Autonomous Vehicle Routing Optimization: A survey

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Abstract Industry 4.0 era is characterized by several technological advances, such as the technology of Autonomous Vehicles, which is expected to increase mobility efficiency. A critical component in the autonomous vehicle navigation process is path planning. To this end, the present survey focused on the investigation of research contributions on the optimal path/routes scheduling of autonomous vehicles. The main objective of the conducted review is the classification of published relative research papers, according to their optimization criteria, optimization models, and optimization methods.

1 Introduction

Routes optimal scheduling constitutes a core operation in transportation and logistics optimization problems (38; 19). Such problems can be divided into path optimization or routing optimization problems, either for a single vehicle or multiple vehicles. Moving toward Industry 4.0, new research trends have emerged in such network optimization problems, such as considering autonomous vehicles (38; 42). The technology of Autonomous Vehicles is expected to eliminate accidents and emissions and increase transportation efficiency (42).

According to international standards for driving automation, developed by the Society of Automotive Engineers (SAE) (`https://www.sae.org/standards/content/j3016_202104`), six levels of automation have been reported. The first three levels refer to some supportive driving features, while the driving control is

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fully human-oriented. On the contrary, the last three levels contain automated driving features. More specifically, a taxonomy of these features, as they have been adopted by the National Highway Traffic Safety Administration of the United States Department of Transportation (`https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety`), is provided as follows:

- *Level 0: Momentary Driver Assistance*. Herein, features such as automatic emergency braking and warnings are included.
- *Level 1: Driver Assistance*. This class contains features that are continuously provided to drivers, such as lane centering.
- *Level 2: Additional Driver Assistance*. This class refers to vehicles that can simultaneously provide different types of supportive driving features. For example, both lane centering and adaptive cruise control can be provided to the driver, simultaneously.
- *Level 3: Conditional Automation*. This is the first class that refers to automated driving features. Vehicles of this class can be driven by an automated system under the co-occurrence of specific conditions. According to SAE, the traffic jam private driver system is an example of such autonomous driving features.
- *Level 4: High Automation*. This class refers to fully automated driven vehicles. However, such features are available in limited service areas. Local driverless taxis are a relative example provided by SAE.
- *Level 5: Full Automation*. Vehicles of this class are fully automated driven, independent of environmental conditions and service areas.

A critical component of the autonomous navigation process is the operation of path planning (42). To this end, the present chapter aims to provide an overview of research contributions focusing on optimal route scheduling under the consideration of autonomous vehicles. The survey attempts to provide different taxonomies of the reviewed research works based on the optimization models considered, the type of optimization methods, and the optimization criteria. The methodology of the literature review conducted is provided in Section 2. Section 3 provides the results of the analysis performed, while Section 4 presents a summary of the key findings.

2 Methodology

A systematic literature review was designed to conduct a valid analysis of relative research contributions and finally to present different taxonomies of them. This systematic research process consists of three key steps. In the first one, the identification of the research gap and the formulation of pertinent research questions were performed. The next step was focused on locating the research contributions, as well as the selection of the most relative of them. In the final step, the core literature analysis was performed.

2.1 Identification of research gap & formulation of research questions

To identify research gaps, seven recent surveys related to the utilization and routes planning of autonomous vehicles were found in the open literature.

- A survey on perception systems design for the development of autonomous vehicles conducted by Van Brummelen et al. (2018) (42).
- A survey on the potential impacts of adopting shared autonomous vehicles conducted by Narayanan et al. (2020) (29).
- A survey on Vehicle Routing Problems under the consideration of Unmanned aerial vehicles, conducted by Rojas Viloria et al. (2021) (32).
- A survey on the impact of adopting shared autonomous vehicles on the delivery of smart urban mobility, conducted by Golbabaei et al. (2021) (8).
- A survey on the planning and control operations of autonomous mobile robots in intralogistics, conducted by Fragapane et al. (2021) (7).
- A survey on two-echelon Vehicle Routing Problems under the consideration of ground- and unmanned aerial vehicles, conducted by Li et al. (2021) (21).
- A survey on shared autonomous vehicle systems, conducted by Zhao and Malikopoulos (2022) (53).

The first survey focuses on the current state-of-the-art technology of autonomous vehicles (42). The authors investigated the advantages, disadvantages, and limitations of currently available autonomous vehicles' sensors, as well as the autonomous features available in the case of research and commercial vehicles, and the methods developed for critical operations of localization and mapping. The next survey presents a comprehensive review of research works on the domain of shared autonomous vehicles' services (29). The authors investigated several aspects of shared autonomous vehicles services development, by focusing on the proposed business models, the reported requirements on policies, and the potential impacts of such services. The third survey is directly related to our work, as it provides a review of research contributions on the optimization of drones-based Vehicle Routing problem (32). The authors presented several classifications of the selected research works, according to their key research components, such as optimized objectives and solution methods. In the next survey, the authors studied the critical role of shared autonomous vehicles in the case of on-demand mobility services in the context of smart urban deliveries (8). The fifth survey found focuses on technological advances regarding the control and planning operations of autonomous mobile robots in the context of intralogistics activities (7). The authors studied several decision domains, such as the methods developed for route scheduling and path planning. Two-echelon Vehicle Routing Problems that combine both ground vehicles and unmanned aerial vehicles were investigated in the sixth selected survey (21). The authors of this survey provided a classification of research contributions based on modeling approaches for the connection of the two echelons. In the final considered survey, the authors studied research contributions that focused on the adoption of shared autonomous vehicle systems and investigated potential internal and external implications (53).

Despite the existence of various surveys that delve into different aspects of autonomous vehicle mobility systems, few of them specifically address the optimization of route scheduling for autonomous vehicles. However, these surveys provide valuable insights that contribute to a comprehensive conceptual understanding of the subject. In particular, they emphasize the crucial role of path planning or route scheduling within the broader development of autonomous vehicle mobility systems. Although two of these surveys focus on investigating this essential operation, they are conducted within certain limitations. In this context, the current survey stands apart from its predecessors, as it focuses exclusively on the optimization of routes for autonomous vehicles, without imposing constraints related to vehicle type or technology, nor application type. By eliminating such restrictions, this survey aims to provide a more inclusive and comprehensive analysis of route optimization for all types of autonomous vehicles, thereby contributing significantly to the existing body of knowledge in this field.

The subsequent phase of this initial step in the formulated systematic research methodology entailed the formulation of the ensuing research inquiries:

1. What are the prevailing transportation/logistics optimization models employed for addressing the path/routes scheduling process of autonomous vehicles?
2. Which categories of optimization methods have been devised to attain optimal or near-optimal route schedules?
3. What are the predominant optimization criteria considered when dealing with the optimal scheduling of paths/routes for autonomous vehicles?

2.2 Locating studies & selection

An advanced search of relative research contributions was performed in the Scopus scientific database. More specifically, the search was performed based on the following combination of boolean operators and keywords: *("route" OR "path" OR "Vehicle Routing") AND ("optimization" OR "optimisation") AND autonomous)*. Also, the following limitations were applied:

- Search terms applied only on the title of articles.
- Search period: (2012 - 2023) [up to 22/7/2023].
- Journal articles.
- Language: English.

The search carried out under the limitations mentioned above led to 62 research contributions. The relevance assessment of each study was achieved by applying the following exclusion criteria:

- Research contributions that do not focus on path or routing optimization of autonomous vehicles were excluded from the present review.
- Research works pertaining to the path planning of surgical autonomous robots were omitted from consideration.

The implementation of the aforementioned exclusion criteria culminated in the inclusion of 47 research contributions.

2.3 Analysis of the literature

The last step of the adopted research approach focused on the analysis of the selected articles. The objective of this step was the investigation of each study in order to extract the information necessary to synthesize the answers to the established research questions. The analysis was performed in two stages. In the first stage, key review elements were extracted, while in the second stage additional useful information was also selected. The key elements of the present survey are illustrated in Figure 1. The results of this step are provided in Section 3.

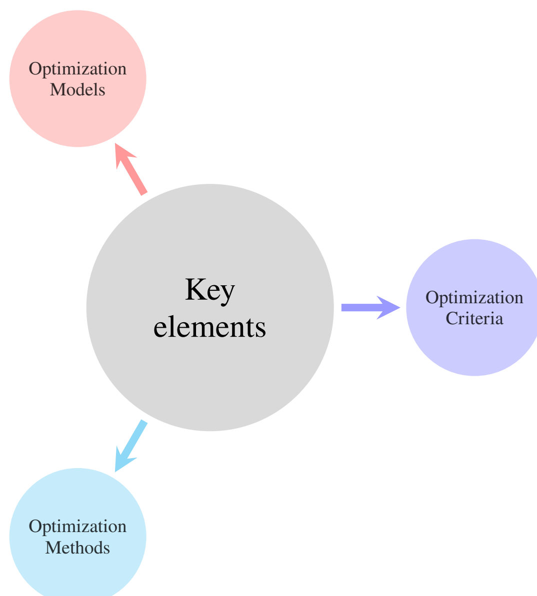

Fig. 1: The key elements of the present survey

3 Results

This section presents the results of this survey. A summary of the findings is provided in Table 1. The first column mentions the considered research work. The second column, *OptModels*, provides the optimization model that better describes the problem tackled in each publication. The value *SPP* denotes that the problem studied is a variant of the Shortest Path Problem, the value, *TSP*, means that the problem studied is described by the Traveling Salesman Problem, and the value, *VRP*, denotes that the investigated problem is a variant of the Vehicle Routing Problem. The third column presents the optimization method developed to solve the path planning or route scheduling problem in each research contribution. The next column represents the type of autonomous vehicle utilized in each work, while the sixth column, *NoVeh*, marks the number of autonomous vehicles in each application. The following column indicates the number of objective functions in each research contribution, and the final one, *TiC*, receives the value 1, if the factor of time was taken into account in the corresponding work, and the value 0, otherwise. The value *NS* is the abbreviation of "not-specified". Moreover, it should be clarified that the research contributions in all the following Tables are presented in chronological order, starting from the most recent to the oldest one.

Table 1: Overview of the literature

Study	OptModel	Method	Type of Vehicle(s)	NoVeh	Objective(s)	TiC
(18)	SPP	Hybrid	Mobile Robots	1	Single	0
(16)	SPP	Hybrid	Tractor-scraper	1	Multiple	0
(27)	SPP	Hybrid	NS	1	Bi	0
(20)	SPP	Hybrid	Autonomous Surface Vehicle	1	Multiple	0
(49)	SPP	Metaheuristic	Autonomous Underwater Vehicle	1	Multiple	0
(13)	TSP	Heuristic	Mobile Robots	1	Single	0
(34)	SPP	Metaheuristic	Unmanned Ground Vehicle	1	Multiple	0
(24)	VRP	Metaheuristic	Shared Autonomous Electric Vehicles	Multiple	Multiple	1
(41)	VRP	Approximate	Autonomous & Conventional Buses	Multiple	Single	0
(50)	SPP	Hybrid	Autonomous Underwater Vehicle	1	Single	1
(48)	SPP	Metaheuristic	Autonomous Underwater Vehicle	1	Single	0
(54)	SPP	Hybrid	NS	1	Single	0
(47)	SPP	Metaheuristic	Autonomous Underwater Vehicle	1	Single	0
(51)	SPP	Exact	Mobile Robots	Multiple	Single	0
(36)	SPP	Hybrid	NS	1	Bi	0
(4)	SPP	Metaheuristic	Mobile Robots	Multiple	Single	0
(17)	SPP	Metaheuristic	Autonomous Underwater Vehicle	1	Single	0
(2)	SPP	Metaheuristic	Autonomous Bulldozer	1	Single	0
(5)	SPP	Metaheuristic	Autonomous Underwater Vehicle	1	Single	0
(1)	SPP	Metaheuristic	Mobile Robots	1	Bi	0
(12)	SPP	Metaheuristic	Autonomous Surface Vehicle	1	Multiple	0
(9)	SPP	Metaheuristic	Mobile Robots	1	Bi	0
(22)	VRP	Metaheuristic	Autonomous Delivery Vehicles	Multiple	Single	0
(44)	SPP	Metaheuristic	Autonomous Marine Vehicles	Multiple	Single	1
(10)	TSP	Metaheuristic	Unmanned Aerial Vehicle	Multiple	Single	1
(55)	SPP	Metaheuristic	Autonomous Underwater Vehicle	1	Bi	1
(6)	SPP	Metaheuristic	Mobile Robots	1	Single	0
(45)	VRP	Hybrid	Autonomous Flight Vehicles	Multiple	Single	1
(43)	SPP	Metaheuristic	Unmanned Aerial Vehicle	1	Single	0
(30)	VRP	Exact	Autonomous Trucks	Multiple	Single	1
(3)	SPP	Exact	Autonomous Underwater Vehicle	2	Bi	1
(56)	SPP	Hybrid	Autonomous Underwater Vehicle	1	Bi	1
(14)	SPP	Metaheuristic	Autonomous Container Truck	1	Single	0
(11)	SPP	Metaheuristic	Mobile Robots	1	Single	0
(33)	SPP	Metaheuristic	Unmanned Ground Vehicle	1	Bi	0
(31)	SPP	Metaheuristic	Unmanned Aerial Vehicle	1	Single	0
(40)	SPP	Metaheuristic	Mobile Robots	1	Multiple	0
(52)	SPP	Exact	NS	1	Single	1
(37)	SPP	Metaheuristic	Mobile Robots	1	Single	0
(25)	VRP	Exact and Metaheuristic	Shared Autonomous Electric Vehicles	Multiple	Single	1
(35)	SPP	Metaheuristic	Autonomous Underwater Vehicle	1	Single	0
(28)	SPP	Heuristic	NS	1	Single	0
(26)	VRP	Exact	Shared Autonomous Electric Vehicles	Multiple	Multiple	1
(15)	SPP	Metaheuristic	Mobile Robots	1	Bi	0
(39)	SPP	Exact	Autonomous Electric Vehicles	Multiple	Multiple	1
(23)	SPP	Heuristic	Mobile Robots	1	Single	0
(46)	SPP	Metaheuristic	Autonomous Underwater Vehicle	1	Bi	0

Of the 47 studies included in this review, 38 of them (80.9%) tackled a variant of the Shortest Path Problem. It is also notable that, the majority of the considered studies (66%) developed pure heuristic/metaheuristic solution methods to obtain optimal/near-optimal paths/routes. Typically, the adoption of Level-5 autonomous vehicles in the case of specific missions requires online path/route optimization, which justifies the selection of heuristic/metaheuristic optimization methods. According to the consideration of the factor of time, it is mainly approached through the adoption of time windows or traveling time of vehicles. However, only 27.66% of reviewed works considered the time factor in their problems/applications. Also, it should be noted that, based on the type of autonomous vehicles, most publications utilized Underwater Autonomous Vehicles (23%) and Mobile Robots (25.5%).

The following subsections are dedicated to the key elements of the analysis performed in this review. Typically, the selection of one or more optimization criteria, respectively, leads to the formulation of a specific problem modeling, which finally requires the development of proper optimization methods. Thus, the key elements of the conducted analysis are examined sequentially, as illustrated in Figure 2.

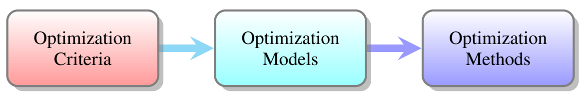

Fig. 2: The sequential investigation of literature review key elements

3.1 Optimization Criteria

This section focuses on the optimization criteria adopted by the publications included in the present survey. The distribution of publications according to the different optimization criteria is illustrated in Figure 3.

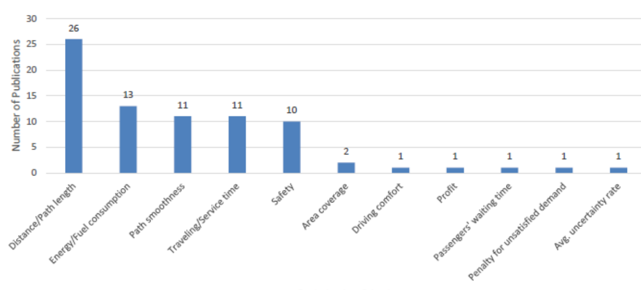

Fig. 3: Distribution of publications based on the optimization criteria

Figure 4 provides the classification of these works based on the optimization criteria, that were taken under consideration, in each of them.

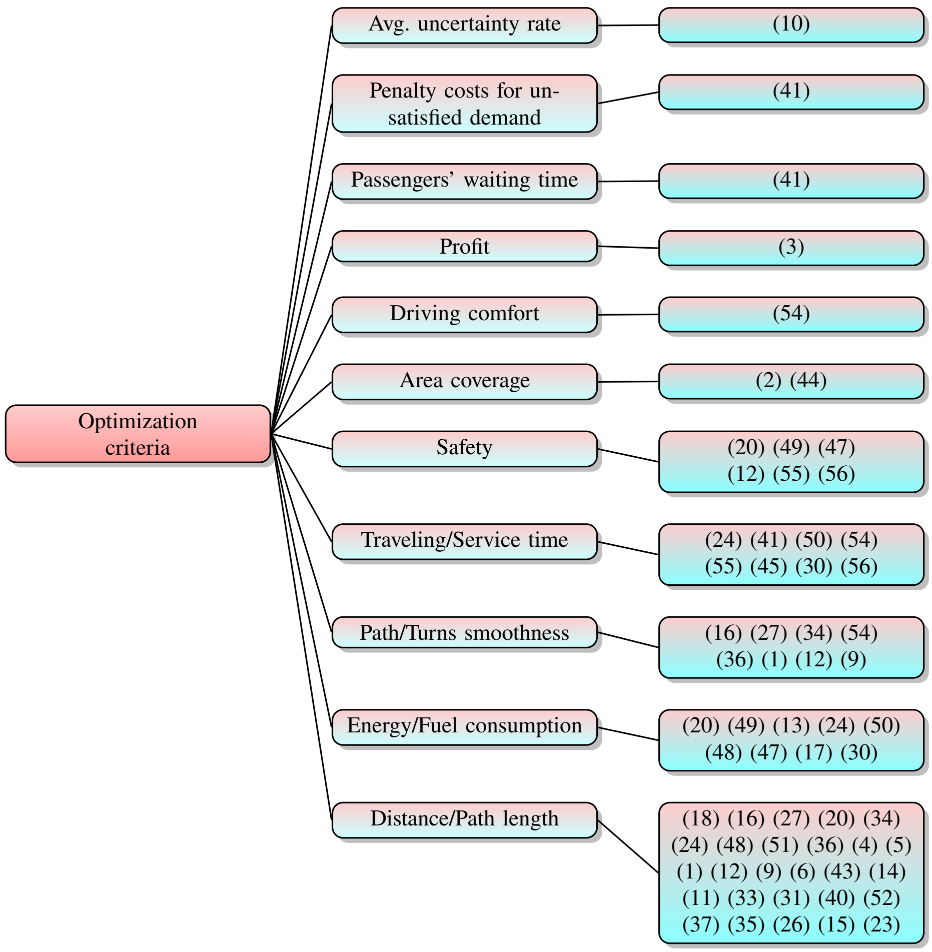

Fig. 4: Literature classification based on the optimization criteria

3.2 Optimization Models

Optimization models are the second key element of our review study. This class mainly refers to classic optimization problems which can properly describe the tackling problems of each research contribution included to the present survey.

Initially, Figure 5 illustrates the distribution of the reviewed research contributions according to their optimization models.

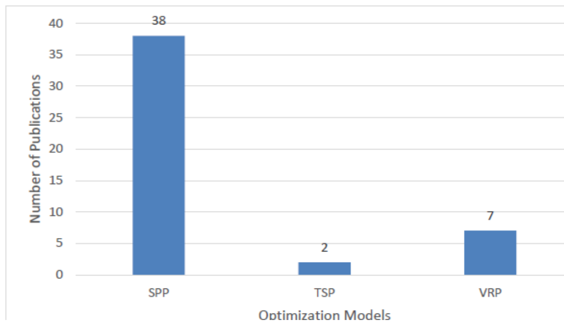

Fig. 5: Distribution of publications based on the considered optimization models

It is clear that, the majority of the reviewed publications focused on single path operations which can be approached by the well-known Shortest Path Problem. However, in cases of routing-based operations, Vehicle Routing Problem variants were the most frequently used optimization models. Figure 6 provides a classification of the selected publications according to their optimization models.

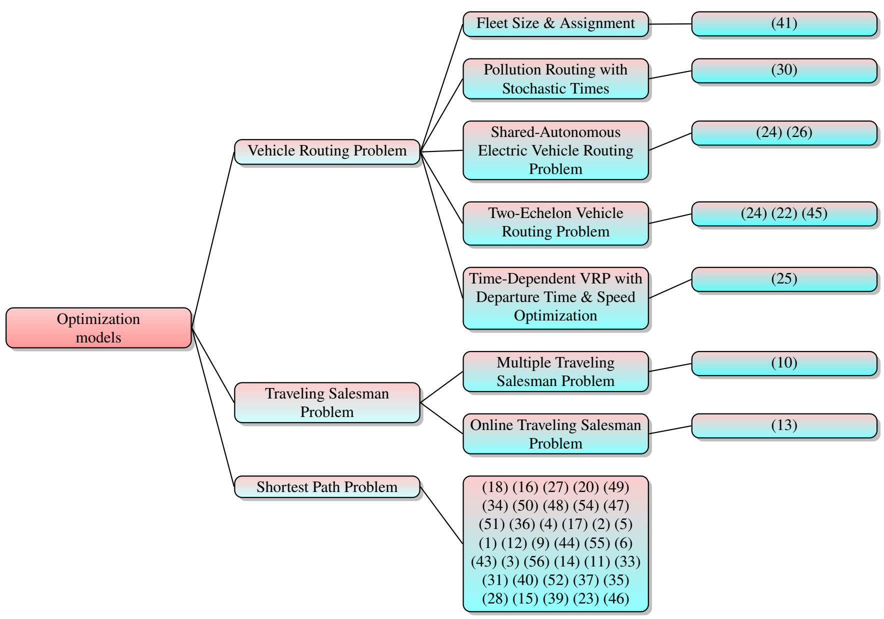

Fig. 6: Literature classification based on the optimization models

3.3 Optimization Methods

Optimization methods constitute the third key element of the study conducted in this survey. Figure 7 provides the distribution of the works based on the type of their optimization methods.

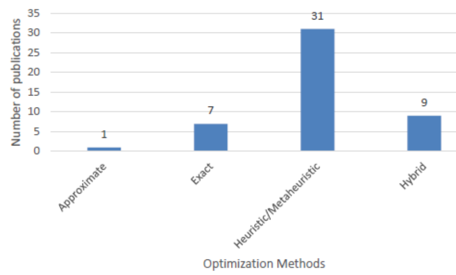

Fig. 7: Distribution of publications based on optimization methods

As it has already been mentioned, most of the works focused on the development of pure heuristic/metaheuristic optimization methods. The second most preferred solution approach is hybrid algorithms, which are also based on metaheuristic approaches.

Herein, a classification of the works based on their optimization methods is provided as follows:

- ***Exact:*** (51), (30), (3), (52), (25), (26), (39).
- ***Approximate:*** (41).
- ***Heuristic/Metaheuristic:*** (49), (13), (34), (24), (48), (47), (4), (17), (2), (5), (1), (12), (9), (22), (44), (10), (55), (6), (43), (14), (11), (37), (25), (35), (28), (15), (23), (46).
- ***Hybrid:*** (18), (16), (27), (20), (50), (54), (36), (45), (56).

A more detailed classification of the reviewed works based on the particular solution methods, instead of their general categories, is also made and provided below:

- **Exact methods.**
  - *Floyd-Warshall algorithm:* (51).
  - *Bellman-Ford algorithm:* (51).
  - *Dijkstra's algorithm:* (51).
  - *CPLEX solver:* (30), (25).
  - *GUROBI solver:* (3).
  - *Depth First Search algorithm:* (52).
  - *Weighted Sum method:* (26), (39).

- **Approximate methods.**
  - *Sample average approximation with quadratic transformation and linear alternating:* (41).
- **Heuristic/Metaheuristic methods.**
  - *Adaptive Large Neighborhood Search:* (24), (25).
  - *Ant Colony Optimization:* (5), (44), (43), (14).
  - *A-star:* (28).
  - *Bacterial Foraging Optimization:* (11).
  - *Dynamic group-based cooperative optimization:* (**?**), (31).
  - *Firefly Algorithm:* (10).
  - *Genetic Algorithm:* (2), (22).
  - *Grasshopper Optimization Algorithm:* (37).
  - *Greedy Heuristic:* (13).
  - *Grey Wolf Optimization:* (4), (9), (35).
  - *Q-Learning Algorithm:* (23).
  - *Particle Swarm Optimization:* (1), (12), (9), (22), (55), (40), (15).
  - *Random Frontier points' optimization:* (6).
  - *Teaching-Learning-based Optimization:* (34), (33).
  - *Tuna Swarm Optimization Algorithm:* (46).
  - *Water Wave Optimization:* (47), (17).
  - *Whale Optimization Algorithm:* (49), (48).
- **Hybrid methods.**
  - *Ant Colony Optimization - Artificial Potential Field:* (45).
  - *A^*-Iterative Anchoring Path Smoothing with Piecewise-Jerk Speed Optimization:* (54).
  - *Dijkstra's algorithm - Ant Colony Optimization:* (27).
  - *Firefly Algorithm - Artificial Potential Field:* (36).
  - *Multi-Objective Evolutionary Ant Colony Algorithm:* (16).
  - *Particle Swarm Optimization - Legendre pseudospectral method:* (56).
  - *Quantum-behaved Particle Swarm Optimization - Interval Optimization:* (50).
  - *Quarter Orbits Algorithm - Ant Colony Optimization:* (18).
  - *Visibility graphs - Particle Swarm Optimization:* (20).

4 Conclusions

This survey develops a systematic research methodology to conduct a review of the literature on research contributions focused on optimal path/routes scheduling under the consideration of autonomous vehicles. More specifically, based on a three-step methodology, 47 published research works between 2012–2023 were systematically investigated to answer three key research questions and finally to provide different classifications.

According to the optimization criteria, the majority of the research works reviewed focused on minimizing distance, energy consumption, and time, while a significant amount of works focused on the optimization of traveling/service time, path smoothness, and safety. Moreover, based on the optimization models, the classic Shortest Path Problem is the most commonly selected model in path-based applications, while the Vehicle Routing Problem is the most selected model in the case of routing-based problems. Finally, heuristic and metaheuristic optimization methods were found to be the most widely adopted solution approaches for the optimal scheduling of paths/routes in the case of autonomous vehicles.

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