

Downstream Logistics Optimization at EWOS Norway

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Presentation roadmap

- 1 High level overview of our problem.
- 2 Comparison to similar problems.
- 3 Operational and business complications.
- 4 Mathematical formulation of the optimization problem.
- 5 Solution methods: construction heuristic, tabu search and clustering heuristic.
- 6 Historical-data simulation and empirical results.
- 7 Conclusions, implications and discussion points.

Our conditions

- Company: EWOS AS, Norway.
- Product: aqua feed for salmon farming.
- Network: 3 production plants, approximately 300 coastal customers.
- Fleet: 10 dedicated vessels.
- Our goal - optimize logistics

Industrial setting

- EWOS operates three Norwegian production plants: Florø, Halså and Bergneset.
- Customers are fish farms distributed along the coastline, so routing is maritime rather than road-based.
- Customer orders are normally known at least 10 days in advance.
- Customers can change order amounts, within reasonable limits, until vessel departure.
- Demand peaks in summer due to the biological growth cycle of farmed fish.
- We therefore want to plan out each 10 day window

Why this is not a simple routing problem

Classical vehicle routing problem (VRP)

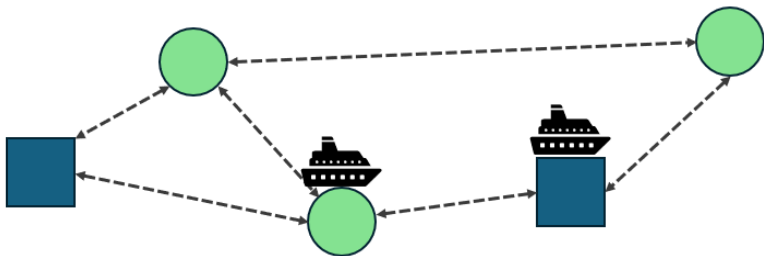
- Customers need deliveries.
- Vehicles have capacity limits.
- Routes should minimize travel cost.

EWOS-specific complications

- Multiple factories/depots.
- Heterogeneous vessels.
- Time windows for orders.
- Vessels can make multiple trips.
- Inter-depot routing is allowed.
- Rolling horizon and dynamic availability.

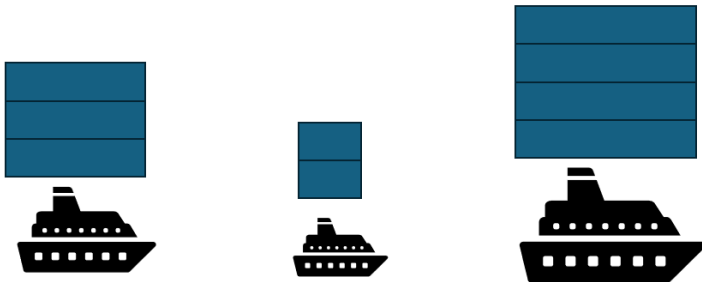
Specific complications

- **Multiple factories**
- Allows inter-depo routes.
- Complicates loading/rerouting of ships



Specific complications

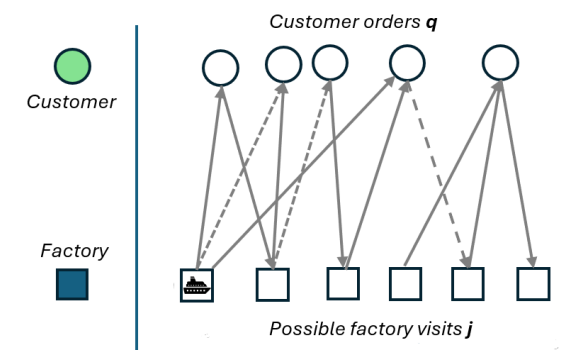
- **Heterogenous vessels**
- Vessels have different specifics (speed,load capacity, etc...)
- All variables (cost, time per route, etc...) need to be vessel specific



Specific complications

Time window for orders

- Each order has a specific time horizon in which it needs to be fulfilled.
- Each site gets a set of nodes representing orders
- Each factory gets a set of nodes representing intervals for filling up



Existing practice before optimization

- EWOS used a system of mostly fixed routes.
- Route planning was decentralized by factory: each plant planned deliveries for its own region.
- Current customer orders primarily determined how vessels were filled before departure.
- Fixed routes changed seasonally, but were not dynamically re-optimized for each rolling planning horizon.

Main opportunity

Centralized, dynamic planning can exploit unused capacity, cross-depot flexibility and better timing across the whole network.

Main research question

Can operations research methods produce practically better vessel routes for EWOS than the company's historical manual/fixed-route planning?

Operational measures of success

- Lower total sailing distance.
- Higher vessel fill-rate.
- Feasible satisfaction of customer orders and time windows.
- Potential reduction in fuel use, environmental impact and fleet size.

Operational problem: what must be planned?

- Which vessel serves each order.
- In what sequence customer orders are visited.
- When each service starts, respecting delivery windows.
- When vessels return to depots, reload and begin another voyage.
- Which depots are used at the start, between voyages and at the end.

Key physical and business constraints

- Vessels visit many customers.
- Route durations vary from hours to days.
- Loading/unloading times are significant.
- Service time is proportional to cargo amount.
- Each order has earliest and latest delivery time.
- Each order must be delivered completely by one vessel.
- Vessels differ in speed, capacity and cost.
- Some vessels may already be underway at planning start.

Rolling horizon interpretation

- Orders are known for an upcoming planning horizon, typically around 10 days.
- At the start of an optimization run, not all vessels are necessarily idle at a depot.
- A vessel's starting node and availability time reflect where and when it becomes available after ongoing routes finish.
- The algorithm can therefore be invoked repeatedly as new information appears.

Computational complexity

- The paper notes that the problem is NP-hard.
- Reason: it generalizes the vehicle routing problem with time windows.
- VRP with time windows generalizes the traveling salesman problem with time windows.
- Therefore, exact solution approaches are unlikely to scale to EWOS-sized instances.

Model type

Paper's formulation

A mixed-integer linear program for a multi-depot vehicle arc routing model with delivery time windows, heterogeneous fleet and multiple inter-depot routes.

- Time is continuous, not discretized.
- Arcs indicate immediate precedence: vessel ν goes from node n to node n' .
- Inventory/load variables are included because vessels may perform multiple trips and reload.
- Factory visits are represented by pregenerated nodes rather than only three physical depots.

Index sets

Symbol	Meaning
V	set of vessels ν
J	set of pregenerated factory-visit nodes j
Q	set of customer orders q
Q_ν	orders feasible for vessel ν
$N = J \cup Q$	all ordinary service nodes
$N_\nu = J \cup Q_\nu$	service nodes feasible for vessel ν
$o(\nu), d(\nu)$	initial and final vessel positions
$N_\nu^o = N_\nu \cup o(\nu)$	Service nodes w/ initial position of vessel
$N_\nu^d = N_\nu \cup d(\nu)$	Service nodes w/ final position of vessel

A customer may place multiple orders; each order is a separate node in Q .

Decision variables

Variable	Meaning
$x_{nn'\nu} \in \{0, 1\}$	1 if vessel ν services node n' directly after node n
$t_n \geq 0$	start time of service at node n
$y_{\nu n} \geq 0$	on-board inventory of vessel ν after servicing node n
$a_{\nu n} \geq 0$	amount loaded or unloaded by vessel ν at node n

The model combines sequencing, timing and cargo-flow decisions.

Parameters

- $c_{nn'\nu}$: cost of vessel ν sailing from n to n' .
- D_q : requested quantity for order q .
- U_n : loading/unloading time per unit at node n .
- K_ν : capacity of vessel ν .
- T : planning horizon.
- $T_{nn'\nu}$: travel time between nodes for vessel ν .
- $T_n^{\min}, T_n^{\max}$: time window for service at n .
- $o(\nu), d(\nu)$: start and end node for vessel ν .

Objective function

$$\min \sum_{\nu \in V} \sum_{n \in N_{\nu}^o} \sum_{n' \in N_{\nu}^d} c_{nn'\nu} x_{nn'\nu} + \alpha \sum_{\nu \in V} t_d(\nu).$$

- First term: transportation cost, often distance or fuel consumption.
- Second term: penalty for vessels finishing later.
- α lets the planner tune the importance of completion time.

Vessel flow constraints: node use

$$\sum_{\nu \in V} \sum_{n \in N_{\nu}^o} x_{nj\nu} \leq 1, \quad j \in J,$$
$$\sum_{\nu \in V} \sum_{n \in N_{\nu}^o} x_{nq\nu} = 1, \quad q \in Q.$$

- Each factory-visit node is used by at most one vessel.
- Each customer order is served exactly once.
- This is where the no-split-delivery requirement begins: one order must be assigned to one predecessor/vessel combination.

Vessel flow constraints: start, continuity, end

$$\sum_{n \in N_\nu} x_{o(\nu)n\nu} = 1, \quad \nu \in V,$$

$$\sum_{n \in N_\nu^o} x_{nn'\nu} = \sum_{n \in N_\nu^d} x_{n'n\nu}, \quad \nu \in V, n' \in N_\nu,$$

$$\sum_{j \in J} x_{jd(\nu)\nu} = 1, \quad \nu \in V,$$

$$\sum_{q \in Q} x_{qd(\nu)\nu} = 0, \quad \nu \in V.$$

- Each vessel leaves its start node once.
- Flow conservation maintains route continuity.
- Vessels must end through a factory visit, not directly from a customer.

Time constraints

$$\begin{aligned}x_{nn'\nu} (t_n + U_n a_{\nu n} + T_{nn'\nu} - t_{n'}) &\leq 0, \\ T_n^{\min} &\leq t_n \leq T_n^{\max}, \\ t_{o(\nu)} &= 0.\end{aligned}$$

- If arc (n, n') is used by vessel ν , service at n' cannot start before service at n plus service time plus sailing time.
- Time windows are hard constraints.
- The nonlinear implication can be linearized with a big- M expression using the planning horizon T .

Cargo flow equations

$$x_{nj\nu}(y_{\nu n} + a_{\nu j} - y_{\nu j}) = 0$$

$$x_{nq\nu}(y_{\nu n} - a_{\nu q} - y_{\nu q}) = 0$$

$$a_{\nu o(\nu)} = 0, \quad y_{\nu o(\nu)} = 0$$

$$y_{\nu j} \leq K_{\nu} \sum_{n \in N_{\nu}^o} x_{nj\nu},$$

$$y_{\nu q} + a_{\nu q} \leq K_{\nu} \sum_{n \in N_{\nu}^d} x_{qn\nu},$$

$$D_q \leq \sum_{\nu \in V} a_{\nu q}.$$

loading at depot,
unloading at customer,
empty start,

What the MIP formulation accomplishes

- It precisely describes the operational requirements in mathematical form.
- It integrates routing, timing and loading decisions.
- It supports heterogeneous vessels and multiple depots.
- It permits multiple trips and inter-depot movement.
- It makes clear why the real problem is computationally difficult.

But

The authors report that direct MIP solution was practical only for small instances, roughly up to about 15 nodes.

Why heuristics are needed

- EWOS instances contain about 100–200 order nodes in typical operational cases.
- The number of binary arc variables grows rapidly with nodes and vessels.
- Time windows and capacity constraints make feasible routing highly constrained.
- Exact MIP solving becomes too slow for operational decision support.

Heuristic path in the paper

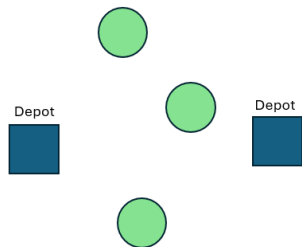
Construction heuristic → tabu search improvement → clustering heuristic plus tabu search.

Construction heuristic: high-level idea

Construction heuristic – building routes one order at a time

Step 1

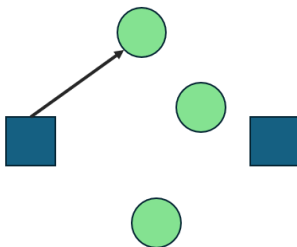
Start with an open route



We have one open route + several unserved orders

Step 2

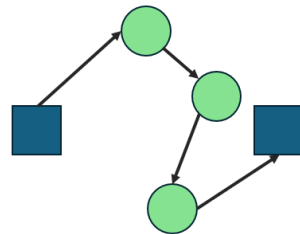
Append a feasible order



Pick a feasible order that fits our time window + capacity, and add it to the route

Step 3

Keep appending, then close at a depot



Repeat. When the ship is empty enough, finish the route at a depot.

Construction heuristic: algorithm structure

- 1 Initialize open routes using each vessel's starting depot and availability time.
- 2 Sort orders by time windows and ships by capacities.
- 3 Select orders sharing a common time window.
- 4 For each candidate order and open route, test insertion feasibility.
- 5 Choose the best feasible insertion using distance or regret-like criteria.
- 6 If no feasible insertion exists, classify remaining orders as unsatisfied.
- 7 When a vessel reaches capacity tolerance, close the route at the closest depot and open a new route from that depot.

Construction heuristic: strengths and weaknesses

Strengths

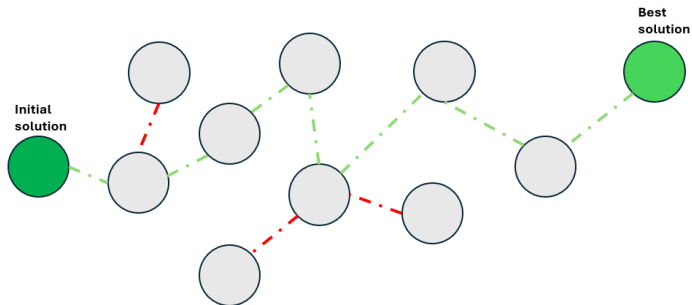
- Fast and intuitive.
- Respects operational concepts such as open routes and depot returns.
- Can produce initial feasible solutions.

Weaknesses

- Greedy decisions can block later improvements.
- Solution quality was not fully satisfactory by itself.

Tabu search: general concept

- Tabu search is an iterative neighbourhood search metaheuristic.
- It moves from one solution to a neighbouring solution, sometimes accepting a worse solution to escape local optima.
- Recently reversed or undesirable moves are temporarily forbidden by a tabu list.



Tabu search solution representation

- Basic unit: a **voyage**, defined by a vessel ν and route r .
- A route is a sequence of node visits:

$$r = (n_1, n_2, \dots, n_m).$$

- First and last nodes are depots.
- Intermediate nodes are customer orders with time windows.
- Each vessel may have a sequence of follow-up voyages.

Arrival and departure time propagation

Each node stores four timing quantities:

- earliest arrival t_n^e ,
- earliest departure o_n^e ,
- latest arrival t_n^l ,
- latest departure o_n^l .

$$o_n^e = t_n^e + U_n a_n,$$

$$t_{n'}^e = \max\{T_{n'}^{\min}, o_n^e + T_{nn'\nu}\},$$

$$t_n^l = o_n^l - U_n a_n,$$

$$o_n^l = \min\{T_n^{\max} + U_n a_n, t_{n'}^l - T_{nn'\nu}\}.$$

Feasibility test in tabu search

Time feasibility

A route sequence is time-feasible if

$$t_n^e \leq t_n^l \quad \text{for every node } n.$$

- Earliest times propagate forward through the route.
- Latest times propagate backward through the route.
- If earliest arrival exceeds latest arrival at any node, the sequence violates time windows.

Tabu search evaluation function

$$\sum_r L_r + \beta_1 \sum_r \max \left\{ 0, \sum_{n \in r} a_n - K_{\nu_r} \right\} + \beta_2 \sum_r \sum_{n \in r} \max \{ 0, t_n^e - t_n^l \}.$$

- First term: total route length.
- Second term: capacity violation penalty.
- Third term: time-window violation penalty.
- Penalty coefficients β_1, β_2 change during the search.

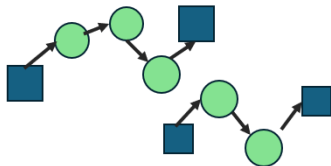
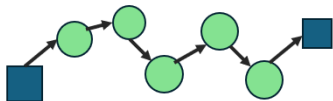
Important

The search may temporarily consider infeasible solutions but penalizes them, allowing exploration beyond a narrow feasible region.

Tabu neighbourhood moves

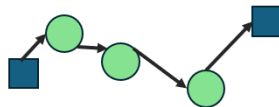
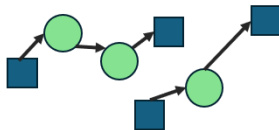
Allowed moves in Tabu heuristics

1) Split voyages



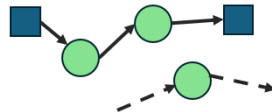
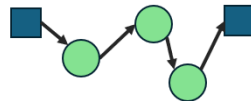
Insert a depot return inside a voyage, thus dividing it into two voyages

2) Merge voyages



Remove a depot between two consecutive voyages

3) Move node



Remove a customer node from one voyage and insert it to another.

Tabu search control parameters

- Split/merge tabu tenure: 20 iterations.
- Node-move tabu tenure: randomized, with mean equal to one third of the number of nodes.
- If a constraint class is violated, its penalty coefficient is increased by 20%.
- If the constraint class is satisfied, its penalty coefficient is decreased by 80%.

Clustering heuristic: motivation

- The authors first used the construction heuristic to initialize tabu search.
- They later replaced it with a clustering heuristic.
- The clustering heuristic was faster and cooperated better with tabu search.

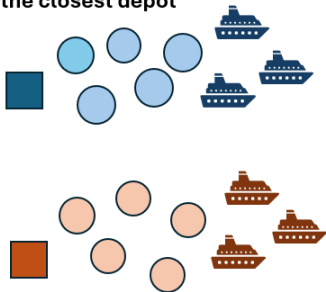
Reasoning

A good initial solution does not need to be perfect if tabu search has a large, effective neighbourhood. It needs to place orders into broadly sensible vessel/depot groups.

Clustering heuristic

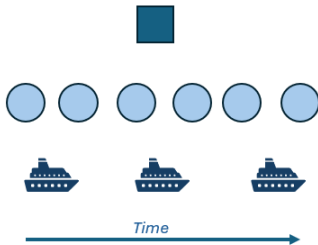
Clustering heuristic – an overview

1) Assign vessels/orders to the closest depot



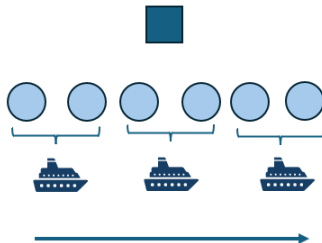
Selected based on distance/time to get there.

2) Sort each group by earliest arrival / earliest departure



We therefore have a sorted list of vessels and orders

3) Assign approximately equal groups to each vessel



We get a decent, oftentimes non-feasible solution.

Clustering heuristic: expected properties

- Produces geographically coherent initial groupings.
- Respects starting depot structure.
- Does not guarantee time or capacity feasibility.
- Provides a useful starting point for tabu search refinement.

Trade-off

The clustering heuristic sacrifices initial feasibility guarantees for speed and compatibility with improvement search.

Why large neighbourhoods are viable here

- The authors describe their neighbourhoods as large, with complexity roughly $O(n^2)$.
- This would be expensive for very large VRPs, but EWOS test instances have about 100–200 nodes.
- Large neighbourhoods reduce sensitivity to the starting solution.
- The result is a custom method tailored to medium-sized but operationally rich maritime routing.

Historical data design

- EWOS collected detailed operational data during autumn 2010.
- The authors reconstructed voyage sequences for Q2–Q4 2010.
- The simulation chooses a historical time instant.
- Ongoing real voyages are allowed to finish.
- Then the tabu search heuristic takes over routing for unsatisfied orders in a 10-day horizon.

Comparison principle

Optimized routes are compared against the routes that EWOS actually operated historically over the corresponding order set.

Order set construction in tests

The test order set includes:

- 1 all unsatisfied orders within the 10-day planning horizon; and
- 2 additional orders beyond the 10-day horizon if they belonged to any historical route containing orders from the base set.

Why add beyond-horizon orders?

This makes the comparison fairer because real historical routes may combine near-horizon and later orders in the same vessel voyage.

Test case summary

Start	Horizon	Orders	Optimized km	Historical km	Improvement
2010-10-14	10	118	8680.7	12923.3	32.8%
2010-10-24	10	124	10405.6	14595.3	28.7%
2010-11-06	10	139	9935.9	13753.4	27.8%
2010-11-15	10	113	9015.7	12679.5	28.9%

Headline

Distance reductions are consistently close to 30% across four historical cases.

Fleet and order characteristics

- Fleet size: 10 vessels.
- M/S RUBIN capacity: 350 tons.
- Other vessels: roughly 600 to 1650 tons.
- Average vessel capacity: about 1200 tons.
- Speeds: 17 to 24 km/h.
- Average order size: about 80 tons.
- Typical inter-location distances: tens to hundreds of kilometers.

Detailed comparison: historical routes

Table: Recorded historical routes.

Vessel	From	To	Fill	Days	Dist. [km]	Visited
M/S ARTIC FJORD	F	F	0.47	2.5	888.4	14
M/S ARTIC FJORD	F	F	0.77	1.8	667.4	12
M/S ARTIC FJORD	F	F	0.31	1.2	267.4	6
M/S ARTIC SENIOR	F	F	0.77	3.5	1045.0	5
M/S ARTIC SENIOR	F	F	0.74	1.8	616.5	12
M/S FEED BALSFJORD	H	H	0.63	3.0	848.1	7
M/S FEED BALSFJORD	H	H	0.45	2.5	795.1	6
M/S FEED TROMSØ	B	H	0.40	3.2	719.5	6
M/S FEED TROMSØ	H	B	1.16	3.3	1188.2	14
M/S HOLMEFJORD	F	F	0.17	2.3	492.1	4
M/S MIKAL WITH	H	H	0.36	3.6	1287.8	5
M/S MIKAL WITH	H	H	0.49	2.1	1422.7	10
M/S RUBIN	B	B	0.29	7.0	650.0	1
M/S SAFIR	B	B	0.55	2.2	614.9	6
M/S SAFIR	B	B	0.35	3.7	1176.3	5

Detailed comparison: optimized routes

Vessel	From	To	Fill	Days	Dist. [km]	Visited
M/S ARTIC FJORD	F	F	0.98	8.1	1512.0	28
M/S ARTIC LADY	F	F	0.94	7.9	1522.6	16
M/S ARTIC SENIOR	F	F	0.55	5.7	76.1	4
M/S FEED BALSFJORD	H	H	0.99	7.3	1398.1	14
M/S FEED TROMSO	B	B	0.90	6.9	1037.0	15
M/S HOLMEFJORD	F	F	0.84	3.7	521.3	9
M/S MIKAL WITH	H	H	1.00	6.5	2038.1	20
M/S RUBIN	B	B	0.91	5.5	535.6	3
M/S SAFIR	B	B	1.00	5.6	375.0	4

The optimized plan generally uses fewer, longer and much fuller voyages.

Historical routes: what differs?

- Historical operation used more separate routes.
- Many historical fill rates were far below the optimized fill rates.
- Some vessels made multiple shorter voyages with moderate or low utilization.
- Optimized routes accepted longer voyage durations in exchange for better consolidation.

Example route: M/S ARTIC FJORD

- Fill-rate: 0.98.
- Duration: 8.1 days.
- Distance: 1512.0 km.
- Visits: 28 customer stops before returning to Floro.
- Includes waiting periods, including one long wait of 38.9 hours.

Counterintuitive insight

A long wait inside a route may still be globally beneficial if it allows one vessel to cover a sequence of orders efficiently while respecting time windows.

Computational runtime

- Reported solution time for test cases was approximately 2 hours.
- Hardware reported: 2.53 GHz Intel Core 2 Duo, 4 GB RAM, Mac OS.
- For operational planning, this is plausible for batch planning over a 10-day horizon.

Modern perspective

The absolute runtime would likely improve substantially on current hardware, but the paper's point is methodological feasibility rather than real-time optimization.

Main conclusions of the paper

- The EWOS problem is a rich, real-world maritime VRP.
- Direct exact optimization is too limited for real-sized instances.
- A custom heuristic framework, especially clustering plus tabu search, can solve realistic cases.
- Historical-data tests show substantial distance savings and fill-rate improvements.
- These improvements imply lower fuel use, environmental benefits and possible fleet down-scaling.

References for slides

- M. Branda, K. K. Haugen, J. Novotny and A. Olstad, “Downstream Logistics Optimization at EWOS Norway,” *Math. Appl.* 6 (2017), 127–141.
- Core concepts used in the presentation: vehicle routing problem, multi-depot VRP, heterogeneous fleet, time windows, tabu search, clustering heuristic and mixed-integer programming.

Questions?