Dynamic Vessel-to-Vessel Routing Using Level-wise Evolutionary Optimization

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Introduction

Modern practical optimization problems are too often complex, nonlinear, large-dimensional, and sometimes dynamic making gradient-based and convex optimization methods too inefficient. In this paper, we present a formulation of a dynamic vessel-to-vessel service ship scheduling problem. In a span of several hours, the service ship must visit as many moving vessels as possible and complete the trip in as small a travel time as possible. Thus, the problem is bi-objective in nature and involves a time-dependent traveling salesman problem. We develop a level-wise customized evolutionary algorithm to find multiple trade-off solutions in a generative manner. Compared to a mixed-integer programming (MIP) algorithm, we demonstrate that our customized evolutionary algorithm achieves similar quality schedules in a fraction of the time required by the MIP solver.

DV2VRP

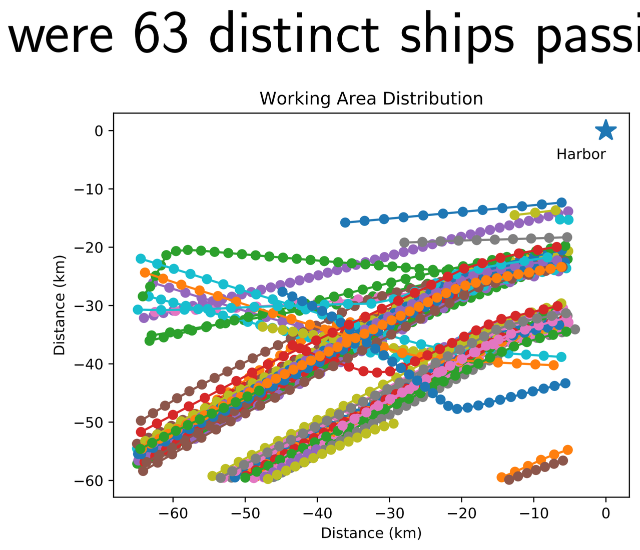
A service ship must leave from the harbor and simultaneously:

- ▶ Maximize the number of different target ships visited (α)
- ▶ Minimizing the total distance traveled (d)

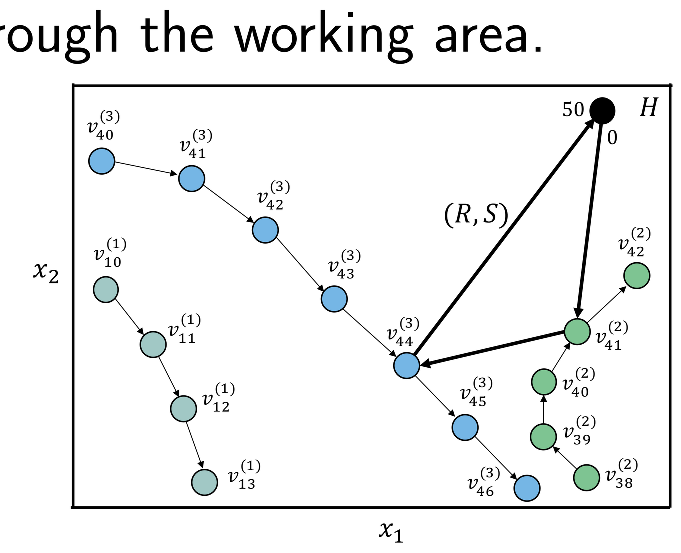
and finally return to the harbor within a predefined time window T_w.
Our approach is composed of three levels:

1. α-level: Defining the subproblem and sequence length (α)
2. Upper level: Custom GA for optimizing routes given α
3. Lower level: Optimizing schedules given a route by using dynamic programming

Designing routes for a given α gets increasingly more complex as the number of ships through the working area increases. In our data-set there were 63 distinct ships passing through the working area.



(a) Sample Work Area Distribution with 63 ships



(b) Example route sketch

α-level

Each α-level is a bi-level subproblem with sequences of length α. The upper level responsible for designing optimal routes and a lower level designing optimal schedules. To advance to the next α-level we define a transition function to increase α.

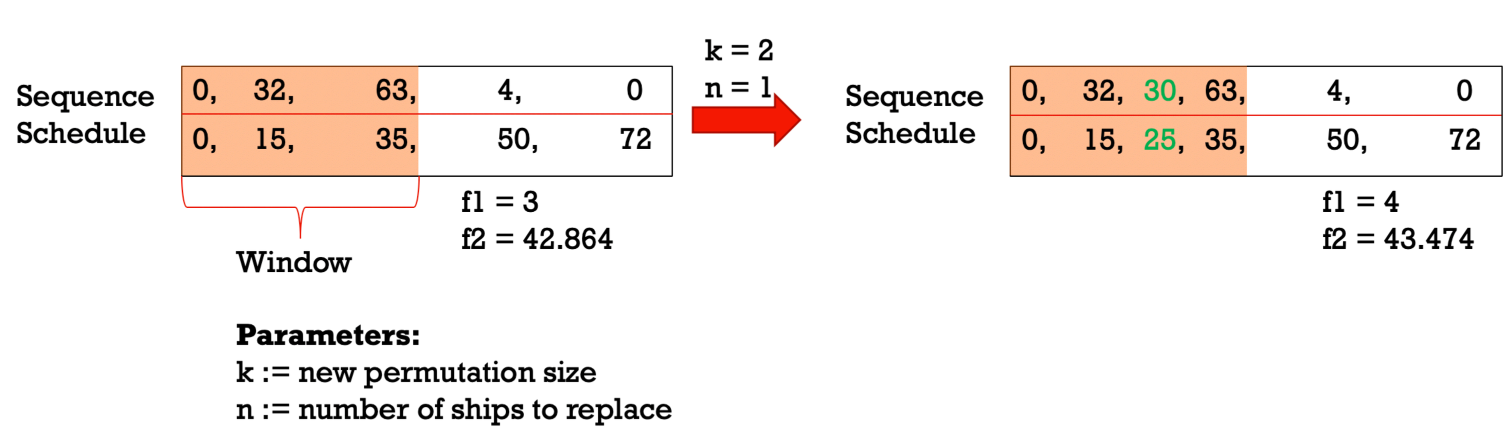


Figure 2: Transition function

The transition function selects a window of size n from an existing schedule, denoting which ships should be replaced. Then it generates a permutation of size k from target ships available within the associated time window. In the example above $n = 1$ and $k = 2$, thus we replace the subsequence [32] with a new subsequence [32, 30] resulting in α increasing from 3 to 4.

Upper Level

The upper level uses a genetic algorithm with random mating selection, a single-point crossover, and a customized mutation operator, to generate optimal routes of length α.

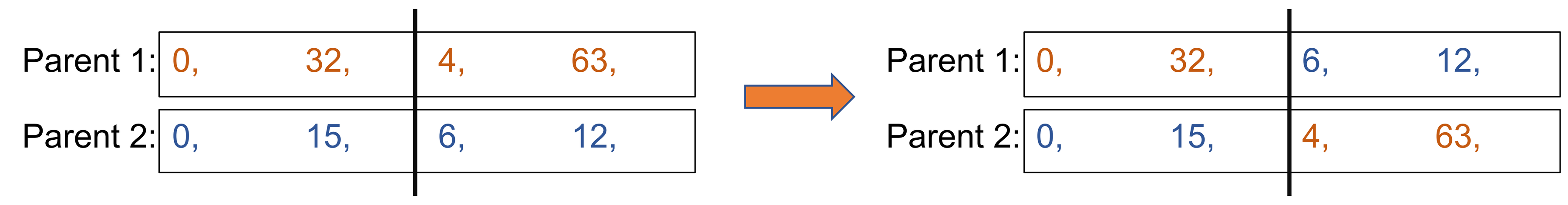


Figure 3: Example single-point crossover with two parents

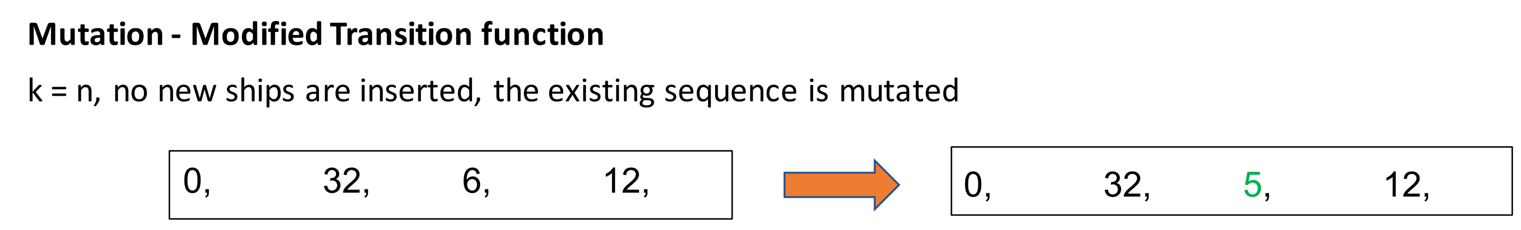
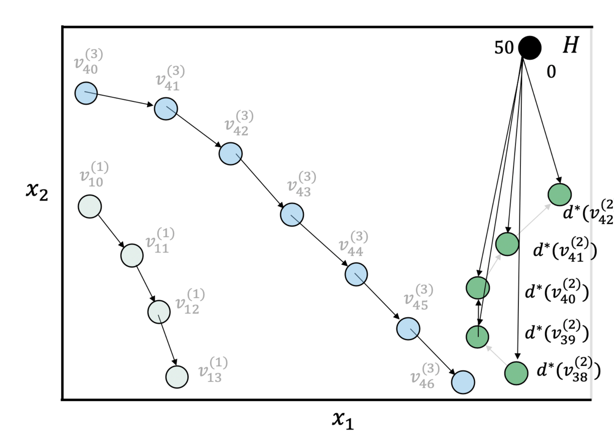


Figure 4: Example mutation of a route

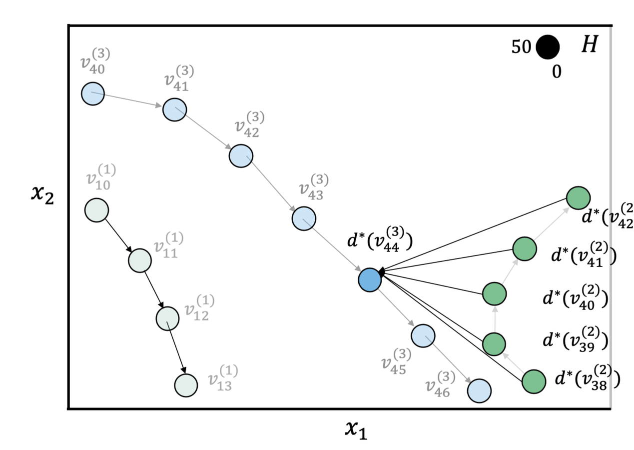
The crossover is a single-point crossover on a randomly selected point within the first parent's sequence, such that the lengths of both resulting sequences remain α after the process.
The mutation operator employs a variant of the transition operator from the α-level with the condition that $k = n$. This ensures that the length of the sequences remains the same.

Lower Level

The lower level is a dynamic programming solver that accepts a sequence as input, and returns a schedule and distance calculation for that route as output.



(a) First step in distance evaluation



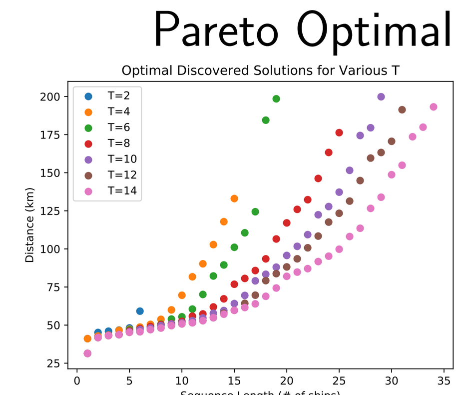
(b) Second step in distance evaluation

The following equation describes the optimal schedule for a given route based on the sub-optimality criteria specifying that the minimum feasible distance between two adjacent ships in a sequence is the optimal transition between them. Where $v_q^{(Rk)}$ denotes the position of ship R_k in the sequence at time q, and d^* represents the minimum total distance.

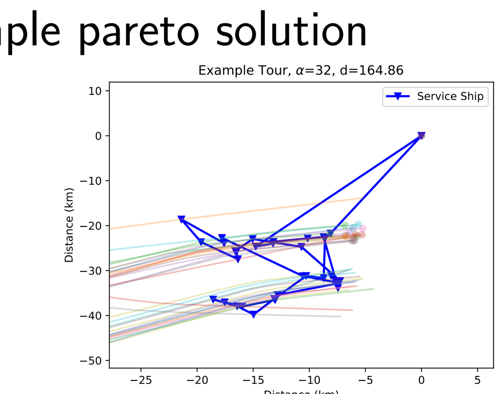
$$d^*(v_t^{(R+1)}) = \min_{q \in \Omega(v^{(R_k)})} [d^*(v_q^{(R_k)}) + c(v_q^{(R_k)}, v_t^{(R_{k+1})})]$$

Results

Pareto Optimal Solutions and Example pareto solution



(a) Pareto Optimal solutions for various values of T



(b) Example Solution with 32 ships

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