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Maritime Vessel Routing problems with safety concerns - a review

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Abstract – Nowadays, a large proportion of international trade relies on maritime transport. Hence, route optimization of cargo vessels is an essential planning problem. Safety is an important research area in maritime transportation. The last decade has seen a growing interest in considering safety aspects in routing problems. Safety is a crucial aspect and an all-time concern to any captain and this even prior the ship's sailing. Therefore, there is a need to understand the models and methods used to consider safety in previous studies. This work presents a maritime-specific review of routing problems coupled with safety aspects, along with relevant examples of other transportation industries such as road, rail, and air. Our review highlights the need for decision support tools that can effectively manage multiple objectives, including safety-related objectives, in maritime routing problems.

Keywords –Vehicle routing problem, Safety, Maritime transportation, Multi-objective optimization, Shipping.

1 INTRODUCTION

Nowadays, a substantial proportion of international trade is transported by sea. Therefore, the voyage optimization of vessels becomes essential. Before starting the navigation, one of the captain's concerns is selecting an efficient route with respect to many objectives. For example, fuel consumption and route duration are two critical objectives in voyage routing problems. In cargo ships, not only is the crew's safety essential but the safety of the ship's structure and cargo should be guaranteed. Hence, vessel route planning is a multi-dimensional problem considering time, fuel consumption, and safety. The compromise between these objectives is a crucial key of a transoceanic voyage. The optimization of ship routing is dependent on vessel characteristics and weather factors. The safety issues for different vessel characteristics (e.g., size and load) arise with weather information such as wave size and direction, wind direction and strength.

Vessel route optimization is one of the crucial problems in the maritime route plannings. Routing algorithms can play a crucial role in helping planners navigate the most cost-efficient, energy-efficient, and safe routes possible. It can be obtained by taking into account factors such as distance, route time, fuel consumption and safety criteria, using weather conditions and vessel characteristics. The quality of the optimized route depends on the quality of the data on these factors as well as the level of the details and decisions, and the solution approaches. By using routing algorithms, planners can optimize their travel plans and reduce transportation costs, while also minimizing environmental impacts and promoting safety for crews, cargo, and vessel structure. The main purpose of this review is to investigate how safety is included in routing problems in maritime transportation industry coupled with some examples of such problems in other sectors including road, rail, and air. The route optimization problems are solved using a grid system, where the search area is divided into a grid of discrete cells. The latter is a network of connected nodes and arcs that indicate the precise location of features on a map (e.g., roads, railways, air routes, maritime routes). The grid system represents the connectivity and structure of the network, which can be used in routing algorithms for finding the best path between a start and end point in a network. Most cases of route plannings embedded safety considerations are multi-criteria planning problems finding the optimized route by determining the trade-off between the objectives using a weighted objective approach.

The isochrone method developed by James (1957) was one of the first approaches for solving routing problems considering the weather forecast. Essentially, an isochrone represents a group of points on a map that can be reached by a ship starting from a single point and traveling in any direction within a specified time limit. The safety concern in vessel routing problems has gained increasing attention from maritime research communities over the years. In general, "safety" refers to the condition of being protected from danger, risk, or injury. The first thing captains must attend to before starting their navigation is safety at sea. Maritime navigation safety depends on the vessel's characteristics, the weather condition, and the navigators' skills. *Hard* and *soft* constraints are related to the safety of the vessel crossing the ocean. *Hard* constraints prevent navigating in areas that put the vessel in danger of capsizing, grounding, pirates, war, colliding with oil platforms, etc. On the other hand, *soft* constraints are restrictions that are not strictly enforced but instead involve a penalty for not being satisfied. For instance, in the case of hurricanes, a vessel must keep a minimum distance to avoid capsizing, which is a hard constraint, while the soft constraint increases the distance to hurricanes as much as possible. Typically, a safer route might be a long one with higher costs related to fuel consumption. Hence, vessel route planning problems become complex as they involve multi-objective programming with conflicting objectives. These objectives integrate navigation safety with the related economic impact in terms of voyage duration and fuel consumption. Therefore, it is essential to balance different objectives so that the vessel's safety is guaranteed, and the optimized route is both cost and fuel effective. Moreover, the methodologies to solve these problems become complicated since finding a reliable and precise trade-off between the objectives is challenging. This paper aims to provide a review of the studies on vessel route planning problems coupled with safety considerations. The main focus of this review is to investigate the previous methods to deal with multi-objective vessel route optimization considering safety aspects. Although the review is mainly for the maritime industry, we also include some studies in the road, railroad, and air transportation sectors to expand the understanding about safety and how it is modelled in routing problems.

2 THE BACKGROUND REVIEW

This paper provides a review of how safety concerns are addressed in routing problems, including the methods used to solve them. For this purpose, we developed a set of research questions to be addressed in this review:

- What kinds of safety concerns were addressed in previous works?
- How are these safety issues modelled and included in routing problems?
- What methodologies are proposed to find the trade-off between multi-objective routing problems?
- What methods are developed in multi-criteria route planning problems?

Although we acknowledge the potential operational safety issues associated with traffic and the passage of the ship through the canals, our primary focus is directed towards open map maritime routing problems. Our literature search yielded 53 relevant papers, which underwent a rigorous screening process resulting in the selection of 28 papers for inclusion in our review.

2.1 Maritime routing problems associated with safety

In adverse weather conditions, a ship may encounter different dangerous phenomena that put the vessel at risk of capsizing or damaging cargo, equipment, and persons on board. These dangerous phenomena vary from one vessel to another depending on stability parameters, hull geometry, ship size and ship speed. However, in vessel route planning problems, various safety issues should be considered. IMO guideline (IMO, 2007) adopted the safety regulations related to a set of safety aspects as follows. The *surf-riding and broaching-to* phenomena are situations associated with wave and ship speed. They may occur when the vessel's speed is the same or less than the wave's speed, causing the vessel to heel at a significant angle or suddenly change its heading. As a result, the vessel would be in danger of capsizing. This phenomenon may happen if the vessel encounter angle is in the range [135º, 225º] and the vessel speed exceeds a specific value (IMO, 2007). *Successive high-wave attack* is the probability of a vessel to be encountered by a group of dominant waves with the same speed. It would induce the danger synchronous rolling motions, parametric rolling motions, intact stability reduction or combination of various phenomena (IMO, 2007). *Synchronous rolling motion* happens when the natural rolling period of a ship is the same as the encounter wave period in following and quartering seas. The synchronization between the ship's rolling period and the wave period can result in a back and forth rolling motion that can cause instability and increase the risk of capsizing. *Parametric rolling motions* may arise based on the vessel's position on the wave crest and wave trough, which puts the vessel in danger of a large heeling angle, subsequently increasing the risk of capsizing. It occurs when the encounter period equals or is half the rolling period. The aforementioned phenomena have been derived from the IMO guideline document (IMO, 2007). Depending on the related safety concern, these safety issues are affected by the vessel’s speed, wave height, wave period, and the encounter angle between waves and the vessel’s direction. When these safety aspects are combined, they represent both non-dangerous and dangerous zones that are limited by vessel and weather data. The terms “dangerous zone” and “non-dangerous zone” refer to the hard and soft constraints, respectively.

Moreover, vessels have six motion behaviors in the ocean, including three linear motions along longitudinal, transverse, and vertical axes and three rotational motions along these axes. The theory behind these behaviors is referred to as seakeeping characteristics in the vessel industry (Pennino, 2020). Ship speed is one of the most critical factors affecting vessel safety when it comes to controlling safety issues related to ship's motions. Ship speed reduces in hazardous weather due to the added resistance introduced by waves, wind, and ship motions. The interaction between the ship's hull and the surrounding water leads to additional resistance to the ship's movement, known as ship added resistance. The ship's propulsion system must overcome the added resistance to its forward movement caused by this interaction. Environmental conditions and wave actions are generally the causes of added resistance that can affect a vessel’s speed and fuel consumption. A background review of previous studies in maritime research that considered safety aspects in routing problems is provided in this section.

The Multi-criteria evolutionary weather routing algorithm (MEWRA) is an evolutionary algorithm that uses Pareto optimization to find the optimal path concerning multiple conflicting criteria (Szłapczyn, 2009). Regarding weather routing, this algorithm determines an optimal route that mainly takes into account weather conditions, fuel consumption, and safety. Genetic algorithms and swarm optimization are two evolutionary methods used in MEWR algorithms to find the best path. These techniques evaluate potential routes based on how well they meet the criteria. Swarm optimization (Kennedy and Eberhart, 1995) is a technique that involves a population of candidate solutions, referred to as particles, exploring the search space to find the optimal solution. The particles are affected by their own previous experiences as well as the experiences of other particles in the swarm. The ultimate goal is to converge to the best solution by combining the information gathered from the individual particles with the collective knowledge of the swarm. Krata and Szlapczynska (2012) developed a MEWR algorithm to find the optimized route where time, fuel consumption and safety index were minimized. In this study, the safety hard constraint was related to the IMO guideline (2007) described earlier. To account for soft safety constraints, the authors introduced a safety index. This index was calculated based on dangerous and non-dangerous zones as in IMO guideline (2007). The safety index was defined as the ratio of the non-dangerous area to the sum of both areas. In earlier work, with respect to the studied safety in Krata and Szlapczynska (2012), Szlapczynska (2015) considered static (time-independent) constraints alongside dynamic (time-dependent) ones. The static constraints referred to the areas that must be excluded from the passage (e.g., the location of pirates), while the dynamic constraints were based on weather data that could change the navigation during route planning period. One of the methods dealing with multi-objective shortest path problems is the Martins' labelling algorithm introduced by Martins (1984). Martins' labeling algorithm is a technique for determining the shortest path between two nodes in a graph with non-negative edge weights. The approach involves assigning a label to each node that represents a potential path from the starting node to the node in the graph. Each label includes details about the path's cost in relation to the problem's objectives or criteria. The algorithm continually updates the node labels iteratively until it identifies the shortest route to the destination node. In each iteration of this algorithm, two labels are defined: permanent and temporary. The algorithm chooses the next node to be visited through a depth-first search strategy among all the sets of temporary labels and converts it to a permanent one if it is non-dominated. Then all the temporary labels of its successors receive the information contained in this label. One of the applications in this field is presented by Fabbri and Vicen-Bueno (2019). They proposed a multi-criteria vessel routing problem that balances time, ship navigation added resistance and navigation safety/risk. The solution approach was based on providing a set of Pareto dominant solutions using Martins' labeling algorithm. The authors considered IMO safety measurement as studied by Krata and Szlapczynska (2012). They chose a strategy that involved removing the areas where navigation might be unsafe or risky while taking into account ad hoc constraints that might lead to a smaller solution space.

Veneti et al. (2017) presented a nonlinear integer programming model to minimize fuel consumption and safety risk in vessel route planning where travel time was constrained. They propose a new labeling algorithm to solve the problem and to find a set of Pareto optimal solutions. In this algorithm, each edge of the network included three costs: fuel consumption, travel time, and safety risk. The algorithm procedure used was identical to Martins' labeling algorithm, with one exception: the node search strategy. They proposed a node search strategy that is random, in contrast to Martins' labeling algorithm, which employs a systematic search strategy. The safety formulation was applied as both soft and hard constraints. On one hand, the hard constraints were applied according to IMO guidelines (IMO, 2007) as described earlier, except that they only included parametric rolling, and surf-riding and broaching-to to construct the dangerous zone. On the other hand, the soft constraints were based on historical data in which the safety risk was formulated as the probability of accidents multiplied by the severity of its consequences for each arc in the network. Krata and Szlapczynska (2018) provided ship routing as a multi-objective optimization problem solved by the MEWRA to provide a set of Pareto optimal paths. The objectives included fuel consumption, voyage duration, and safety. The soft safety constraints referred to the non-dangerous zone, followed by synchronous rolling, parametric rolling, surf riding and broaching-to, according to IMO guidelines (IMO, 2007). The hard safety constraints were based on the dangerous zones restricted by the aforementioned safety phenomena. Zaccone et al. (2018) presented a dynamic solution approach to minimize fuel consumption as a single objective. It also considered the ship's six motions based on seakeeping criteria (as described earlier) as hard safety constraints. The six ship's motions were constrained by the acceptable range that it could get. The paper mainly focused on optimizing the fuel consumption and the ship speed profile coupled with ship propulsion performance and hydrodynamic response of the vessel to different weather and sea conditions, such as wave height and wind speed. Padhy et al. (2008), discusses an approach to weather routing of ships in the North Indian Ocean that prioritizes safety by controlling vessel speed according to seakeeping criteria. The author assigned weights to the edges of the graph and applyed Dijkstra's algorithm to find the minimum time route between two neighboring nodes. The weights were defined as the time to travel between two neighboring nodes where the speed was determined based on the vessel's calm water resistance and mean added resistance obtained from weather data. Pennino et al. (2020) used Dijkstra's algorithm to optimize ship routing by maximizing the vessel's Seakeeping Performance Index (SPI). The SPI is used to measure how efficiently a vessel can operate in the sea. It is calculated by producing a single numerical value that represents the overall seakeeping performance of the vessel based on five reference criteria: Root Mean Square (RMS) of pitch amplitude, RMS of vertical acceleration at forward perpendicular, Motion Sickness Incidence (MSI), Slamming, and Green water probabilities.

Challenges may arise in optimizing vessel routing when dealing with uncertain factors such as weather, sea conditions, and vessel performance. Although classical state-of-the-art models are considered a satisfactory method, in practice, they are affected by uncertainty in weather data. Vettor et al. (2020) developed a multi-objective metaheuristics (MOMH) approach considering uncertainty in weather conditions. In this paper, achieving accurate weather forecasts was challenging, which had an impact on the quality of the results. In the short term, they evaluate the dangerous situations to measure safety risk followed by a sea state scatter diagram. The scatter diagram shows how different sea conditions are distributed and the likelihood of encountering waves of different heights and periods at a specific location. Vettor et al. (2020) used a Gaussian probability density function to calculate this likelihood and developed a probabilistic model based on the Gaussian distribution to assess the navigating safety risk in rough seas. They identified which portions of the likelihood corresponded to unsafe wave conditions based on established seakeeping criteria. In the long run, weather routing was adopted with a combined objective function that considers both time and safety risk. This objective function was formulated by multiplying the safety risk by the ratio of the time required to travel between neighboring nodes to the total voyage time. By combining these two factors, the proposed approach aimed to optimize vessel routing for both efficient travel time and safe navigation.

Overall, the above papers address the integration of safety, fuel, and time in maritime routing problems. These criteria affect the constraints or objective functions depending on the situation. Regarding safety concerns, different dimensions have been studied and formulated in vessel routing problems. These dimensions can be referred to the IMO guidelines, seakeeping criteria and other safety issues investigated previously. However, including all the safety issues simultaneously, besides other objectives (fuel consumption and route time), remained unexplored. Hence, there is a need to include all safety aspects in vessel routing problems to comprehensively ensure safety regarding cargo, vessel structure, and crews/passengers during navigation. Given that incorporating safety-related objectives can increase the complexity of determining objective weights, our review emphasizes the necessity for advanced decision support tools that can effectively manage multiple objectives in maritime routing problems.

2.2 Road routing problems associated with safety

"The number of deaths on the world's roads remains unacceptably high, with an estimated 1.35 million people dying each year." (World Health Organization, 2018). This statement shows the importance of safety on road. Including safety concerns in road routing problems can improve accident prevention by taking into account the risk of crashes. There is a noticeable difference between routing problems in road and maritime transportation. In road routing, the network is generated using pre-constructed roads whereas such a concept is not applicable in maritime routing problems. Moreover, the available data in the road industry may include road characteristics (e.g. road curvature, speed limit). In the maritime sector, the most critical aspect is considering weather data to ensure the safety of the ship's structure, crew, and cargo and control the vessel’s speed for safety purposes. On the other hand, when it comes to road routing, weather data is usually not regarded as the most crucial aspect. This is because road vehicles are typically better prepared to handle severe weather conditions, and the effect of weather on road safety is frequently less serious than in the maritime industry. In road routing industry safety can be divided into two main areas: road safety and traffic safety. The concept of "traffic safety" involves strategies to ensure a safe and efficient flow of traffic on roads and highways. On the other hand, the term "road safety" refers to the general safety of roads and highways, with an emphasis on avoiding accidents and minimizing the crash risk to those using the roads, including drivers, passengers, and other users. A background review has been done on road safety and traffic safety in the following sections.

In the road transportation industry, there is a negotiation between shippers and carriers about how the payments for transportation should be based on. The significant problem is that the shortest path may be based on something other than the drivers' preferences due to the contractual distance-based payments. For instance, while a company prioritizes shorter road lengths to minimize costs, a transporter may prioritize faster travel times to maximize payment, potentially resulting in longer routes due to road speed limits. Hence, finding the best routes based on the user's preferences becomes challenging. Besides, road safety is one of the crucial aspects that any driver must consider. It can be evaluated by historical data and individual users' judgments (Sarraf and McGuire, 2020) and also be measured based on road characteristics such as hilliness and curvature (Rönnqvist et al., 2017). In this regard, Flisberg et al. (2012) used the Dijkstra algorithm to find the minimum cost route where the transportation cost was based on road characteristics and road safety. The road characteristics and safety were formulated as a weighting of the road features (e.g., road class, road width, or speed limits), but finding proper weights was challenging. Hence, inverse optimization was proposed to find suitable weights for different attributes to generate the routes based on the drivers' preferences. This paper contributes to safety by combining path cost and safety to find a more efficient routes for drivers and customers. By taking into account factors such as road class, traffic flow, and road safety, the proposed method can help identify potential risks and mitigate them, leading to improved overall safety on the road. Considering the same safety aspects, Rönnqvist et al. (2017) developed the Calibrated Route Finder (CRF) using inverse optimization. CRF is a distance measurement system and route selection tool that balances conflicting objectives, including quantitative and qualitative factors. An inverse optimization approach was presented to find the trade-off between various objectives concerning road characteristics that included the same safety attributes in Flisberg et al. (2012) and drivers' preferences through the best practice routes generated by the users.

Akay (2020) implemented a geographic information system (GIS)-based network analysis method to find the optimum route in the forestry transportation industry. GIS is a computer-based system for visualizing and analyzing geographic information associated with a specific location or region of research (Lü et al., 2019). It also assists users in inserting problem-related features and analyzing patterns and relationships with specific data. The paper proposes two optimization scenarios for determining the best route: one focuses solely on transportation costs related to truckload capacity and driver hourly pay, while the other takes into account safety considerations to determine the safest route. They dealt with safety as a risk function by analyzing a range of factors that contribute to the likelihood of accidents involving logging trucks. The paper identifies several factors that may affect the safety of a given route, including road type and conditions, traffic volume, and accident history. To assess the safety risk of each potential route, the paper assigns weights to each of these factors based on their relative importance. The findings revealed that transportation costs rise when the route's safety is considered.

The Floyd-Warshall algorithm is a well-known method that determines the shortest route between any two vertices in a weighted graph, even when negative edge weights are present. The difference between this algorithm and the Dijkstra algorithm is in the free nature of the edge weights. The problem with this algorithm is the possibility of negative cycles which lead the solution to incorrect results or go into an infinite loop. Moreover, in optimization problems, fuzzy logic is one of the algorithms that deals with uncertainty and provides approximate solutions rather than exact ones. Accordingly, it does not return true or false to a statement; instead, it specifies a certain range (Novák, 2006). Regarding the above description, Pešić et al. (2020) developed the Fuzzy Floyd's algorithm to optimize transportation routing through bi-objective programming concerning road safety and travel time. The authors of the paper utilized a two-criterion Fuzzy Floyd's algorithm to determine the optimal route while considering safety and travel time as the two criteria. They used a questionnaire answered by ten experts to obtain a safety indicator based on road characteristics such as the number of junctions, road width, road equipment, and pavement quality. The scores obtained from the questionnaire were averaged to derive the safety indicator. The authors used fuzzy techniques to handle the uncertainty associated with travel time and safety indicators. They used triangular fuzzy numbers to represent three possible values for an uncertain parameter, which allowed them to consider multiple possible values for the travel time and safety indicators. To convert the fuzzy triplet numbers into a single value, they used an alpha-cut method (Kaufman and Gupta's (1985) that involves setting a threshold or level of membership in the fuzzy set. Values in the fuzzy set with a membership degree greater than or equal to this threshold are included in the alpha-cut set, which is a non-fuzzy set that represents a subset of the original fuzzy set.

In recent decades, traffic accidents have become a growing concern, leading to an increase in both traffic safety issues and crash risk exposure. To address this issue, Chandra (2014) developed a multi-objective shortest path (MSP) algorithm based on the median shortest path problem to simultaneously minimize travel time and car accident probability. The author proposed a safety indicator to predict the likelihood of a car crash based on sparse traffic, dense traffic, and an intersection collision. Sparse traffic occurs when there are few vehicles on the road. In contrast, a dense traffic condition refers to a situation where many vehicles are on the road. The median shortest path problem is based on graph theory, primarily introduced by Current (1987). This is a statistical method used to estimate the typical distance between pairs of nodes in a network. In a network, the shortest path between two nodes is the path with the fewest number of edges. The median shortest path is the value that divides the distribution of shortest path lengths into two equal parts, meaning that half of the shortest paths are shorter than the median and half are longer. Omidvar et al. (2017) presented two mixed-integer linear programming (MILP) formulations for the problem of routing and scheduling of vehicles while considering crash risk. The crash risk was determined using historical crash records and was used in the first model. The first model included two objective functions, travel time delay and crash risk. They used the weighted method to deal with multi-criteria problems in which the weights were determined by decision maker's judgment. The authors solved a second optimization model that considers each route as an independent path. In this phase, the optimal speed on each arc is modified and the departure times of each vehicle from each node are rescheduled accordingly. They used Simulated Annealing (SA) algorithm to solve the two stages iteratively in a shorter amount of time. This method begins with a random solution and tries to find a better solution with minor changes (Brooks and Morgan, 1995). Sahnoon et al. (2018) established a GIS-based approach using the Dijkstra algorithm to deal with travel time and crash risk. This study modeled the safety risk using a probabilistic approach based on historical data on fatal and injury crashes. The proposed cost function combined time and safety risk based on the weighted method. Then, the authors surveyed different scenarios of the weights for a case study in the United Arab Emirates.

Guo et al. (2020) developed a safe transportation routing model as a bi-objective problem, considering travel time and safety risk. The safety risk was associated with factors such as road geometry, traffic volume, and population density. The authors proposed two different solution algorithms based on different assumptions. The first approach assumed that there exists at least one safest path among the set of shortest paths, and the second approach assumed that the safest path may not be a part of the set of shortest paths. To solve these two problems, the authors used the A-star algorithm for the first approach and designed the GA-star algorithm for the second approach, which combines a genetic algorithm with the A-star search. A-star is considered to be one of the best pathfinding algorithms due to its ability to find the shortest path quickly and efficiently in a graph with weighted edges. The difference between this algorithm and Dijkstra is that A-star algorithm includes a heuristic function to direct the search towards the destination node. In GA-star approach, the edges of the shortest paths were removed from the graph, then the algorithm would find the safest path in the second shortest path set. Sarraf and McGuire (2018) proposed a data-driven approach to find the safest path in vehicle routing problems. Given that the route-finding method was based on the Dijkstra algorithm, the objective function aimed to minimize the crash risk where the shortest path was neglected. Methodologies for calculating crash risk are essential safety criteria in route planning problems. Kingsbury (2016) provided two methodologies to quantify the crash risk to be minimized in the vehicle routing problem, besides other factors such as travel time and distance. The safety risk determined in the first model aimed to predict the likelihood of crashes relying on the historical data within the regression model. On the other hand, the second method estimated the crashes based on regression algorithms that correlate road characteristics with the crash performance indices. Furthermore, the weighted multi-objective model was optimized using the Dijkstra algorithm. They provided a set of weight settings for the problem through a sensitivity analysis.

While there are already established methods for assessing risk factors such as road geometry and traffic volume, these models may not be enough to capture the complex and dynamic nature of safety risks. There is a need for more advanced models that can account for factors such as driver behavior, weather conditions, and vehicle characteristics, among others. In addition, there is a research gap in considering the mentioned safety risk with historical data that lead the safety model to be more accurate in vehicle route plannings. Another important gap is optimizing fuel consumption that can be included in traffic problems. This is a crucial aspect to consider as it not only benefits the environment but can also help reduce vehicles operating costs.

2.3 *Railroad routing and scheduling problems associated with safety*

Unlike the previous routing problems where typically involved balancing both soft and hard constraints, railroad routing optimization incorporates safety concerns as hard constraints in the proposed models. In the rail transportation industry, safety regulations impose a minimum distance between trains travelling in the same direction. This requirement translates into a "minimum headway" between two consecutive trains, which depends on various factors such as the length of the specified track, train speed and length (Samà et al., 2017). For each pair of adjacent trains on the same track, the time gap between them should be greater than or equal to a safe headway time. By including this constraint in the optimization problem, the routing algorithm can ensure that the solution obtained satisfies such safety requirement. Bożejko et al. (2017) proposed a modification of Dijkstra algorithm to find the shortest path in the cargo rail transportation industry. The safety criteria constrained the model to control the safe headway time and avoid collisions. The proposed method involves using an estimation of minimal arrival time to each node, and a set of unvisited nodes. The algorithm updates the estimation of arrival time for each node and selects the next node to visit based on the minimum estimated arrival time. The main steps of the modified algorithm are similar to the original Dijkstra algorithm, but the difference occurs in the way the estimation of arrival time is updated. Samà et al. (2016) proposed a MILP model to minimize train delays with respect to minimum headway time between trains. Given the lengthy computational time, the author devised a novel approach based on the relaxation of some constraints in order to produce a good quality lower bound for optimization. Then the lower bound was transformed by a constructive metaheuristic approach into a feasible solution to find a good-quality upper bound. In another work by Samà et al. (2017), a MILP model was developed for the minimum consecutive delay measured by makespan minimization. The paper focuses on developing an optimization model that can handle delays and disruptions in the railway system. The term “consecutive delay” referred to the total amount of delay that occurs in each time window in which a train is scheduled to pass. The aim was to minimize the consecutive delay, which represents the total amount of delay that occurs during the scheduled train journeys. They used makespan minimization to find a schedule and route for a set of trains that minimizes the time it takes for all trains to complete their routes. In addition, the safety regulation was applied as a constraint to impose a minimum separation between two consecutive trains, the same as in previous studies. The solution method was based on the branch-and-bound algorithm. With respect to the minimum safe headway time, Meng and Zhou (2014) proposed a parallel technique algorithm to find the optimized path. The objective function was to minimize the total cost of the train schedule, which is calculated as the weighted sum of train delays, waiting times, and infrastructure usage costs. Then the solution was obtained through a set of scenarios for the weights. The authors used a Lagrangian relaxation to relax the constraints related to train sequencing, essentially allowing trains to be violated to some extent for faster computation. The authors developed a DSS software program that creates train schedules for railway systems. Creating these schedules involves a lot of complex calculations, which can be time-consuming. To speed up the process, the authors used a tool that allowed to distribute the work of creating train schedules across multiple cores in the processor of the system. In another study (Meng et al., 2016), the authors focused on the stochastic environment when an incident affects track capacity and running timetables. Then the dispatchers need to reschedule the trains. The objective function was replaced by the expected total delay time to address the uncertainty situation. Although previous works concentrated on the safe distance between trains, there are other safety requirements to guarantee the safety of the trains. Xu et al. (2017) developed an Integer Linear Programming (ILP) model aiming to minimize the train deviations between the trains' arrival time at the destination. They model was subjected to the trains' minimum safety headway. In this work, the train's departure and arrival safety headway times were considered in both the same and opposite directions to ensure that the trains could not cross over each other in the same direction. Another vital criterion is avoiding head-on collisions while crossing trains in two-way traffic flow by switching tracks. In addition, rear-end accidents can happen when two trains travel in parallel but one of them enters to another track at the next intersection. All situations, as mentioned earlier, have been added as constraints in Xu et al. (2017) approach.

Based on the reviewed literature, it is essential to consider multiple factors in train routing and scheduling. One such factor is the duration that trains wait in stations before departure, along with delay time, arrival time, and the number of delayed trains. These factors act as objectives that can be addressed through multi-objective optimization techniques. Moreover, train routing and scheduling can be significantly impacted by hazardous weather conditions, including heavy snow, ice, rain, flooding, high winds, or extreme heat. These severe weather conditions can create safety risks and make it challenging or even impossible for trains to operate safely but their impact on rail routing problems has not been studied.

2.4 Aircraft routing problems associated with safety

Safety is crucial in Air Transportation Systems (ATSs) due to its destructive effects on human life since the consequences of accidents can be catastrophic and potentially fatal. With the rapid expansion of flight use, developing advanced decision support tools is critical to improving Air Traffic Management (ATM) systems, particularly when considering the transport's safety and capacity. Aircraft corridors limit aeroplane trajectory, which distinguishes air transportation problems from maritime applications. However, aircraft routing applications are similar to maritime transportation problems, which tremendously depend on weather data, and there is flexibility in the selected trajectory. Accordingly, severe weather conditions put the aircraft in a dangerous situation. These effects include the localized region of strong wind shear, violent updrafts and downdrafts. Strong wind shear can damage the aircraft's body, while violent updrafts and downdrafts cause the pilot to lose control of the aircraft due to the considerable change in altitude. Some examples of aircraft routing problems associated with safety concerns are provided.

In the situation of facing a thunderstorm, the only way to prevent the aircraft from losing control or getting damaged is to make a detour path around it. Bokadia and Valasek (2001) developed an A-star search to optimize route time from the origin to the destination. This research only considered hard safety constraints associated with severe weather. The A-star heuristic cost function has two components: the first one is the distance travelled by the flight from the starting point to the reached node, and the second one is the estimated path cost from the reached node to the destination. It determines the path by a straight line from the start point to the end point. If there is a thunderstorm on the path, this line would be deviated to detour. The information about the position and intensity of the thunderstorm is taken from the radar image. The areas with intensities above a particular threshold would be considered inaccessible zones. Air traffic flow management (ATFM) is a well-known topic in the air transport industry. ATFM is the collaborative process of managing air traffic flow to provide a safe and cost-effective routing to ensure an appropriate balance between air traffic demand and Air Traffic Service (ATS) capacity. Furthermore, maintaining a suitable and safe horizontal distance between aircraft is critical in aircraft traffic flow. Prete and Mitchell (2004) developed the Flow-Based Route Planner (FBRP) navigation system to find shortest route while respecting three safety constraints: turn and curvature, avoiding hazardous weather and maintaining a minimum distance from other aircraft. In this study, first, the shortest path is determined using the A-star search algorithm, such that areas with a specific intensity threshold are avoided, and a safe distance to other planes is respected. Second, given the determined route, a simplification approach reduced the complexity of the turning and curvature of the route to find a safer path near the original one.

Although previous works concentrated on the horizontal distances between planes, there are other dimensions to consider in separating the flights. Yang et al. (2020) proposed a MILP model to deal with the flight arrival and departure schedules in a 4-dimensional trajectory (3-D space and time) by doing so. It was based on a stochastic optimization scheme to address uncertain flight arrival time and weather conditions. To deal with uncertainty, severe weather was formulated as a probability function, and expected arrival time was considered. The severe weather probabilistic approach involved analyzing historical weather data to estimate the probability of certain weather conditions at specific times and locations. Heuristic techniques were used to reduce the computational complexity and solve the model in a timely manner. To ensure safe routing, constraints were formulated to ensure at least onedimensional minimum safety separation between aeroplanes in the latitude, longitude, or altitude axis.

A research gap among the review papers is the development of more comprehensive risk assessment models that take into account a wider range of potential hazards and their likelihood of occurrence. Hence, it is crucial to focus on developing risk assessment models that are more inclusive and accurate, incorporating data from a range of sources, such as weather radar, satellite imagery, and real-time flight data. This would enable more effective identification of potential hazards and the development of safer and more efficient flight routes.

3 CONCLUDING REMARKS

The above papers highlight the importance of considering safety, fuel consumption, and travel time in transportation routing problems. In the maritime sector, safety should adhere to international guidelines provided by the IMO. Vessel characteristics and weather data are required to assess compliance with these rules. While some safety concerns have been studied, there is a need for more comprehensive research to incorporate all safety aspects in maritime routing problems, ensuring the safety of vessel, cargo, and persons on board. For road routing problems, advanced models should be developed to capture the complexity of safety risks, including driver behavior, weather conditions, and vehicle characteristics. In railroad applications, research should focus on minimizing delay time and exploring the impact of weather conditions on routing and scheduling to improve efficiency and safety. Similarly, in the aircraft industry, developing advanced models that account for safety distance dimensions and weather conditions is necessary to optimize fuel consumption and improve safety during routing.

A summary of the surveyed papers is provided in Table 1. Heuristic algorithms have been widely used in recent papers due to their efficiency in solving complex routing problems. Heuristic algorithms are popular due to their ability to provide efficient solutions within a reasonable time frame. These algorithms are well-suited for addressing large-scale problems, and they can be easily adapted to different transportation modes. In practice, heuristic algorithms are often utilized in conjunction with optimization-based algorithms, which offer an optimal solution but can require substantial computational resources. Selecting the most appropriate algorithm depends on the unique problem and the optimization objectives. In situations where safety is a top priority, pathfinding algorithms like Dijkstra and A* might be more favorable than heuristic algorithms. Conversely, in situations that entail a vast search space, evolutionary algorithms may yield better results than other algorithms. The reason is because of their capability in maintaining a diverse range of candidate solutions, conducting a global search of the entire search space, and adjusting to changes in the search space. These features enable evolutionary algorithms to explore multiple regions of the search space and prevent them from getting trapped in local optima, potentially leading to finding the optimal solution. Furthermore, in the summary table, we have presented the decision-making approaches utilized for balancing multiple objectives in the context of multi-objective problems. It was observed that among the selected papers, the most prevalent approach utilized for this purpose was the subjective judgment of the decision maker.

Overall, enhancing the accuracy and reliability of safety models in routing problems is essential for improving transportation safety. By prioritizing safety and investing in research to improve these models, we can reduce the likelihood of accidents, injuries, and fatalities, benefiting everyone who uses and depends on transportation systems. The reviewed papers emphasize the significance of using advanced algorithms to optimize routing in transportation systems. By continuously improving and implementing these algorithms to real-world problems, it is possible to enhance the effectiveness and safety of transportation networks.

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Table 1. The summary of the surveyed papers on routing problems

Transportation mode	Author	Method														Solution approach for determining objective weights				
		Dijkstra	GIS	A_star	MSP	Martins	MEWR	Heuristic	MILP	MIP	NLIP	ILP	Fuzzy Floyd	MOMH	DP	Pareto Frontier	DC judgment	A table of weight scenarios	Inverse Opt.	Other
Maritime	Pennino et al. (2020)	*																		*
Maritime	Vettor et al. (2020)													*						*
Maritime	Fabbri and Vicen-Bueno (2019)					*										*				
Maritime	Krata and Szlapczynska (2018)						*										*			
Maritime	Zaccone et al. (2018)														*			single objective		
Maritime	Veneti et al. (2017)										*					*				
Maritime	Szlapczynska (2015)					*											*			
Maritime	Krata and Szlapczynska (2012)						*										*			
Maritime	Padhy et al. (2008)	*																		*
Road	Akay (2020)		*													*				
Road	Guo et al. (2020)			*																*
Road	Pešić et al. (2020)												*				*			
Road	Sahnoon et al. (2018)	*																*		
Road	Sarraf and McGuire (2018)	*																Single objective		
Road	Omidvar et al. (2017)								*								*			
Road	Rönnqvist et al. (2017)	*								*									*	
Road	Kingsbury (2016)	*																*		
Road	Chandra (2014)				*											*				
Road	Flisberg et al. (2012)	*																	*	
Rail	Bożejko et al. (2017)	*																Single objective		
Rail	Samà et al. (2017)								*									Single objective		
Rail	Xu et al. (2017)											*						Single objective		
Rail	Meng et al. (2016)							*										*		
Rail	Samà et al. (2016)								*									Single objective		
Rail	Meng and Zhou (2014)							*										*		
Air	Yang et al. (2020)								*									Single objective		
Air	Prete and Mitchell (2004)			*														Single objective		
Air	Bokadia and Valasek (2001)			*														Single objective		

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