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Routing Approaches used for Electrical Vehicles Navigation: A Survey

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Abstract: The growing demand for Electric Vehicles (EVs) depends on the high integration of this technology in many areas. Therefore, an important area of research raises interest in finding the optimal path-planning solution for electric vehicles. This paper discusses several reviews and analyzes some of the constraints of the techniques used to improve these systems. The paper discusses common models used in Unmanned Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGV). This paper investigates the planning approaches that lead to finding the optimal route for the tour from the source to the destination. The review outlines the different models and systems of Unmanned Ariel Vehicles (UAV) and Unmanned Ground Vehicles (UGV). This paper can be considered as comprehensive survey research for EV routing techniques to assist researchers choose the appropriate approach for developing a system based on optimization techniques, machine learning, or Hybrid Approaches (HAs) techniques. Optimization techniques are mostly used to find the optimal path and achieve multi-objective goals. Some findings were approved as the best models inspired by natural biological as genetic algorithms, Particle Swarm Optimization, and Ant Colony Optimization. In addition to machine learning techniques as Reinforcement Learning. The hybrid approach techniques that combine optimization and machine learning techniques can increase robustness in solving routing problems.

Keywords: Electronic Vehicles (EV), Unmanned Aerial Vehicles (UAV), Unmanned Ground Vehicles (UGV), Path Planning.

1. INTRODUCTION

An Electric Vehicle (EV) is defined as any vehicle that uses electrical energy within an electrical system and enables the use of artificial intelligence. Can have many types including Ground Vehicles (GV) within different categories, which include Unmanned Ground Vehicles (UGVs). Additionally, electric aircraft and the well-known type, an Unmanned Aerial Vehicles (UAVs), as well as underwater vehicles such as unmanned underwater vehicles called Autonomous Underwater Vehicles (AUVs). Electric Vehicles are technologies used in many applications. They rely on electric refueling by charging batteries and were introduced to promote a cleaner environment by reducing pollution, as well as finding a more cost-effective source of fuel for vehicles. The types of electric vehicles discussed in this paper include only UAVs and UGVs. These vehicles are used in various sectors including medical, military, commercial, customer services, agriculture, transportation, rescue missions, and waste management systems. They are considered significant factors in smart city systems. The electric vehicle system plays a vital role in the Intelligent Transportation System (ITS) and is an essential component for smart city architectures. There is an Increasing demand for high-performance transportation network design to ensure environmental protection and address significant issues related to high-density traffic while reducing pollution. Furthermore, the development of the EV system has an impact on the revenues of numerous industries that benefit from UAVs and UGVs, and the system's performance can also drive income. Electric vehicle systems can be optimized using various methods, including machine learning and optimization techniques or by designing a system that integrates these technologies. The selected methods will be explicitly discussed in this paper, based on the necessary constraints being met. A comparison of both EV subtypes of UAV and UGV systems concludes with significant growth in research areas in the past five years. Figure 1 shows a comparison of machine learning for path planning in UAV systems and UGV systems over the period from 2016 to 2022 within the IEEE Xplore (IEEE) database. The framework of this review is organized as follows. Section 2 analyzes the review papers in the context of challenges and opportunities for EV technologies while the third section describes the methods used for electric

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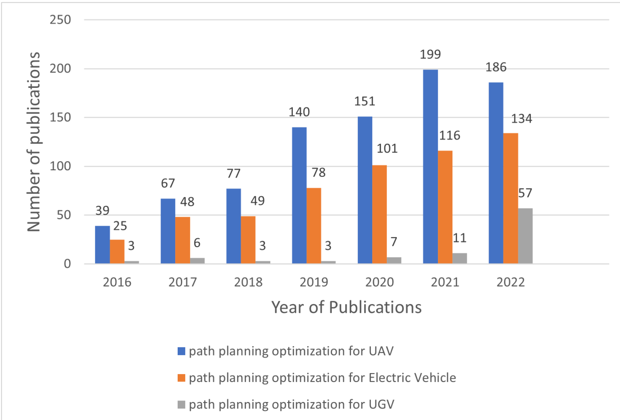

Figure 1. Comparison of two types of EV path planning optimization from 2016 to 2022 based on the IEEE Xplore (IEEE) database.

vehicle systems, including machine learning approaches, optimization methods, and hybrid technologies. Finally, the last section is the conclusion and future work directions.

2. CHALLENGES

The fields of electric vehicle systems are widely used in many applications and confront problems that require consideration and focus on research in this field. Thus, improving the performance of electric vehicle systems needs to address these issues and analyze potential techniques based on previous research. The two types ranked based on this survey can be illustrated. UAVs can perform many tasks more efficiently than traditional methods such as waste management, agriculture, delivery of packages, security, rescue missions, military purposes, etc. UGVs are interested in new technology that supports green energy, autonomous vehicles, reduced energy use cost, and meets the requirements of smart cities. The significant role of the electric vehicle in the matter of industry and environmental protection can be confirmed by research studies, and from our observations, we can infer the main challenges and constraints that need to be addressed and the various approaches used to improve its system. Most of the challenges that an electric vehicle system can face are constraints that must be respected. One of the famous problems is the Traveling Salesman Problem (TSP) [1] which solves travel between different cities connected to each other by edges and between every two cities carrying the necessary weight to find the shortest travel route or visiting each city and ending in the same city that started from. The important constraint is that each city should visit only once. There is no mathematical solution that can have an optimal solution which is defined as Polynomial Non-Deterministic Hardness (NP-hard) problem. Moreover, the second well-known problem is the Vehicle Route Problem (VRP), which solves the customer delivery problem with the best efficiency and lowest cost by having a route per vehicle and includes a combination of routes with multiple vehicles starting and ending with the same station. VRP evolves in many variants and extensions depending on real-world constraints as the Capacitated Vehicle Routing Problem (CVRP) means, it has only limited carrying capacity, the Vehicle Routing Problem with Multiple Trips (VRPMT) can handle multiple routes, and Open Vehicle Steering Problem (OVRP) that does not need to return to the warehouse, etc. The main constraint that can be noted in UAV reviews is the shortest path, which reduces the total path time which positively affects lower cost and power consumption. These constraints should be compatible with the real world by reducing computational time and complexity. Vehicle capacity restrictions do not exceed vehicle weight; therefore, the total beams are within the space and payload range of the vehicles. Many solutions use known methods to initiate their new approaches such as applying the k-means algorithm to solve the collection waste. Collected Waste depends on the nearest point to be collected determined by the k-means algorithm. In addition, the improved k-means algorithm finds the optimal path with certain constraints such as time with a controlled search interval. This algorithm can reliably solve the traveling salesman problem when combined with other heuristic algorithms. An important constraint is the age of the data that can be received from the sensors or Global Positioning System (GPS) to calculate updated information that can influence model decision-making, primarily used in a dynamic environment. In addition to these constraints, the mange speed, rotation rate, and altitude of the drones are all controlled to avoid obstacles such as buildings or other drones. It also needs to coordinate with other drones to maintain safety standards for drone routes. Moreover, constraints can be achieved based on preemptive priorities which create a balance between priority and optimization for the best-required solutions. Additionally, UGV has comparable constraints to UAVs such as reducing path distance, time, cost, and power consumption to enhance durability range and reduce charging energy waiting in queues, which is user convenience defined as a net charge per unit of energy. In another study, an EV charging pricing strategy [2], was formulated to balance the profits of several charging stations. These constraints can be influenced by the User Equilibrium (UE) which is the user's response to finding the lowest charge when selecting a charging station. Additionally, reduce the number of vehicles used in certain ratings. In most cases, avoiding traffic jams helps find the shortest route to ensure all required tasks are met. It generates minimal carbon dioxide emissions to preserve the environment. The dynamic environment satisfies collision avoidance and finds alternative routes in case of any trap. The optimal path does not always mean the shortest path, rather it must be achieved to solve problems based on their constraints and priority. For example, a less-traffic route achieves lower trip duration and costs with less computation time and lowers energy consumption better than the shortest path with more congestion, greater wasted travel time, and increased energy consumption. Many researchers use hybrid methods integrating optimization methods and machine learning to solve path-planning problems. A hybrid approach that combines honeybee Mating Optimization [3] and six loading heuristics is used to solve the drone loading constraints. In addition, some other approaches use a hybrid approach within Constraint Logic Programming (CLP) and Mathematical Programming (MP). To reduce the total tours based on the allocation assessments needed to address the problem by applying a hybrid approach based on Clark and Wright's savings algorithm [4] along with the Genetic Algorithm. Another method is to combine the Simulated Annealing (SA) heuristic algorithm [5] based on the Petal algorithm to find the initial solution generation, a binary integer programming model for path selection, and a local neighborhood search algorithm to discover better solutions. This approach can also save energy impacting maximum flight time and payload capacity constraints. In general, utilize various hybrid approaches [6] including Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Genetic Algorithms (GA) to determine the optimal route planning which is affected by reduced computational time, lower transportation cost and vehicle capacity. Most of the publications regarding solution methods are listed in Table V. Generally, it is noticed that the genetic algorithm is a promising method for finding the optimal path. To reduce UGV mileage, a hybrid heuristic can be used to combine a variable neighborhood search algorithm with a Tabu Search (TS) heuristic. Besides the heuristic k-Shortest Path (KSP) algorithm, it solves the environmental routing problem of the shortest travel path. Moreover, applying an ant colony algorithm based on parameter optimization with a particle swarm algorithm [7] can improve the optimal route chosen based on the path of the least traffic congestion. Apart from that, the corresponding data packets are updated to ensure suitable real-time decision-making solutions for autonomous and dynamic controls. Furthermore, the Reinforcement learning-based combines the three algorithms, GA-based [8], Q-Learning, and the greedy strategy used to update information in real-time. In particular, the multi-objective UGV system has been used in several promising solutions approaches such as the PSO, NSGA-II, and ACO which are combined in some studies as a two-stage optimization strategy. In addition to this, Floyd's algorithm is used to create a multi-stage two-layer optimization algorithm includes the PSO to obtain voltage deviation rate reduction with load constraint. In addition, reinforcement learning [9], and transfer learning accelerate real-time business intelligence acquisition using recurrent neural networks and fuzzy logic. Due Reinforcement learning can be combined with several methods such as the Markov Decision Process (MDP) [10], Deep Neural Networks (DNN), Maximum Entropy Principle (MEP), and Q-Learning algorithm, which such integration can solve various constraints as the optimal path based on different driver behavior, dynamic environment, traffic congestion collision avoidance, fastest track, and energy saving. In the same vein, energy-saving constraints for UAVs have been used several methods such as genetic algorithm and PSO. Overall, it can be more effective to modify these algorithms to counteract constraints. Energy saving constraint UGV used the PSO algorithm to find the optimal path based on the rate of charge combining EV Heuristic Bidirectional Martins' Algorithm (EHBMA) and Charging Selection-Based Adaptive Pricing Strategy (CSBAP) that maximized energy cost revenue while balancing with optimization path. Another optimization technique is the Genetic Algorithm and Gain-Based Green Ant (GG-Ant) [11] which is a modification of the ACO that can be used for the shortest path and energy efficiency. Without a doubt, Machine learning algorithms can be applied as solutions for path planning systems such as Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Long Short-Term Memory (LSTM), and DNN. Based on some research a multi-objective system solution needs integration between SA with the A^* algorithm [12] and Dijkstra algorithm [8] with Gated Recurrent Unit (GRU) neural for path selection based on the charging pricing network to determine the optimal charging cost path. Finally, the safety constraints can be resolved using Deep Reinforcement Learning (DRL) based on other optimization algorithms such as Proximal Policy Optimization (PPO) algorithm or Dueling Double Deep Q networks (D3QN) algorithm. In the same context, the Green Vehicle Routing Problem (GVRP) [13] is a vital issue in the case of preserving the environment and reducing emissions of harmful gases through the concept of Alternative Fuel Vehicles (AFVs) based on the use of harmless conventional fuels. GVRP algorithms can be categorized as Exact methods which include linear or dynamic programming, mathematical and approximate algorithms, etc. Approximate algorithms are divided into heuristic, meta-heuristic, hybrid, and machine-learning methods. In this research based on their review, the most commonly used method for finding the optimal path is meta-heuristic algorithms. Many of the proposed algorithms applied to the system are novel algorithms and methods inspired by other well-known algorithms such as the bidirectional Martins' algorithm and PSO. Drones can avoid obstacles using a novel path-planning optimization algorithm. Otherwise, UGV uses an artificial potential field method with deep reinforcement learning. To generate an occupancy grid map, feature learning can be beneficial in a fully convolutional model.

3. ROUTING APPROACHES USED FOR EVs SYSTEMS

This section introduces and analyzes most of the methods and techniques for improving the performance of finding the optimum routes using various types of electric vehicle systems. The following subsections present several studies for EV routing that achieved comparably high performance using various techniques such as optimization, machine learning, or a hybrid approach.

A. *Optimizations approaches*

Optimization techniques are methods that modify parameters and hyperparameters to find optimal solutions by maximizing or minimizing constraints using one of the various optimization techniques. Table I summarizes the Optimization approaches in both types of EVs.

1) Optimizations approaches in UAV

Optimization techniques aim to control the drone distance, obstacle avoidance, and flight time management which can overcome the problem in path planning by finding the best design variables to locate the optimal solution for the UAV route system. Optimal path planning is one of the most important problems that drones encounter. It contains major problems such as solving TSP [14] and VRP problems. The genetic algorithm can solve the problem and find the optimal flight path for the drone in a 3D environment. The proposed method using the genetic algorithm ensures that Check Points (CPs) are not visited twice, and redirection should occur at checkpoints outside the no-fly zone. Unfortunately, this approach does not support dynamic real-life scenarios. Mesquita et al. [15] proposed a novel path planning optimization algorithm based on PSO to find the optimal path which can reduce energy consumption, enhance flight time constraints, and lower computational costs. Some software was used to simulate the efficiency of the proposed algorithm via Ground Control Stations (GCS) and Mission Planner that autonomously control UAVs and visualize the stream in real-time. Their algorithm could not be compared with similar studies, so to examine the accuracy of the results, it was compared to three case studies. Two of the case studies applied simulation software to simulate the efficiency of the proposed algorithm via GCS and Mission Planner that autonomously control UAVs and visualize the flow in real-time. The third case study compared the real field recorded final errors for the entire path planning distance, which amounted to 10% resulting in an average of less than 7% when considering all three case studies. Although the final error is 3%, the average of all cases is 1%, but it is not practical in the simulation cases, in summary, the average execution time error for all cases is 5%. Similarly, a survey [16] compares 231 various studies from 2008 to 2017. It has been found that the top-ranked algorithms which outperformed the other algorithms in terms of performance are GA, ACO, Learning-Based methods (LB), PSO, and fuzzy algorithm (FL). Platanitis et al. [17] addressed a solution to the path planning problem in UAVs focusing on energy reduction and the creation of a safe flyable path, an instantaneous ideal path as the shortest one was obtained by the genetic algorithm method. GA generates different seeds to find the best flyable path corresponding to each gene for each chromosome. Crossover, mutation, and fitness processes have been used to find the shortest path and the least waypoint distance. The simulation map implementation of the test environment involves only static sampling, so using a variable sample will increase the efficiency of experimenting with the results. One additional application uses optimal path planning layout as cinematography. In this study, a novel formulation approach [18] was used for a method based on nonlinear optimization that runs multiple drones to find the best paths and coordinate collision avoidance in a dynamic environment that uses priority-based computation. This technique improves filming shots and becomes smooth with the mutual camera visibility, which also reduces jerky movements. Even so, this method needs to compare its results with other known methods such as reinforcement learning to check the feasibility of their approach. Waste management was used for a method based on nonlinear optimization that runs multiple drones to find the best paths and coordinate collision avoidance in a dynamic environment that uses priority-based computation. This technique improves filming shots and becomes smooth with the mutual camera visibility, which also reduces jerky movements. Even so, this method needs to compare its results with other known methods such as reinforcement learning to check the feasibility of their approach. Waste management [19] is an important sector in solving the Vehicle Routing Problem, which is a two- phase approach to the Maximum Waste in the Minimum Time during each Tip (MWMTT). The first step is to increase the capacity of hazardous waste with the shortest path. Then in the second phase, distribute tasks to multiple groups to avoid charging drones and manage continuous flights to the target. This proposed approach contains two trials, the first involving small-sized instances of around 10 to 40 and medium- to large-scale instances of 48 cases within 41 to 981 sites. The results were compared with the lower bound and linear programs. Particularly MWMTT achieves a performance error of less than 10% in small cases. On the other hand, a linear program cannot solve more than 40 cases. The lower bound is used to evaluate the efficiency of the approach which satisfies small-scale cases otherwise it requires further optimization to solve medium and large scales. Many waste management systems [20] use the Internet of Things (IoT) technology to collect data continuously to manage waste path planning. Like other systems GA is a valuable approach for waste management in a smart city. In this research case study experience in the Bakirkoy district of Istanbul, a traditional city with its old infrastructure causes inconvenient results, so the planning routes to turn around the city must be considered in this proposed approach. A study suggested solving the Capacitated Vehicle Routing Problem with Pickup and Alternative Delivery (CVRPPAD) through a hybrid approach of CLP [21] to pre-solve the model and MP with heuristic optimization creation inference. To generate an initial solution, another study used the SA heuristic algorithm [22] based on the petal algorithm to find path selection via a binary integer programming model using a local neighborhood search algorithm. The main objective of the model is to reduce the Expected Loss Of Demand (ELOD) by utilizing the Drone Delivery Schedule model with drone Failures (DDS-F) which is determine each drone task to Subset customers with trips sequence and compares the results with the Makespan problem model to find a better path, increase flight time, and payload. S. I. Khan et al. [23] discuss the most widely used heuristic algorithms to determine the optimal path planning for medical emergencies using drones that can save lives and reduce cost and computational time as CVRP algorithm, GA, ACO, and PSO. The CVRP algorithm attained the highest performance compared to the other algorithms used in the proposed model. PSO can find exact local minima and global minima to locate the optimal path within the best target location. In addition, ACO and GA have the ability to get the shortest path, while ACO results perform better than GA. However, the algorithm's achievements require benchmark solutions that are optimally comparable in terms of accuracy. Additionally, it should be evaluated based on the number of patients that can serve, considering the urgency and level of risk in their situations. Another research proposed a real-time distributed path planning [24] that can track moving targets on the ground using fixed-wing drones. The proposed method aims to solve the constraints such as real speed and turning rate, control input saturation, collision avoidance, and obstacle avoidance. UAV speed and turning rate can be taken based on the changeable movement of the target. The onboard sensors use to solve occlude buildings. It set the target coverage degree instead of the target distance and it includes control input cost and sensor energy consumption. Priority objectives are fuzzified and a satisfactory degree and the Generalized Varying Domain (GVD) is used to stabilize between the optimization and priority. The Distributed Model Predictive Control (DMPC) is combined with the system to create a distributed cooperative path-planning model for each drone. The simulation results show the effectiveness of the proposed method by comparing it with the Hierarchical Optimization (HO) method. Each UAV can achieve the optimum path at every selection time. On the contrary, the detection performance building evaluation criterion sometimes obstructs the sensor's line of sight when the distance between the drone and the target cannot be captured. In addition, this model only uses the simulator and does not examine it in real life.

2) Optimizations approaches in UGV

Optimization methods improve autonomy, localization, and navigation, and avoid obstacles. Liu. et al. [25] Employ a genetic algorithm in an electronic vehicle path learning model to improve energy efficiency to increase endurance mileage. The charging state has an important impact on the travel route which illustrates the problem that finding the shortest path and reducing traffic volume as well. Some of the significant constraints that are essential to how the model works are the state of charge which defines battery capacity, along with the charging pile, queue length, and path direction depending on the nature of the selected route. As the freeway has its own features, besides the origin of the starting journey, and the destination, Finally the charging nodes. The proposed method reduces travel time by up to 6.5%. Furthermore, the research analyzes various parameters that affect the model as the high volume of traffic will increase the path because the alternative path with a long distance can be chosen, thus the power consumption will be increased as well. Moreover, the temperature will have a greater effect on the driving path, and therefore when the temperature drops, a shorter vehicle endurance occurs. In addition, when speed increases it reduces travel time and increases average power consumption. This approach can limit the vehicle paths obtained to only start from specific origins and destinations. It should be noted that the speed analyzes are determined between 90 km / h and not exceeding 120 km / h. Therefore, it does not consider all user behavior and different vehicle speed in real life. Users may encounter special circumstances that require reducing vehicle speeds below 90 km/h, such as in the event of a traffic accident. In [26] consuming Gain-Based Ant Colony Optimization (GACO) and GGAnt as modified colony optimization algorithms to solve Path Planning Problems, are examined by pseudo-code representation of modified ACO as the proposed algorithm. Optimum path planning not only finds the shortest route but also reduces the cost and time of the journey with less computation time. Clearly, GG-Ant is the energy computed for the best path and ignores all other paths. The sigmoid function was used in the GG-Ant which provided smooth rotations. To demonstrate the new approach to UGV power reduction has recorded lower computation time and efficient power saving. While it can end at the local optimum when the environment complexity increases, then attempt to solve it with the global optimal solutions. Automated guided vehicles (AGVs) [27] have been a critical factor in the efficiency of manufacturing workshops. The AGV is a multi-objective optimization problem with main key objects such as transport distance, energy consumption (EC), and cost based on the energy-efficient AGV Path Planning (EAPP) model. It aims to find the best path using Dijkstra's algorithm which is a type of graph search algorithm that finds the shortest path between any two nodes in a region, but it can't consider all the nodes in the entire path. Thus, some improvements had been done to compute all the shortest nodes in an EV path using the Search Path algorithm. While comparing several algorithms, PSO, NSGA-II, and ACO, all registered the same best path while PSO takes longer run time created on priority-based indirect particle encoding. Additionally, PSO granted an efficient scheme that extracts the path from heuristic information based on priority nodes. Therefore, the EAPP problem is solved by a two-stage solution and PSO. The extraction method is improved to prevent backtracking, and path loops and can reduce driving time. This method needs improvement in the cases of several AGVs and multiple AGV loads that suffer from a shortage of the EC data acquisition system. Zhou. et.al. [28] proposed a new intelligent path planning strategy based on the Floyd algorithm which is used to find the best shortest path in a given weight between two nodes. This system is integrated between the electrified transportation network and the power grid. In addition, Dynamic Wireless Power Transfer (DWPT) is integrated into this EV system as the primary charging method, which is expected to become the predominant method in the future. This is in contrast to battery swapping, which increases charging costs and time. The multi-stage two-layer optimization algorithm has been added to the framework to verify the charging power between the links of the nodes. In addition, the upper layer uses PSO to estimate the charging power decision, while the lower layer is employed to solve the optimal power flow problem by determining the voltage deviation rate. The proposed system respects travel time, user convenience, power charge, and cost. Moreover, a novel charging path planning algorithm [29] based on bidirectional Martins' algorithm is proposed to guide the user with an optimal path at a cost-effective charging station. The PSO was integrated with the proposed EV path planning framework cost-effective charge station. This framework was designed based on multi-objectives such as driving distance, total route time, energy consumption, and energy charging cost. The multi-objective decision-making problem used different methods to handle this kind of problem such as the information synergy entropy (ISE) based interval intuitionistic fuzzy TOPSIS (ISE-IITOPSIS) method [30], and the weighted method which is the simplest way to solve this problem by assigning an exceptional weight to each objective and normalizing all parameters. In addition, graph-based theory as a yen algorithm is applied to reduce waiting time caused by traffic congestion. Furthermore, Dijkstra algorithms, Martin's algorithms, and various heuristic algorithms are used to determine the optimal paths for electric vehicles. In particular, an important factor of electric vehicles is the pricing mechanism at the charging station which reflects the selection of the best charging cost and affects the route of the electric vehicle. Fixed electricity pricing, time-of-use pricing, and real-time pricing adjust the electricity pricing model to maximize charging station revenue more efficiently when the PSO algorithm is applied. Indeed, the new algorithms represent enhancements of Martins' Algorithm (MA), and the Bi-directional Martins Algorithm (BMA) [11] referred to as EHBMA designed to address the EV charging path problem while accommodating heuristic constraints more effectively than traditional models. CSBAP is also used to raise the energy cost revenue of electric vehicles by adjusting more profit than fixed cost due to increased lower price demand, which affects the selection of charging stations and resolved routes. To create a more accurate charging lane planning model, it is essential to take into account the more complex road conditions and driving conditions for electric vehicles. Without a doubt create user avatars that execute better fit recommended charging routes. Alizadeh. et al. [31] discuss solving the travel path decision problem for electric vehicles with two main constraints being the shortest path and charging locations across the social planner to reach balanced electricity prices. The decision was made based on the traffic situation, electricity prices by location, and charging rate, which are the main objectives of solving this problem. Electric or intelligent transportation systems include the power system, transportation network, and electric vehicle owners. Importantly, their approach examines the effect of EV owners to solve the problem based on main policies as the social planner's solution is Social Optimum (SO) which reduces the cumulative path and time cost to the population in a centralized manner. In addition, the UE is an individual decision based on the lowest cost and Disjoint Pricing (DP) examines the separation between intelligent transportation and energy systems. As a result, this approach reaches the lowest cost and UE recorded less iteration time. Although the cost of electricity increases. Whereas the influence of diverse user categories based on travel time is not discussed in this approach, most user behavior is based on cost. The waste management approach can be a very promising application in smart cities. One study [32] combines three popular algorithms for building productivity and scalability systems: genetic algorithm, ant colony, and tabu search. The Waste Collection Vehicle Routing Problem (WCVRP) is managed by combining these metaheuristic algorithms. The proposed model meets the shortest path constraints, time window, computation cost, and service priority over the needs of each customer. This study investigates the case study of Luxembourg which is a waste management company that deals with dynamic waste collection optimization models that find in large organizations such as shopping malls, restaurants, etc. In addition, the database is collected from sensors based on the filling of customer bins, the number of trucks, location, and availability of trucks based on customer need, all these data can affect the working efficiency of the model. Despite the good results of ACO and TS, the computation time takes a lot and affects the dynamic VRP solution. As a result, GA outperforms the other two algorithms that achieve effective cost and time on a priority basis. Unfortunately, fixed route planning solutions cannot be able to waste operate system management in real life. Based on their conclusion when experimenting with the results of efficient solutions for only finite nodes are not necessarily applicable in real life. Similar to the previous study, another case study of the Al-Awali district in Makkah [33], Saudi Arabia, GA was chosen to enhance the dynamic path VRP of the waste management system. In summary, GA performs better than other metaheuristic algorithms in computational time reliability, shortest path, and lowest fuel consumption. In experiments, many path planning methods were not the best path solution between two nodes. Undoubtedly, if VRP solely concentrates on finding the shortest path without addressing other constraints, it will fail to achieve the primary objective of reducing costs for enterprises. As well as Solid Waste Management (SWM) [34] uses GA in its system because it has the ability to converge which can indicate the performance of the GA on the right track. Another study defines the smart clean city system [35] as a dynamic waste collection system with actual data that accepts any emergency situation from a predetermined schedule path based on the optimal path to achieve. The proposed model uses a rerouting optimization algorithm that can improve constraints such as path cost and additional capacity. Due to the dynamic path planning is proposed as an improvement of the ant colony algorithm [2] by optimizing its parameter along with the particle swarm algorithm. Two of the experiments were examined for regular traffic, and the third experiment was for heavy traffic. The proposed method achieves greater accuracy and reduces the congestion rate. Especially when the method replaces the road length with the road condition feature. Nevertheless, the optimization process itself requires computation time and increases computational complexity.

TABLE I. Summaries optimization approaches

Ref	Approach	Methodology	Application	Limitations	Type
Sonmez et al.2015	Finding the optimal flyable path for the UAV in a 3D environment.	GA	Multiple applications (Military and civilian missions).	Dynamic environment	UAV
Mesquita et al. 2021	Finding optimal path which can reduce the limitations of energy efficiency and flight time, as well as reduce the computation and cost round control stations.	Novel path planning optimization algorithm based on PSO.	Agriculture (birds eat and damage fruit in orchards, making them susceptible to infection and reducing their quality thus using drones to solve this problem).	Their algorithm cannot be compared with similar studies, so they examined the results from 3 case studies.	UAV
Platanitis et al. 2020	Solve offline UAV path planning problem, through the principles of safe flyable candidate trajectories, and energy reduction.	GA	Real-world applications with real geospatial DTED.	Involves only static sampling in simulation map.	UAV
Nguyen et al. 2021	Define paths as desired and directed paths and implement them independently.	Drone management system and its component systems.	Civil and commercial application.	Need more investigations and real tests.	UAV
Alcantara et al. 2021	Propose a method for planning optimal trajectories of UAVs performing autonomous cinematography.	Novel optimization non-linear formulation.	Autonomous cinematography.	Need to compare the results with other known methods as reinforcement learning.	UAV
Sitek et al.2019	Solve CVRP problem with CVRPPAD.	Merging CLP and MP	Multiple applications.	The model does not handle some constraints (route length, number of route points, prioritization of items, timeouts).	UAV
Torabbeigi et al. 2021	Reduce the ELOD. The optimization model (DDS-F) was developed to determine the assignment of each drone to a subset of customers and the corresponding delivery sequence.	SA heuristic algorithm based on the Petal algorithm to find initial solution generation, a binary integer programming model for path selection, and a local neighborhood search algorithm to find better solutions.	Parcel delivery.	The exact method failed to find a solution for cases with more than 12 clients, it was impossible to compare SA performance in larger cases.	UAV

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Ref	Approach	Methodology	Application	Limitations	Type
Khan et al. 2021	Achieve optimal route planning (vehicle routing) through a proposed algorithm.	PSO, ACO, and GA.	Medical domain.	Need benchmark solutions that are optimally comparable to the level of accuracy and can additionally be evaluated to the number of patients that can be served based on the intensity of their urgent situations of risk.	UAV
Hu et al. 2021	Cooperative path planning with different priorities via DMPC-GVD (Solve multiple goals with priorities).	Fuzzy multiobjective optimization via DMPC-GVD.	Tracking a ground moving target in urban.	The detection performance building evaluation standard sometimes obstructs the sensor's line of sight when the distance between the drone and the target cannot be captured. Using the simulator only.	UAV
Liu. et al.2021	EV Path planning model to develop the driving competence of electric vehicles on the highway.	GA	EV path planning.	limit the vehicle paths obtained to only start from specific origin and destinations/ speed analyzes are determined between 90 km / h and not exceeding 120km/h.	UGV
Sangeetha. et al.2019	Reduce energy (cost and time) during path detection.	GACO and GG-Ant.	New approaches to energy-based path planning.	It can end at the local optimum when the environment complexity increases.	UGV
Zhang. et al.2021	Solve the problem of AGV path planning and energy efficiency considering EC in a manufacturing workshop environment (Time and cost).	PSO-NSGA-II and ACO-Dijkstra algorithm-The two-stage solution.	Pick-up and drop-off locations for every transport task.	Not building an EC data acquisition system/Not a multi-load AGV and multiple AGVs.	UGV
Zhou. et al. 2021	The proposed path planning strategy considers travel time, power charge, charging cost, and user convenience.	Floyd algorithm and multi-stage two-layer optimization algorithm (PSO-voltage deviation rate).	Urban electrified transportation network.	Did not mention	UGV

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TABLE I – continued from previous page

Ref	Approach	Methodology	Application	Limitations	Type
Hou. et al.2021	Guiding the user on the optimal path at a cost-effective charging station.	PSO algorithm is applied to solve the optimal solution to the charging station and charging rate.EHBMA to solve the EV charging path problem, consider the heuristic constraints CSBAP is also used to increase the energy cost revenue of EVs. A novel freight-route planning algorithm based on the bidirectional Martins' algorithm.	Large-Scale EVs	Create user avatars to better fit recommended charging routes, More complex road conditions and driving conditions for electric vehicles must be considered to obtain a more accurate charging lane planning model.	UGV
WU.et al.2020	Proposes a dynamic path planning method based. on ACO algorithm in high traffic.	Enhance ACO based on optimizing its parameters via PSO algorithm.	Dynamic path planning	The optimization process itself requires computation time and also increases computation complexity.	UGV
Alizadeh. et al.2021	Find travel routes including charging locations and associated fee amount under time-varying traffic conditions as well as dynamic location-based electricity pricing.	SO reduces the cumulative path and time cost to the population. UE is based on an individual decision based on lower cost. disjoint pricing.	Intelligent transporting system	The influence of heterogeneous user types is left inconvenience travel time for future work.	UGV

B. Machine learning approaches

Machine learning (ML) techniques encompass a variety of efficient learning algorithms that enable the creation of models capable of interacting with static and dynamic environments to optimize system solutions to the highest degree. ML [36] can find the best path with minimal computing for real-time actions, the shortest route with obstacle avoidance, energy management acquisition, and electric vehicle system cost reduction. Table II summarizes the machine learning approaches in both types of EVs.The following subsections describe the methodologies and approaches used in the most recent research on UAVs and UGVs.

1) Machine learning approaches in UAV

UAV systems utilize ML models to forecast UAV trajectories, with the models being trained on data collected to predict optimal paths. ML algorithms are used in increment Path efficiency for multi objectives. Sequential decision-making problem-solving based on intelligent mission planning methods [37] can be used in the Suppression of Enemy Air Defense (SEAD). The experiments study DRL based on a PPO algorithm that considers the basis of DRL to gain high performance and robustness. DRL is used as trial and error with dynamic learning created on agent action within its environment. The experience needed further investigation of the complex large-scale combat and multi-agent cooperative planning problem. As in the previous study, the DRL was used to handle drone path planning in dynamic environments [38] for military applications while maintaining safety standards for any opportunity for enemy threats. The information used for system training is collected from the radars needed to create a situation map of enemy threats. A modified D3QN algorithm was used to predict Q values for all procedures. The chosen action policy is based on a combination of ϵ-greedy strategy and heuristic research. The real-time reaction has been achieved with good results, although it is not possible to collect data in all cases from just one drone that requires system optimization within several drones that can communicate with each other to perform better in the real world. Consequently, managing drone communications can robust the system. Machine learning algorithms, particularly DRL, encounter challenges and considerations in drone applications, notably within the specific domain of the Green Vehicle Routing Problem (GVRP) [39]. It should be used in further research due to its reliability, robustness, and problem-solving efficiency. Quadrotor UAVs are a specific type of UAV [40], and it is a proposed supplementary controller. That uses Reinforcement Learning (RL) to enhance the control of this type of UAV. Thus, this model suffers from uncertainty and external disturbances. RL has two main functions, the policy that takes action to control the value and the value function that evaluates effectiveness. In addition, this approach can also be applied to online drone controllers. Furthermore, Lyapunov's theory applies to check the convergence of RL, this model uses three simulations to demonstrate the accuracy of the methods. The simulation includes learning mode and test mode, the learning mode means the drone starts the trajectory at a random point and ends at the target to have more range for exploration. Additionally, test mode means starting from a stable node and aiming at their target. RL has QLearning that gives less variation to actor training and Time Difference (TD) that updates continuous steps that can be run online with experience to increase the rate of training, on the other hand, this approach works well but is not tried in real life. DRL is used to solve Autonomous Motion Planning (AMP) problem and to solve the Multi-UAV Target Assignment and Path Planning (MUTAPP) problem for UAVs using a Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithm. Novel algorithms proposed identified as Simultaneous Target Assignment and Path Planning (STAPP) [41] based on MADDPG. This approach needs to solve many tasks required to be solved within discrete routes, manage a dynamic environment, and improve the quality of training. Despite the efficient outcome, training convergence becomes more complex when agents increase, otherwise, agent rises do not affect the training time.

2) Machine learning approaches in UGV

ML algorithms have demonstrated significant promise in identifying optimal charging paths for Electric Vehicles while simultaneously minimizing costs and emissions. DRL [42] reduces the time interval of an uncertain logistic transport pathway and is suitable for a complex problem model when compared with traditional methods by 60.71%. Numerous researchers are striving to address previous challenges while developing solutions for common path problems. These include methods such as the Markov decision-making [43] method, Monte Carlo algorithm, and Rollout algorithm which decreases runtime. Overall, the DRL has recorded very promising results in the case of optimizing uncertain logistics transportation systems. A study introduced innovative techniques using the full convolutional model [44] of path design in a grid map as a deep learning approach to global path planning. The deep neural network trains a synthetic dataset to find the optimal waypoints and then removes unnecessary nodes to add the required nodes. The Density-Based Clustering Algorithm (DBSCAN) is used to group nearby nodes based on field geometry. Further, the search algorithm A* is used to calculate the final global path to cover the crop area. The field of agriculture used UGV to increase crop quality, harvest yield, and reduce cost. Since synthetic datasets are used when the real dataset is difficult to find in the real world. Therefore, design an algorithm to generate an occupancy grid map, which dataset includes 1000 synthetic images that were evaluated after the training phase, hence the method showed scalability and robustness. The system can be optimized by using remote sensing color space to integrate Deepway computing with a segmentation network that connects waypoints with the relevant occupancy grid map. Nonetheless, this approach skips various inadequate map regions that can affect the overall prediction. Another study [45] suggested a new method based on DRL and the artificial potential field method. The artificial potential field can improve the effective path planning to solve the local stable-point problem which means the agent entrap in one point of the complex environment as a specially shaped obstacle or is trapped inside a barrier and cannot reach the target. The DRL combines with a Black Hole Potential Field (BHPF) that is used as a DRL environment which can be under static or dynamic conditions. A trained agent can handle real-time obstacle avoidance competently. On the contrary, optimizing the system requires enhancing the proposed algorithm to avoid collisions between more than one agent and to ensure agent cooperation with a multiagent reinforcement learning algorithm. The system can achieve adaptation to different environments and smooth trajectories through real-time calculations. Even so, the model requires prior optimization of the BHPF domain to adapt to diverse environments. Obviously choosing a wide range can affect multiple gravitational superpositions that the model could fail to avoid obstacles, on the other hand, a small domain may miss agent detection. Shibl. et al. [46] conducted an examination of six ML algorithms, including RF, SVM, DT, LSTM, DNN, and KNN, to address power loss, load variance, charging costs, and voltage fluctuations. Among these algorithms, LSTM achieved the highest accuracy, estimated at 95%. The system achieves robustness, and performance, and increases protection from data uncertainty to optimize the route charging of the EV to charging stations based on the charging speed. Utilizing a Vehicle-to-Grid (V2G) technology reduces power requirements, as well as adding Gaussian White Noise (GWN) techniques that support system preservation of data uncertainty. Thus, the results show only a slight improvement when this specific technology is used. However, these methods require a comparison of their results with other systems, especially due to a lack of data. The multidisciplinary approach [47] used in this system is based on the method of artificial intelligence, which uses deep learning as reinforcement learning to path learning and localize vehicles at the high and low levels with respect to the real-time decisions made by cloud facilities and advanced resources through transfer learning. Additionally, Recurrent Neural Network (RNN) is employed for power management to reduce cost and control power usage because it contains memory that is continuously learning using time series data. Several methods engage speed control as fuzzy logic, Radial Basis Function Network-Based Adaptive Fuzzy System (RBFN-AFS), and Direct Torque Control (DTC). SVM has a high potential to minimize CO2 emissions within the satisfied travel time cost function using RL techniques [48] [48] solved via the KSP algorithm and resolves the environmental routing problem. Additionally, SVM exhibits durability for handling overfitting and high generalization problems, as is extremely estimating for many emission problems. To validate this method, it compares several regression-based models for machine learning namely the EOPS model, SIDRA running model, VT-Micro model, and ANN model. EOPS model for mean correlation velocity, VT-Micro model for velocity, and

acceleration estimation. The SIDRA model operates based on vehicle acceleration, deceleration, and a backpropagation neural network based on CO2 emissions. In addition to using some statistical metrics to estimate performance such as Mean Absolute Percentage Error (MAPE) and squared correlation coefficient. It found that the SVM model is gaining better than other classic models. These results research affects market penetration based on travel time and environment saving, this approach can be included within Electric Vehicles, or with Plug-in Hybrid Electric Vehicles (PHEV) and autonomous vehicles to solve some of the constraints that are vital in this study as determining the shortest path problem. This model does not discuss the different emissions ratios that depend on the vehicle's driving condition at various speeds. Not only measure CO2 emissions but also this model needs to consider other toxic gases such as NOx and HC. Furthermore, Dijkstra's algorithm is used to find the shortest path of waste management systems for smart city systems [49] that use priority based on needs combining IoT alerts and SMS. It has the ability to separate wet and dry waste by using a moisture sensor which achieves efficient garbage collection. Many solutions utilize well-known methods to start their new approaches such as applying the k-means algorithm which is used to solve collection waste. It's collected the waste based on the most weight amount of waste that is first collected. The k-means algorithm determines the nearest point to be collected. In addition, the improved k-means algorithm [50] finds the optimal path with certain constraints such as time with a controlled search interval. This algorithm can be approved when it comes up with other exact or heuristic algorithms that solve the traveling salesman problem.

C. Hybrid approaches

Many studies combine multiple methods and algorithms to perform better than a single algorithm can achieve. Modify and combine multiple algorithms whether in optimization or machine learning techniques as a combination of both approaches. These hybrid methods can solve complex problems and overcome some problems such as optimizing local and global search for collision-free and avoiding local minima problems. Moreover, it designs an ideal space, improves convergence, and produces better routes. Table III summarizes the hybrid approaches in both types of EVs. The following subsections describe hybrid techniques used in some of the research on UAVs and UGVs.

1) Hybrid approaches for UAV

Hybrid approaches tend to overwhelm the limitations of single or conventional technologies by combining efficient methods that can meet the limitations in systems used mostly for dynamic environments or for efficient drone navigation etc. The main objective of VRP is to reduce the cost of routing, path, time, and the number of used and overloaded vehicles. Thus, metaheuristics are applied to find fundamental solutions with less computation time and to enhance possible solutions. Similar to CVRPPAD which allows only one trip and the possibility of alternate drop-off locations. In contrast, the model does not deal with constraints such as route length, number of route points, item prioritization, and timeout. Another study investigates the Flying Companion Traveling Salesman Problem (FSTSP) [51] which is a new version of the traveling companion problem, that uses hybrid vehicles such as drones and regular trucks. Its main objective is to reduce the full delivery distance of trucks in the depot after all supplies. This method solves this problem via a hybrid approach including a genetic algorithm and a well-recognized heuristic approach based on Clarke and Wright's savings Algorithm. In turn, this approach may increase the truck waiting time for the drone, and there is no comparison with other similar studies.

TABLE II. Summaries Machine learning approaches

Ref	Approach	Methodology	Application	Limitations	Type
Yue et al. 2022	Solve sequential decision-making problems with intelligent drone mission planning based on DRL.	DRL based on PPO algorithm.	SEAD mission planning.	Needed further investigation of the complex large-scale combat and multi-agent cooperative planning problem.	UAV

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TABLE II – continued from previous page

Ref	Approach	Methodology	Application	Limitations	Type
Rigas. et al. 2014	Intro Solve energy-efficient routing problem (Survey).	G2V or in V2G model and AI techniques.	Integration of EVs into the smart grid.	Some constraints not satisfied as (Uncertainty-Dynamism-Privacy-Real-world validation-Interoperability).	UGV
Yan et al. 2019	DRL method for path planning of drones in dynamic environments with potential enemy threats.	DRL based on D3QN algorithm.	Anti-terror missions.	Data can be collected from only a single UAV / Need to improve the system within several UAVs which can communicate with each other to perform better feasibility in the real world.	UAV
Yuan. et al. 2021	The path planning scheme is proposed to solve the uncertain logistics problem.	Reinforcement learning.	Transportation Scheduling (Package delivery).	The model requires prior optimization of the BHPF domain to adapt to diverse environments.	UGV
Shibl. et al.2021	Used to direct electric vehicles to charge stations to reduce load variation, power loss, voltage fluctuations, and charging cost while considering conventional and fast charging and V2G charging technologies.	ML create accurate future decisions based on historical data, which are DT, RF, SVM, KNN, LSTM, and DNN, the best result is LSTM.	Electric vehicle charge management systems.	Require a comparison of their results with other systems, especially due to a lack of data.	UGV
Mazzia et al.2020	Create an autonomous global path capable of covering the entire crop extension.	feature learning fully convolutional model.	Improving crop quality and seasonal productivity.	Lack of real data - skips various inadequate map regions that can affect the overall prediction.	UGV
Zeng. et al.2014	Define an eco-friendly route that produces minimal CO_2 emissions while meeting a travel time budget (similar to the shortest path travel solution).	SVM has a high potential to minimize CO_2 emissions, Heuristic KSP algorithm and resolves the environmental routing problem of shortest path travel.	PHEV and Autonomous Vehicles.	The model does not discuss the different emissions ratios that depend on the vehicle's driving condition at various speeds - Needs to consider other toxic gases such as NOx and HC.	UGV

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TABLE II – continued from previous page

Ref	Approach	Methodology	Application	Limitations	Type
YAO. et al.2016	Effective path planning method.	Artificial Potential Field method with DRL.	Effective Path planning method for automated vehicles.	Cooperating with different agents.	UGV

Ruan et al. [52] proposed a hybrid approach integrating honeybee mating optimization and six-loading heuristics to solve a 3D Loading Capacitated Vehicle Routing (3L-CVRP) problem. This approach achieves the reduction of transport costs while serving all customer requirements and the load-bearing capacity does not exceed the vehicle's loading space. These constraints use Three-Dimensional Bin Packing Problems (3BPP) are the overall weight and loading space of items provided by customers that cannot exceed the vehicle's weight capacity and loading volume, respectively. Items have a fixed top and can be rotated 90 on the horizontal plane, while inverted rotation is not allowed. Items are loaded orthogonally to the vehicle, with a fixed orientation for each item. The element stability requirements must also be respected, and the required support provided during the loading process. In addition, the Two-Dimensional Loading Vehicle Routing (2L-CVRP) Problem is utilized by meta-heuristic algorithms as a branch-and-cut algorithm, simulated annealing algorithm tabu search algorithm, and memetic algorithm. The proposed solution solves VRP with Honeybees Mating Optimization (HBMO) and Three-dimensional Loading Problem (3LP) within six heuristics algorithms. The hybrid approach enhances its robustness, and memory usage, 50% lower than others in computing time to find better solutions. Nonetheless, this study does not cover many constraints such as a heterogeneous fleet of vehicles, pickup and delivery, and time windows. Further on applying the Markov model [53] to control the reaction time and distance between UAVs, this method records more accurately based on wind flow and turbulence than the SD method. Develop an automated system that constantly updates their data about location and timing via the GPS along with the Geographical Information System (GIS). Improve trajectory tracking with various methods such as multi-loop PID controller, sliding mode control, backstepping, Linear Quadratic Regulator (LQR), and Line-Of-Sight (LOS) angle constraint which addresses initial large angle errors with acceptable system performance. In addition, both collision avoidance and navigation are important factors for the UAV system. Despite the exact method's failure to find a solution for cases with more than 12 clients, it was impossible to compare SA performance in larger cases.

The agricultural field uses drones to defeat birds that damage crops and affect productivity. To demonstrate a very important matter of information collecting and the importance of sensitive data being updated, defined as the Age of Information (AoI) [54] is a critical object for finding the best UAV path planning model by reducing the amount of expired data for the optimum path solution for the Min-Max-AoI problem. Due to the number of expired data packets is minimized and the number of each carried packet maximizes from each sensor. To improve path planning by reinforcement learning-based and evaluate its efficiency through two benchmark comparisons. As a consequence of comparing their approaches with the two benchmarks used the genetic algorithm is the best method to find the optimal trajectories, while Q-Learning is better in time-consuming, in contrast, the greedy strategy shows the worst-performing solution. In short, the certainty of the data is a very vital constraint for selecting the best path according to the time and dynamic environment. It should be noted that this method is not experimented with in real life.

2) Hybrid approaches for UGV

UGV achieved a highly efficient system using a hybrid approach based on machine learning and optimization methods in autonomous driving, battery saving, navigation, and object detection. Hybrid metaheuristic algorithms achieve high performance as a proposed novel algorithm [55] such as integrating Variable Neighborhood Search (VNS) and Tabu Search to solve Electric Vehicle Routing Problems along with Time Windows and charging stations (E-VRPTW). These algorithms can solve some constraints as recharge times, capacity, customer time windows, number of electric vehicles in use, and cumulative distance for all routes. Besides this search design, the performance measure includes two groups, one with small-scale instances via CPLEX software which enhances the results of the proposed algorithm, and one with large instances. Evidence of the performance of this new algorithm compared to the results of algorithms designed to solve other similar problems such as MDVRPI and G-VRP.

Optimal route planning plays a crucial role in various applications, such as autonomous driving in electronic vehicles. These systems needed to include some constraints that validate the operative approach, these constraints are energy management, cost reduction, path learning, and speed control. You. et al. [56] proposed a model that improves the communication between the electric autonomous vehicle and adjacent vehicles in traffic which enhances the path planning of the driving strategy to find the optimal route based on some constraints. MDP was used to create a policy addressing this problem to design a reward function using the RL approach.

Furthermore, Inverse Reinforcement Learning (IRL) is used when the reward function is ambiguous, thus it used data from previous driving experiences. Following the MEP was used to match the reward with its feature to learn a parameterized feature reward function and for unknown rewards, the DNN was used. The Q-learning algorithm is also used to observe the typical driver behavior as tailgating and overtaking. The performance of this proposed method was demonstrated with simulated results. Moreover, the difference between RL and IRL is that RL maximizes the reward based on the sequences of current states to take an action. On the other hand, IRL learns from the behavior of the agent to take states and actions which are called demonstrations. Despite the proposed model, it does not distinguish different vehicle velocities nor experiment with real-world driving scenarios. To provide the optimal route, some research [57] has combined route planning algorithms to satisfy traffic and charging costs based on various trip objectives via an application where user input has been entered. To Reduce the total tours based on the allocation of the GRU neural network is used to set the time window for the price of electricity, and to predict the optimal path depending on the requirements. EV user journey objectives can be divided into in-situ charging, close-range travel, and multi-site travel.

TABLE III. Summaries Hybrid approaches

Ref	Approach	Methodology	Application	Limitations	Type
Özoğlu et al. 2019	Solve FSTSP (Reduce the total distance of delivery).	A hybrid approach based on Clarke & Wright's savings algorithm and GA.	Customer service delivery.	Increased truck waiting time which is the main drawback of this proposed hybrid algorithm, and the lack of comparison between similar researches.	UAV
Ruan et al. 2013	Solve Three-Dimensional Loading CVRP (Meet customer demands).	Hybrid approach which combines Honeybee Mating Optimization and six loading heuristics.	Customer service delivery.	It does not cover many constraints such as a heterogeneous fleet of vehicles, pickup and delivery, and time windows.	UAV
Li et al. 2019	Propose a UAV trajectory planning model for data collection while minimizing expired data packets in the entire sensor system.	RL-based and among the three algorithms, GA-based, Q-learning and greedy strategy.	UAV trajectory planning model.	This method is not experimented with in real life.	UAV
Schneider et al. 2014	Solve the problem of EV steering with time windows and charging stations (E-VRPTW) - (Cost-optimal routes).	The hybrid heuristic combines a variable neighborhood search algorithm with a tabu search heuristic.	EV for last-mile deliveries.	It can enhance the accuracy of the steering model by considering the loads, degrees, and speeds of the vehicle.	UGV

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TABLE III – continued from previous page

Ref	Approach	Methodology	Application	Limitations	Type
Ramesh et al. 2014	Autonomous driving is the potential for technical innovations in a multidisciplinary approach (Power management - speed and time control).	*DL* is used for localization of vehicles, path planning at a high level, and path planning at low levels and RL and transfer learning to speed up the process of gaining real-time business intelligence - Recurrent Neural Network-Fuzzy logic.	EV with autonomous driving system.	The results need to be compared with other similar methods.	UGV
You et al. 2019	A proposed model for the planning problem of autonomous vehicles in traffic.	MDP -RL and IRL techniques - DNN - MEP - Q-learning algorithm.	Autonomous vehicles in traffic.	Need to experiment on the real-world driving scenario- Model does not distinguish different vehicle velocities.	UGV
LU et al. 2019	Providing a route planning algorithm based on spot price and user Objectives.	Integrated route planning algorithm - *SAA* is combined with A algorithm and Dijkstra algorithm - *GRU* neural network.	Route planning algorithm.	The spot price is not provided in detail in this paper - Need to experiment on real-world driving scenario.	UGV

The first two stations are within their range and explain the condition if there are no charging needs, and the last one is that the user needs to stop at more than one stop to finish their journey. As a result, the route planning algorithm recorded a better impact on travel time and forecast real-time estimated charging rates within user goals. Although spot pricing is not presented in detail in this paper, and similar to the previous approach, there are no experiments with real-world driving scenarios. Traffic congestion is one of the vital factors that can affect the efficiency of optimal path planning. Although the shortest path does not mean the optimal path is due to other limitations such as EV speed and high traffic. In general, these routing approaches used in electric vehicle systems can disclose some advantages and disadvantages based on the goals of the systems and can determine which are the best approaches that can be able to meet the desired needs. Table IV shows the pros and cons of some main methods used in this survey.

TABLE IV. Pros and cons of some main methods

Approaches	Advantages	Disadvantages
Dijkstra algorithm	•Reducing time consumption. •Low complexity.	•This approach gives the shortest path but is not guaranteed to be the optimal path. • Cannot manage negative weights.
A* algorithm.	• Higher efficiency. • Find the lowest cost. • Find the shortest path.	• More computation time. • Continuous path cannot be achieved.
PSO	• Highly accurate. • Easy to implement. • Fast to convergence Completeness.	• In high dimensional space or global search, it could have local optimum. • low convergence speed.
GA	• Solving optimization problems with effective results. • Efficiency. • Robustness.	• Can be trapped to the local optimum when using an inappropriate fitness function that makes GA an expensive and incomplete solution.

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Approaches	Advantages	Disadvantages
ACO	• Suitable for the predetermined problem and goal, which finds the appropriate solution quickly and prevents premature convergence. • Suitable for dynamic environments.	• Increase the search complexity. • The convergence time became uncertain, thus, ACO has the longest simulation runtime.
ANN	• Find the optimal solution within the interconnected network based on learning and error convergence. • Optimize complex environments.	• More extensive datasets for training. • High computational power with long time complexity.
Heuristic Techniques	•Solve problems in the fastest route and reduce cost while finding the shortest path to ensuring system efficiency.	•Solution accuracy couldn't be the optimal ones. •Bias can occur with the final solution.
MDP	• It performs actions at any time and any location randomly to find the best path.	• Actions and rewards are affected only by the current situation, not by history, which affects the entire solution.
TS	• The ability to overcome a local optimum problem. •Tabu list used to avoid reuse of old solutions.	• Tunable parameters can be challenging. • It can include high iteration.
RL	• Used for efficient end-to-end planning and complex data computation. • High performance and durability. • Balancing exploration and exploitation.	• High computation. • It requires a lot of important data.
Floyd's algorithm.	• Handling negative edge weights and graphs with cycles, and a large number of nodes in the graph.	• High-time complexity. • Great memory requirements.
SA	• Finding the best path and fastest convergence. •Dealing with noisy and complex data.	• High-time complexity. • Tunable parameters can be challenging.
Q-Learning algorithm	• Effective for high-dimensional space and dynamic environments, with no need for prior data knowledge for the system environment.	• High computation. • Long time to train and to find the optimal solution.
SVM	• Shows robustness to handle overfitting and high generalization problems. • Reduce the cost of travel time.	• It can't handle big or noisy data.

4. CONCLUSION

UAVs and UGVs represent different types of electronic vehicle systems, This review examines various issues and constraints. The methods and solutions of problems have been investigated to find the optimum solution for path planning based on the demand functions to be fulfilled in these systems. In conclusion, optimizing EV technology is crucial to find optimal methods to improve EV systems and meet their constraints. For example, the application or waste management system is needed to support the load capacity constraints. In military applications, the primal goal is to provide conditions of safety against enemies, and in medical applications favors speed and time to save lives over other constraints. Table V summarizes the approaches used for electric vehicle systems based on constraints. To illustrates GA, PSO, and ACO and heuristic algorithms with search algorithm as neighborhood search algorithm, tabu search heuristic famously use to find optimal path planning. Reinforcement learning based is widely used in autonomous and dynamic environments for obstacle avoidance, real-time business intelligence, and for safety purposes. Additionally, MDP is used to create a policy that addresses this problem or design a reward function using RL techniques. The MDP is one of the well-known algorithms that finds the best probabilities based on the optimal path and makes the best decisions. Floyd's algorithm has been used in various research to find the shortest path. Optimization methods and machine learning algorithms are used to save energy with less path distance and reduce costs such as KNN, LSTM, DNN, A algorithm, and Dijkstra algorithm. Optimization methods are more commonly used in multi-objective systems that can combine two or more algorithms whether it is machine learning or optimization techniques. In general reinforcement algorithms and genetic algorithms are mostly used either separately or as part of various other algorithms with the same system that can solve many different objectives. PSO and ACO also work well with other search and heuristic algorithms. In future work, the high-completion algorithms observed and mostly used in similar EV systems can be applied to improve the performance and robustness of similar applications.

TABLE V. Approaches used for electric vehicle systems based on constraints

Constraints	Most approaches used for EV systems
UAV loading constraints	Heuristic approaches
Shortest path	Genetic Algorithm, Clark and Wright's savings algorithm, SA, heuristic algorithm, PSO, ACO
Multiple objectives	Fuzzy optimization, Floyd's algorithm, multi-stage two-layer optimization algorithm, reinforcement learning, MDP, DNN, MEP, Q-Learning algorithm
Energy saving	genetic algorithm, PSO, GG-Ant, DT, RF, SVM, KNN, LSTM, and DNN. SA, A^* algorithm, Dijkstra algorithm, GRU neural network
Avoid obstacles	Deep reinforcement learning
Safety constraints	Deep reinforcement learning, PPO or D3QN algorithm

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