Optimizing Inventory Routing in Maritime Logistics: A Review of Modelling Approaches and Solution Methods

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Abstract:

The Maritime Inventory Routing Problem (MIRP) examines how to optimize inventory management and product delivery routing for maritime transportation. This paper reviews the key considerations in modeling the MIRP and the algorithms used to derive solutions. The constraints and complexities of maritime logistics are discussed. Mathematical formulations including deterministic, stochastic, and robust models are compared. Exact, heuristic, and metaheuristic solution methods from the literature are analyzed. Recommendations are provided on suitable MIRP models and solution techniques based on problem characteristics. The analysis indicates that hybrid metaheuristics combining swarm intelligence and local search provide a good balance of solution quality and computational effort for many MIRP variants. However, no single approach dominates, and the choice of modeling and solution method should consider trade-offs between optimization objectives, problem scale, and uncertainty. This review synthesizes current knowledge and best practices to guide further research. The paper provides insights for academics studying optimization in maritime logistics and practitioners seeking to improve operational efficiency.

Keywords: *Maritime logistics, Inventory routing, Mathematical modeling, Metaheuristics, Particle swarm optimization, Stochastic programming, Vessel routing*

1. Introduction

Maritime transportation serves as the backbone of international trade and global supply chains. Shipping by sea accounts for over 80% of global merchandise trade volume [1]. Managing the routing and inventory costs associated with global maritime logistics is therefore a major concern. The Maritime Inventory Routing Problem (MIRP) provides a modeling framework to optimize inventory management and shipment routing decisions while considering the unique characteristics of maritime transportation.

The MIRP examines how to fulfill customer demand for a commodity over a planning horizon by optimally routing a fleet of vessels to transport shipments from suppliers to demand ports [2]. The problem encapsulates inventory holding costs at ports, transportation costs for vessel routes, and customer service constraints. Key factors differentiate the MIRP from vehicle routing problems in ground transportation. These include the consolidation of commodities from multiple suppliers, inventory management at multiple port stocking locations, use of heterogeneous vessel fleets, and timing constraints imposed by tides and port access [3].

This paper reviews modeling approaches for the MIRP along with exact and heuristic solution algorithms from the literature. The constraints and objectives of the MIRP are outlined. Mathematical programming formulations are compared. Solution methods are analyzed regarding quality of results, computational requirements, and scalability. Finally, recommendations are provided on suitable MIRP models and solutions methods based on problem characteristics. This review synthesizes current knowledge to provide insights on optimizing inventory routing in maritime logistics.

2. Problem Description

2.1 Maritime Inventory Routing

Maritime inventory routing examines combined inventory management and delivery routing decisions while considering the constraints of maritime transportation [4]. The problem arises in managing the global supply chains for bulk commodities such as crude oil, refined petroleum products, and liquefied natural gas [5].

A typical MIRP involves multiple supply ports, demand ports and vessels over a planning horizon [6]. Supply ports hold inventory of a commodity which can be replenished over time. Demand ports place orders for commodity delivery which consume inventory. A heterogeneous fleet of vessels with varying capacities and costs transport commodity shipments between ports subject to inventory availability.

The objective is to determine optimal inventory levels and shipment sizes along with vessel routes and timings to minimize total transportation, inventory and shortage costs while satisfying all demand [3]. This requires leveraging the inventory holding capacity across ports and the economies of scale from consolidating shipments in vessel routes [7].

2.2 Maritime Transportation Characteristics

Maritime inventory routing decisions must account for unique aspects of transportation by sea [8]:

- Consolidation - Vessels can consolidate shipments from multiple suppliers destined to various demand ports. This allows for economies of scale versus direct delivery.
- Inventories - Ports can hold safety stocks to enable consolidation and hedge against demand uncertainty. Inventory holding costs must be traded off against transportation costs.
- Heterogeneous fleet - Shipping companies utilize fleets with vessels of different sizes, speeds, fuel costs and availability. Optimal assignment of vessel types to routes can reduce costs.
- Tidal constraints - Navigable water depth is tide dependent for some ports. This restricts access and departure times for vessels.
- Access restrictions - Ports may limit availability windows for vessels due to congestion, draught limits or other operational factors.
- Controllable speeds - Vessels can adjust sailing speeds to balance fuel costs against delivery times. Slower speeds reduce costs but extend routes.
- Uncertain demand - Demand at ports varies over time and is not known precisely. Inventory levels must hedge against uncertainty.
- Uncertain supply - Adverse weather or supply chain disruptions can constrain replenishment of inventory at supply ports.

- Environmental impacts - Vessel fuel consumption and emissions depend on engine load which varies with ship cargo and speed. Routing affects sustainability.

These maritime aspects significantly complicate inventory routing optimization versus ground transportation [9].

2.3 Problem Inputs and Decision Variables

Typical inputs for the MIRP include [10]:

- Planning horizon - Number and length of discrete time periods for optimization.
- Port parameters - Inventory capacities, holding costs, demand for each port and period.
- Vessel fleet - Number of vessels, capacities, speeds, fuel costs and availability.
- Travel times - Sailing time between each port pair based on distance and vessel speed.
- Tidal constraints - Time windows for accessible port arrival and departure considering tides.
- Replenishment - Maximum inventory replenished at supply ports for each period.
- Costs - Inventory holding, shortage, and transportation for delivering each unit of commodity.

Decision variables define the solution and include [11]:

- Vessel routes - Sequence of ports visited by each vessel in each period.
- Shipments - Amount of commodity transported on each leg of the vessel routes.
- Inventories - Stock level at each port for each period.
- Speed - Sailing speed on each route leg based on vessel and conditions.
- Timing - Arrival and departure time for each port visit on a route.
- Unmet demand - Amount of demand not satisfied by available inventory.

The values assigned to these decisions must satisfy problem constraints while minimizing total costs.

2.4 Constraints

The decisions for the MIRP must satisfy various operational and logical constraints including [12]:

- Vessel capacity - Total shipment quantity on a route leg cannot exceed vessel capacity.
- Inventory balance - The inventory level at a port for the next period equals current inventory plus replenishments and shipments received minus outgoing shipments and demand.
- Supply limit - Replenishment at a supply port cannot exceed specified maximum for the period.
- Demand satisfaction - Unmet demand occurs if inventory is insufficient to cover orders at a port.
- Port access - Vessel arrival and departure times must comply with port time windows.
- Tidal restrictions - Draft of a vessel entering or leaving a tidal port must meet water depth limits.
- Fleet availability - Vessel assignment must consider other planned routes and maintenance periods.
- Conservation - All vessel trips must start and end at the same port within a finite horizon.
- Non-negativity - Decision variables representing quantities cannot be negative.

These constraints couple the key decisions and ensure operational feasibility.

2.5 Objective Function

The objective is to minimize the total system-wide costs over the planning horizon [13]. Typical cost components include:

- Transportation - Costs for fuel and charter fees based on route distance and vessel type.
- Inventory holding - Financial and physical holding costs for stock stored at ports.
- Shortages - Penalty costs for unmet demand at ports.

- Fixed port calls - Possible fees for vessels docking at a port.
- The relative importance of costs will affect the optimal solution [14]. For example, high inventory costs encourage just-in-time deliveries while high fuel costs may favor slower vessel speeds.

2.6 Complexity

The MIRP encapsulates an inventory management problem within a vehicle routing problem while considering added maritime constraints. This combination of factors creates a complex stochastic and dynamic optimization problem [15].

Challenges include [16]:

- Non-linearities - Costs for inventory holding, fuel consumption and emissions vary non-linearly.

- Combinatorial options - The number of possible vessel routes rises exponentially for problems with more ports.
- Stochasticity - Uncertain demand and supplies require robust solutions.
- Dynamism - Optimal decisions change over the planning horizon as conditions evolve.
- Sequence dependence - Optimal routes depend on port visit order due to inventory impacts.
- Multi-objectivity - Environmental impacts may conflict with minimal costs.

These aspects mean the MIRP lacks optimal substructure and exhibits interdependence between decisions. The problem is strongly NP-Hard with solution difficulty increasing exponentially with problem scale [17].

3. Modeling Approaches

A variety of mathematical models have been applied to formulate the MIRP with differences in how they address uncertainties and dynamics.

3.1 Deterministic Models

Deterministic models make simplifying assumptions that demand, supplies, and travel times are known in advance with certainty over the planning horizon [18]. This enables formulating the MIRP as a static optimization problem.

Initial deterministic models used mixed integer linear programming (MILP) formulations [19]. The MILP model allows linear objective functions and constraints while some decision variables are restricted to integers. This captures discrete decisions like the number of port calls on a route.

More recent deterministic models have adopted nonlinear programming (NLP) formulations to handle nonlinear objective functions and constraints without approximations [20]. However, the absence of dynamics or uncertainty in deterministic models limits their realism for maritime inventory routing [21].

3.2 Stochastic Models

Stochastic MIRP models address uncertainty in key parameters using probability distributions [22]. These models hedge against variability in demand, supplies, travel times and environmental disruptions.

Two-stage stochastic programming is commonly applied [23]. First-stage decisions concerning routing, shipments and base inventory levels are made before uncertainty is realized. Second-stage recourse decisions alter initial routes and policies to address realized demand and events. Probability-weighted costs are minimized across all scenarios.

Chance-constrained models maintain service levels by limiting the probability of inventory shortages [24]. Robust optimization techniques also appear by optimizing the worst-case performance across a range of scenarios [25].

Stochastic models provide less risky and more flexible solutions but are complex to optimize [26]. Uncertainty modeling also requires detailed data on probability distributions.

3.3 Dynamic Models

Dynamic programming formulations model the MIRP with sequential decisions over time periods [27]. The optimization policy adapts as new information becomes available over the horizon enabling dynamic updating [28].

Markov decision processes (MDP) provide a common dynamic approach. The MDP contains states mapped to inventory levels, actions for routing and replenishment, transitions between states, and time-varying cost functions [29]. Optimal policies maximize expected rewards over the planning horizon.

Reinforcement learning has also been applied for heuristic solutions to dynamic MIRP variants [30]. Machine learning trains policies based on simulated experience.

Dynamic programming provides less conservative and more responsive solutions versus static optimization [31]. However, the curse of dimensionality makes it hard to solve large problems [32].

3.4 Multi-Objective Models

Recent works have proposed multi-objective models with competing environmental and economic goals [33]. Additional objectives include minimizing fuel consumption, emissions or waste.

Multi-objective programming optimizes a vector of prioritized objectives subject to constraints [34]. Lexicographic goal programming and epsilon-constraint methods force objectives into a hierarchy [35]. Fuel costs may be minimized first then emissions minimized subject to cost thresholds.

Pareto frontier approaches treat objectives equally generating sets of non-dominated solutions [36]. This enables examining tradeoffs between cost, fuel use, and sustainability.

Adding extra objectives increases difficulty but provides useful insights on environmental impacts [37]. This helps shipping companies consider corporate social responsibility along with profits.

3.5 Model Selection

The most appropriate MIRP model depends on the problem context and available data [38]. Realistic size problems with uncertainty favor stochastic over deterministic models [39]. Dynamism supports dynamic programming formulations if computational limits allow [40]. Multi-objective modeling provides useful sustainability insights but primarily as a secondary enhancement [41].

Available input data also affects model selection. Stochastic models rely on significant data for probability distributions. Dynamic models require extensive forecasts and progressive revelation of information over the planning horizon [42]. Data-driven approximations may be needed to apply more advanced models [43].

Enhanced model realism and complexity comes at the expense of increased solution difficulty [44]. The ability to obtain quality solutions also influences model choice. Discussion now turns to solution algorithms for solving MIRP models.

4. Exact Solution Methods

Exact optimization algorithms guarantee finding the optimal solution to a MIRP model given sufficient computation time [45]. Exact methods have been applied to small problem instances and provide bounds to assess heuristic solution quality on larger problems.

4.1 Mathematical Programming

Deterministic MILP and NLP models can be solved to optimality using commercial mathematical programming solvers like CPLEX, Gurobi or Xpress [46]. These solvers use branch-and-bound and cutting plane methods. SOLVE ENGINE previously provided specialized algorithms for the MIRP [47].

Solution times grow exponentially with problem scale rendering this approach intractable for realistic MIRPs [48]. Exact mathematical programming only solves small cases with less than 15 potential port calls [49].

4.2 Dynamic Programming

Dynamic programming (DP) solves problems by decomposing into sequential single-period subproblems [50]. Each subproblem optimizes decisions for the period given previous states and actions. DP converges to global optimum by recursively solving subproblems from the end of the horizon.

DP has been applied to small MIRP instances decomposed into planning periods [51]. To limit state space growth, states approximate inventory levels and locations. The curse of dimensionality restricts pure DP to trivial cases [52].

4.3 Limitations

Exact methods guarantee optimal solutions but computational requirements make them impractical for full-scale inventory routing problems [53]. Enumerating possible routes is prohibitive except for MIRPs with few ports and periods [54].

Exact algorithms provide few structural insights into quality solutions [55]. Hence many researchers focus efforts on efficient heuristic approaches for realistic maritime inventory routing [56].

5. Heuristic Solution Methods

A variety of heuristic algorithms have been developed to find good feasible solutions for large-scale MIRPs within reasonable computation times. These methods trade off solution quality for efficiency.

5.1 Constructive Heuristics

Constructive heuristics build an initial solution sequentially by adding decisions that appear best at each step based on simple priority rules [57]. This provides a fast baseline solution.

A typical approach initializes empty routes then iteratively adds port visits attempting to minimize costs [58]. Various criteria determine the next port selection such as minimum additional travel distance or unmet demand.

Constructive methods extend routes until all demand is satisfied or limits reached on vessel capacity or route duration [59]. Multiple rounds of construction may improve the solution.

These greedy heuristics are fast but often yield poor quality solutions as they do not backtrack from local decisions [60]. Performance depends heavily on the construction logic. Constructive heuristics appear mainly as sub-components of more sophisticated methods.

5.2 Local Search Heuristics

Local search heuristics start from an initial solution and iteratively move to neighboring solutions aiming to improve the objective [61]. Neighborhoods are defined by simple alterations to the current solution.

Typical local changes for the MIRP include [62]:

- Swap location of two ports in a route
- Move port from one route to another
- Change vessel assigned to a route
- Modify quantity shipped between port pair
- Add or remove port visit from a route

Applying all possible alterations identifies the best neighbor. Moves that reduce costs get accepted. The process repeats until no improvements found in a neighborhood.

Greedy searches that always move to best neighbors are prone to get trapped in poor local optima [63]. Metaheuristics guide the local search to escape local optima as discussed next.

5.3 Metaheuristic Methods

Metaheuristics enhance iterative improvement methods by introducing mechanisms to explore globally beyond local optima [64]. They balance local search intensification with global diversification.

Tabu search (TS) uses a recency-based memory to prevent revisiting previous solutions [65]. This forces the search out of cycling solutions. Applying TS to the MIRP improves local search neighborhoods [66].

Simulated annealing (SA) allows uphill moves to escape local valleys based on a probabilistic acceptance criterion that decreases over iterations [67]. Reheating restarts search from new random solutions. SA has been combined with route construction heuristics for the MIRP [68].

Genetic algorithms (GA) emulate biological evolution using selection, crossover, and mutation operators on a population of encoded solutions [69]. GAs leverage learning across solutions to avoid local optima. Specialized crossover and mutation techniques work for the MIRP [70].

Particle swarm optimization (PSO) simulates social behavior as particles are attracted towards the best previous positions of themselves and neighbors [71]. PSO has solved MIRPs using position velocity updates in solution space [72].

These popular metaheuristics improve over basic greedy local search for maritime inventory routing. Hybrids combining constructive, local search and metaheuristic elements provide the current best performance.

5.4 Matheuristics

Matheuristics hybridize metaheuristics with mathematical programming techniques [73]. Local search heuristics guide exploration while mathematical optimization refines solutions.

Examples for maritime inventory routing include using MILP to refine vessel routes from a metaheuristic [74] and applying greedy construction heuristics to convert an infeasible MILP solution to a feasible one [75].

Collaboration between global stochastic methods and mathematical programming enhances solution approaches for both [76]. Matheuristics leverage the strengths of each method.

5.5 Performance Comparison

Recent computational experiments provide insights on heuristic algorithm performance for various MIRP variants [77].

Constructive methods provide quick feasibility but fail optimality tests on all but the simplest cases [78]. Local search heuristics improve results but still fall well short of optimal on benchmark instances [79].

Metaheuristics like TS, SA and GA find near-optimal solutions on small problems while PSO and matheuristics give the best performance on larger cases [80]. PSO also scales better as problem complexity grows [81].

Overall, hybrid metaheuristics currently dominate research with combinations of PSO, TS, SA and constructive methods yielding top results on MIRPs with uncertainty [82]. Performance also depends on problem parameters such as inventory costs, fleet composition and demand patterns [83].

Combining global search with localized MILP optimization of vessel routes and inventories provides a robust approach [84]. No single heuristic dominates across MIRP variants. Metaheuristic elements enable escaping poor local optima while math programming leverages model structure.

Carefully tuned algorithms provide near-optimal solutions on small tested cases. Optimality gaps grow on bigger instances but remain acceptable for practical purposes [85]. More complex multi-objective MIRPs with sustainability goals require further heuristic research [86].

6. Recommendations

The preceding analysis provides guidance for solving practical maritime inventory routing problems:

- Adopt stochastic optimization for uncertainty and recourse [87]. Dynamic programming also valuable if information emerges over the planning horizon.
- Leverage hybrid metaheuristics to balance exploration and exploitation in the search for near-optimal solutions [88].
- Combine metaheuristics like PSO and TS with MILP optimization of routes and inventories for enhanced matheuristics [89].
- Develop custom constructive heuristics, local moves and solution encoding tailored to the MIRP structure [90].
- Start with simple constructive methods for fast feasibility then improve with metaheuristics [91]. Use exact methods only for small instances.
- Tuning parameters like population size and local search radii is key to metaheuristic effectiveness on a problem class [92].
- No single algorithm dominates across problem variants. Comparative testing needed to identify best performers [93].

- Apply multi-objective techniques as a secondary enhancement for sustainability insights [94].
- Leverage parallel computing and streaming algorithms to scale heuristics for industrial size problems [95].

7. Conclusion

This paper provided a comprehensive review of optimization approaches for the Maritime Inventory Routing Problem. Key aspects of the MIRP were outlined along with mathematical programming formulations. Exact solution methods only apply to small problem cases due to computational complexity. Heuristics provide quality solutions to practical sized inventory routing instances.

Hybrid metaheuristics balancing localized improvement with global exploration demonstrate promise. Matheuristics combining metaheuristics with mathematical programming also perform well. No one algorithm suits all MIRP variants. Several recommendations were presented on suitable modeling approaches, algorithms and computational enhancements. Further research is needed on harnessing parallel computing and strengthening multi-objective techniques for sustainable maritime logistics.

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