\sum_{r\in\mathbb{R}} x_{ij}^{r} = 0, \forall i \in \mathbb{D}^{r_1}, j \in \mathbb{D}^{r_2}, r_1 \in \mathbb{R}, r_2 \in \mathbb{R}, r_1 \neq r_2 \quad (5)$$

$$x_{ij}^{r} = 0, \forall\, i \in \mathbb{D}^{r}, j \in \mathbb{D}\,, i = j \quad (6)$$

ζ_j represents a time stamp, where in Equation (7), the arrival time between two consecutive ports is the voyage time in between seaports. Equations (8) and (9) indicate the nature of time stamp at initial port and destination ports. Equation (10) indicates the binary decision variables.

$$\zeta_j \geq \zeta_i + \frac{d_{ij}}{\varrho(w)} + \left(1 - x_{ij}^{r}\right)M, \forall\, i \in \mathbb{D}^{r}, j \in \mathbb{D}^{r}, r \in \mathbb{R} \quad (7)$$

$$\zeta_{i=0} = 0, \quad (8)$$

$$\zeta_j \geq 0, \forall\, j \in \mathbb{D}^{r} \quad (9)$$

$$x_{ij}^{r} \in \{0,1\}\ \forall i \in \mathbb{D}^{r}, j \in \mathbb{D}^{r}, r \in \mathbb{R} \quad (10)$$

Table 1. Mathematical Notations

Notations	Description
Sets	
$\mathbb{D}$	Set of ports, $\mathbb{D} = \{1, 2, \dots, d, \dots, D\}$,
$\mathbb{R}$	Set of routes $\mathbb{R} = \{1, 2, \dots, r, \dots, R\}$.
$\mathbb{D}^{r}$	Set of destination ports, $\mathbb{D}^{r} = \{1, 2, \dots, i, \dots, D^{r}\}$
Parameters	
w	Wave heights
t_{ij}^{r}	Travel time incurred by a vessel voyage from port i to j on a route-r
ζ_j, ζ_i	Time stamp at port i, port j
d_{ij}	Distance port i to j
$\varrho(w)$	Vessel speed influence by wave height
M	Large constant value
Decision Variable	
x_{ij}^{r}	Binary variable which has a value of 1 if a vessel voyage from port i to j on a route-r; but has 0 value otherwise

To address the optimisation problem, we incorporate neighbour-replacement crossover and swap mutation in GA procedure. Crossover fundamentally represents the process of combining two individuals (i.e., parents) to generate new offspring. However, due to the random selection of individuals and crossover locations, the offspring resulting from the crossover may potentially violate the permutation constraints, as illustrated in Figure 1. Consequently, we proposed the neighbourhood crossover, in which any seaport that appears twice in the chromosome will be replaced by its neighbouring seaport that has not yet appeared (see Figure 2).

Parents 1	1	2	3	6	5
Parents 2	3	1	2	4	5

Child 1	1	2	2	4	5
Child 2	3	1	3	6	5

Figure 1. Cross Over that Violates the Permutation Constraints

Child 1'	1	2	3	4	5
Child 2'	3	1	2	6	5

Figure 2. Cross over with neighbour replacement

1	2	3	4	5	6	7	8	0	0

1	2	6	4	5	3	7	8	0	0

Figure 3. Swap Mutation

Mutation is a process that abruptly changes an individual's traits by randomly altering certain genes in the offspring's chromosomes. In this study, the genetic algorithm (GA) incorporates a swap mutation operator, whereby two genes within a selected individual are randomly selected and then swapped to generate a new chromosome (see Figure 3). In addition, a roulette-wheel selection mechanism is employed to probabilistically select individuals, while an elitism strategy is used to preserve a subset of the best-performing individuals across generations. The detailed procedure for GA is presented in Appendix 1.

NUMERICAL EXPERIMENT

Network Setting

The proposed GA is then applied to the actual pioneer shipping route in East Java, Indonesia, specifically routes R16 and R17 (see Tables 2 and 3 for the route members and distance matrix, respectively).

Before we address the actual pioneer route shipping, we first deal with a small shipping network comprising only seven (i.e., S1) or eight seaports (i.e., S2). We employed complete enumeration to ensure the exact solution and then compared it with the proposed GA. Before we applied to a smaller test network, we conducted the parameter setting to ensure that GA performs at its best. We set the number of individuals, the number of generations, the number of elites, the crossover rate, and the mutation rate. The settings are executed sequentially by evaluating the minimum, average, and maximum fitness values. The parameter-setting results are presented in Table 4.

As shown in Table 5, the results provided by GA are exactly the same as those obtained through complete enumeration, indicating that the proposed GA possibly yields an optimal solution. However, the enumeration-based method cannot be used when more seaports are included. This is because the number of permutations would become very large, resulting in a computational load that a personal computer cannot handle.

Table 2. Routes and Its Seaport Members

No.	Seaports	Routes	No.	Seaports	Routes
1	Port Tanjung Perak (Surabaya)	R16, R17	8	Port Tanjung Wangi	R16
2	Port Masalembu	R16, R17	9	Port Pagerungan Besar	R16
3	Port Keramian	R16, R17	10	Port Matasiri	R17
4	Port Kalianget	R16	11	Port Maradapan	R17
5	Port Sapudi	R16	12	Port Marabatuan	R17
6	Port Sapeken	R16	13	Port Batulicin	R17
7	Port Kangean	R16	14	Port Kotabaru	R17

Table 3. Distance Matrix of Seaports

Port	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0	150	171	72.8	95.3	150.4	177.5	114.1	191	236	233.7	250.8	299.3	298.7
2	150	0	40	113	95.7	90.2	115.4	153.4	122.9	98.1	94.8	111.1	160.5	159.7
3	171	40	0	127.2	128.7	114.4	135.1	185.9	139.9	72	70.5	83.1	128.2	127.7
4	72.8	113	127.2	0	30	77.7	105	70.1	118.4	177.9	177.2	196.6	250.3	249.1
5	95.3	95.7	128.7	30	0	62	82.7	58.1	95.3	168.4	171.5	190.6	246	244.5
6	150.4	90.2	114.4	77.7	62	0	30	91.8	65	129.7	132.2	153.2	210.2	208.2
7	177.5	115.4	135.1	105	82.7	30	0	120	15	134.6	138.7	159.3	215.7	213.4
8	114.1	153.4	185.9	70.1	58.1	91.8	120	0	113.6	214.8	219.4	241.7	298.7	296.8
9	191	122.9	139.9	118.4	95.3	65	15	113.6	0	129.7	136.3	157.6	214.6	212.6
10	236	98.1	72	177.9	168.4	129.7	134.6	214.8	129.7	0	20	28.3	85.1	83
11	233.7	94.8	70.5	177.2	171.5	132.2	138.7	219.4	136.3	20	0	22	79.4	77.4
12	250.8	111.1	83.1	196.6	190.6	153.2	159.3	241.7	157.6	28.3	22	0	62	55
13	299.3	160.5	128.2	250.3	246	210.2	215.7	298.7	214.6	85.1	79.4	62	0	22
14	298.7	159.7	127.7	249.1	244.5	208.2	213.4	296.8	212.6	83	77.4	55	22	0

Table 4. GA Parameter Settings

Parameter Settings	R16	R17
Number of Individual	50	100
Number of Generation	90	45
Cross over rate	0.7	0.6
Mutation rate	0.09	0.02
Number of elites	8	8

Table 5. Results of Enumeration and GA in the Small Test Network

Scenario	Route travel length (miles)		Route order	
	Enumeration	GA	Enumeration	GA
S1	666.3	666.3	1-2-4-5-6-8-7-3-1	1-2-4-5-6-8-7-3-1
S2	620.7	620.7	1-4-5-8-9-7-6-2-3-1	1-4-5-8-9-7-6-2-3-1

Table 6. Results of GA with Neighbourhood Crossover and with ERX

Algorithms	Duration of travelled (hour) with number of seaports-						
	14	13	12	11	10	9	8
GA with neighbourhood crossover	87.61	91.97	63.43	58.99	57.45	51.73	50.65
GA with ERX	88.65	82.38	68.53	64.57	61.38	52.63	50.76

To evaluate the performance of the genetic algorithm (GA) on a larger network, we compared the proposed GA, which incorporates a neighbourhood-based crossover operator, with a GA employing the Edge Recombination Crossover (ERX). ERX is a crossover operator specifically designed for permutation-based problems, as it preserves node adjacency rather than absolute positional information, reflecting the relative importance of successive nodes over their exact index positions. As shown in Table 6, the proposed GA generally produces results comparable to those obtained using ERX.

Routes Scenarios of Pioneer Shipping

We further tested the proposed GA with a larger network inspired by the actual pioneer shipping routing. In the current situation, the route for R16 (i.e., E1) follows these routes: 1-2-3-2-4-5-6-9-7-8-7-9-6-5-4-2-3-2-1, with a voyage duration of 14 days and a distance of 1270 miles (see Figure 4 (a)). Additionally, route R17 (i.e., E2) includes 1-2-3-4-11-12-14-13-14-12-11-4-3-2-1, requiring 14 days of travel and covering 776 miles (see Figure 4(b)).

(a) R16 routes (b) R17 routes

Figure 4. Test the Pioneer Shipping Network

To improve the performance of the shipping route in terms of travel duration, we developed three different scenarios, namely:

- Scenario O: Optimising the existing routes R16 (i.e., O1) and R17 (i.e., O2). In this scenario, the seaport configuration remains the same as the existing one, except for the order of seaport routing. This scenario does not allow one seaport to be visited twice on a single route.
- Scenario F: Fractioning the existing route R16 (i.e., F1) and R17 (i.e., F2). In this scenario, each existing route is divided evenly into two parts, and each route will consist of only half of the seaport members.
- Scenario M: Merging the existing routes R16 and R17 into one route. In this scenario, the existing route (R16 and R17) is merged into a single route, and then the pioneer shipping route includes all seaport members of R16 and R17.

To assess the efficiency of existing and newly developed shipping route scenarios, we evaluate their performance based on route length and duration, as well as the connectivity among seaports. As can be inferred from Table 7, optimising the existing route can reduce travel distance and duration. A similar result was obtained for fractioning the seaport within a route, where the route's travel length and duration decreased relative to the existing conditions.

However, this fractioning route should also include the investment of a new vessel to service the 'new' route. Unlike the fractioning scenarios, the merging scenario can provide efficiency in terms of the number of vessels employed; however, it results in longer travel lengths and durations. It is also interesting to note that the travel time among all seaports decreased in the case of the optimising scenario. The maximum distance travelled across seaports decreases by up to 14.5% compared to current conditions. A similar outcome is observed for the average travel time to all seaports, with reductions of up to 14.8%.

Table 7. Performance of Pioneer Shipping Routes

Scenario		Length of Route's Travelled (mil)	Duration of Route's Travelled (hour)	Distance Travelled among All Seaports (miles)			Seaport visit order
				Min	Max.	Average	
E. Existing	E1. R16	1270	105.83	15	708.3	364.95	1-2-3-2-4-5-6-9-7-8-7-9-6-5-4-2-3-2-1
	E2. R17	776	64.67	20	666.7	343.35	1-2-3-4-11-12-14-13-14-12-11-4-3-2-1
O. Optimising	O1. R16	620.7	51.73	15	605.7	310.36	1-4-5-8-9-7-6-2-3-1
	O2. R17	666.3	55.53	20	646.3	333.15	1-2-4-11-12-13-14-3-1
F. Fractioning	F1. R16	688.2	57.35	15	673.2	339.70	5-4-1-3-2-5 & 5-8-9-7-6-5
	F2. R17	686.2	57.18	20	666.2	345.48	11-2-1-3-4-12 & 11-12-13-14-11
M. Merging	M. (R16+R17)	880.1	73.34	15	865.1	442.08	1-4-5-8-6-7-9-11-12-14-13-10-3-2-1

Considering the Uncertainty of Wave Height

We then proceed with the proposed model to tackle the variation of wave height. The wave height has an influence on ship speed, where when the wave height is low, the ship's speed can be increased, while when the wave height rises or is high, the ship's speed is lowered to avoid accidents or can stop by the nearest harbour. Inspired by Lewis (1955), we modified their equation to fit the current situation of vessel speed in pioneer shipping, which is lower than 12 knots (see Equation 11).

$$z(w) = -0.4w + 12.6 \tag{11}$$

The wave variations are then randomly generated based on the distribution of wave height collected within 2019 - 2023 from Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG). The collected data are then fitted to several distributions based on the Akaike Information Criterion (AIC). AIC is a statistical measure used to evaluate the quality of a statistical model or probability distribution. It accounts for how well the data fit the model and enables comparison with other distributions. In terms of AIC assessment, a smaller AIC value indicates a better fit for the probability distribution, while a larger AIC value suggests a poorer fit. Table 8 presents the AIC results, which indicate that the Weibull distribution better represents the wave height data (see also Figure 5).

Table 8. AIC Result

No	Distribution	AIC
1	Weibull	28793.11
2	Rayleigh	43265.69
3	Normal	37106.13
4	Exponential	29357.07

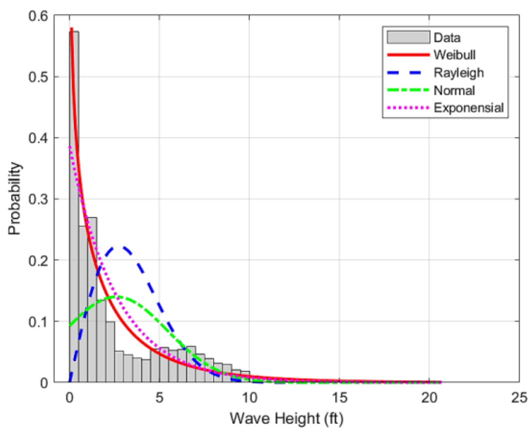

Figure 5. Fitting Distribution on Wave Height

To generate the random wave, we employed the inverse Cumulative Distribution Function (CDF) of the Weibull distribution. The inverse CDF plays a vital role in estimating wave-height probabilities, as it enables the transformation of random numbers into synthetic wave-height data that follows the Weibull distribution. This methodology is essential for facilitating realistic modelling of oceanic conditions, thereby diminishing the necessity for continuous reliance on observational data.

Probabilistic Analysis Based on the Variation of Wave Height

We then tested Scenario PO by adding wave variations to Scenario-O and performed a probability analysis using the 90th percentile. We conducted simulations using 20 different random seeds to model the wave variations along the pioneer shipping routes. The simulation results for route R16 indicated that the longest travel time recorded was 74.66 hours. In comparison, the fastest travel time was 49.48 hours, achieved through varying route sequences, with the starting point consistently being Tanjung Perak (Surabaya). As illustrated in Figure 6, the 90th-percentile travel time is 63.86 hours. This indicates that 90% of the travel times for pioneer ships from the initial port to the final port are below 63.86 hours, while the remaining 10% exceed this duration.

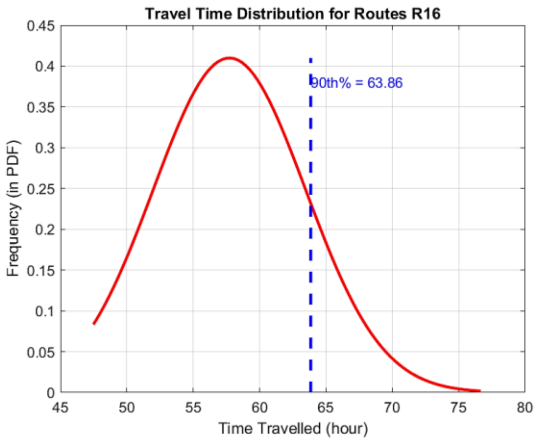

Figure 6. Travel time of R16 due to wave variations

In the simulation results for route R17, the longest travel time is 79.62 hours, whereas the shortest is 53.12 hours. These times are achieved with various route sequences, but both originate from Tanjung Perak Port in Surabaya. As illustrated in Figure 7 (blue line), the 90th-percentile travel time is 66.11 hours. This indicates that 90% of the travel times for pioneer ships travelling from the starting port to the final port on route R17 are below 66.11 hours, while the remaining 10% exceed this duration.

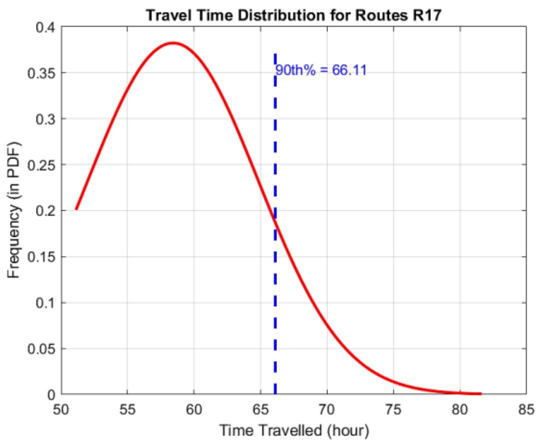

Figure 7. Travel time of R17 due to wave variations

Stochastic Optimisation Based on the Variation of Wave Height

Further tests are conducted by converting the deterministic optimisation to a stochastic optimisation that accounts for wave variations. The objective function is modified as Equation (12). In this stochastic optimisation, the solution technique aims to minimise the expected travel time $\mathbb{E}(t_{ij}^r)$. The expected travel time is calculated by considering the uncertainty of speed due to wave variations $\boldsymbol{w}$. The wave variation is derived from the random variables $\boldsymbol{\tau}$ that follow a specific distribution of wave variations, see Figure 5. A modification of GA was conducted for dealing with stochastic optimisation, which is illustrated in Appendix 2.

$$\min \sum_{r\in\mathbb{R}} \sum_{i\in D^r} \sum_{j\in D^r} x_{ij}^r \, \mathbb{E}(t_{ij}^r \, (w, \tau)) \tag{12}$$

Table 9. Result of Existing Optimization with No Wave Height vs. With Wave Height

Scenario		Duration of Route's Travelled (hour)
O. Optimising without wave variations	R16	51.73
	R17	55.53
PO. Probabilistic analysis with wave variations*	R16	63.86
	R17	66.11
SO. Stochastic optimisation with wave variations	R16	61.38
	R17	56.22

*) 90th% percentile

Table 9 demonstrates that wave height has a significant impact on the travel time of pioneer shipping routes, with higher wave conditions leading to increased voyage durations. These findings highlight the importance of incorporating wave variability into route planning to improve future operational efficiency. The results further indicate that, within a stochastic optimisation framework, the genetic algorithm (GA) produces superior solutions compared with those derived from probabilistic analysis alone. This suggests that deterministic routing solutions may perform sub optimally when wave uncertainty is present, whereas stochastic optimisation approaches that explicitly integrate environmental uncertainty yield more robust outcomes. From an operational perspective, the results emphasise that optimal route selection should consider not only minimum travel distance but also prevailing marine environmental conditions.

CONCLUSIONS

This paper applied a variant of the Genetic Algorithm to optimise the pioneer ship routes while explicitly considering wave height variability. Several improvement scenarios were evaluated, including optimisation of existing routes, route fractioning, and route merging. The results demonstrate that route lengths can be reduced by up to 51% compared with existing operations, highlighting the effectiveness of genetic algorithms in improving shipping efficiency in remote island regions, particularly in terms of distance travelled. The fractioning scenario achieves notable reductions in travel distance and duration but requires investment in an additional vessel to serve the newly created route. In contrast, the merging scenario improves efficiency by reducing the number of vessels required, albeit at the cost of longer travel distances and voyage durations.

Considering wave height variability, the results indicate that wave conditions have a significant influence on the effectiveness of shipping routes, highlighting the importance of explicitly addressing uncertainty in route planning. The simulation results show that wave variations can increase travel time by up to 23%. A comparison between stochastic-based and probabilistic-based optimisation approaches for handling wave uncertainty demonstrates that the stochastic optimisation framework yields superior results. This outcome is expected, as probabilistic optimisation requires an explicit probability distribution to characterise uncertainty, whereas stochastic optimisation relies on weaker assumptions and can adapt more effectively to inherent randomness in environmental conditions.

Further study can then be extended by including the variation in demand that is not considered in this study. Validation across different network sizes is further required to ensure the model's applicability. Additionally, integrating pioneer shipping with land transport development can provide a more comprehensive view of the transportation system in remote areas.

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APPENDIX

Appendix 1: GA Procedure for Deterministic Optimisation

Algorithm 1: GA for Pioneer Ship

1: Input the parameter settings such as population size (N), number of elit (Elit), length of chromosome (L), crossover rate, mutation rate and number of generations (n_iter) .
2: **for** m=1 **to** L
3: Initialise random permutation from 1 to L.
4: Evaluate the objective function as Equation (4).
5: **end for**
6: **for** k =1 **to** n_iter

7: **for** m = *Elit*+1 **to** *N*-2
8: Set m=l as *parent1* and m+1 as *parent2*.
9: generate random number (i.e., **rand**).
10: **if rand < cross over rate**
11: select randomly cross location .
12: cross over *parent1* and *parent2* to obtain *dummy child1* and *dummy child2*.
13: refine *dummy child1* and *dummy child2*to satisfying the permutation constrains, obtain *child1* and *child*2.
14: **end if**
15: **end for**
16: **for** m = *Elit*+1 **to** *N*
17: generate random number (i.e., **rand**).
18: **if rand < mutation rate**
19: select randomly two mutation location .
20: swap the genes based on the mutation location to obtain *child3*.
21: **end if**
22: **end for**
23: Evaluate fitness value of each individual, *child1, child2* and *child3*
24: Calculate the proportion on roulette wheel by dividing the fitness value of each individual 3 with total fitness value.
25: **for** m = 1 **to** *N*
26: Randomly select individual to proceed next generation based on roulette wheel proportion.
27: **end for**
28: **end for**

Appendix 2: GA procedure for Stochastic Optimisation

Algorithm 2: GA for Pioneer Ship

1: Input the parameter settings such as population size (*N*), number of elit (Elit), length of chromosome (*L*), crossover rate, mutation rate and number of generations (*n_iter*) .
2: **for** m=1 **to** *L*
3: Initialise random permutation from 1 to *L*.
4: Evaluate the objective function as Equation (4).
5: **end for**
6: **for** k =1 **to** *n_iter*
7: **for** m = *Elit*+1 **to** *N*-2
8: Set m=l as *parent1* and m+1 as *parent2*.
9: generate random number (i.e., **rand**).
10: **if rand < cross over rate**
11: select randomly cross location .
12: cross over *parent1* and *parent2* to obtain *dummy child1* and *dummy child2*.
13: refine *dummy child1* and *dummy child2*to satisfying the permutation constrains, obtain *child1* and *child*2.
14: **end if**
15: **end for**
16: **for** m = *Elit*+1 **to** *N*
17: generate random number (i.e., **rand**).
18: **if rand < mutation rate**
19: select randomly two mutation location .
20: swap the genes based on the mutation location to obtain *child3*.
21: **end if**
22: **end for**
23: **for** s = 1 **to** S
24: generate random number (i.e., $\boldsymbol{\tau}$) follow Ω distributions for estimating w
25: estimate travel speed due to variations of w
26: calculate fitness value due to variations of w (i.e., z_s)
27: **end for**
28: Evaluate expected fitness value of each individual, *child1, child2* and *child3* based on percentile 90th of z_s
29: Calculate the proportion on roulette wheel by dividing the fitness value of each individual 3 with total fitness value.
30: **for** m = 1 **to** *N*
31: Randomly select individual to proceed next generation based on roulette wheel proportion.
32: **end for**
33: **end for**