A Machine Learning Approach for Design and Control of Automated Guided Vehicle System A Critical Review

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Abstract - This paper presents a critical review of the machine learning approach for the design and control of automated guided vehicle (AGV) systems. The paper discusses the current state of the art in terms of machine learning approaches for the design and control of AGV systems. It also provides a comparison between traditional control approaches and machine learning approaches for AGV system design and control. The paper further explores the potential of machine learning algorithms and their application in the design and control of AGV systems. The paper reviews the various machine learning algorithms such as artificial neural networks (ANNs), support vector machines (SVMs), deep learning, gaussian process regression (GPR), and reinforcement learning (RL) that are used for the design and control of AGV systems. It also discusses the advantages and disadvantages of using each of these algorithms for AGV system design and control. The paper further presents a case study of an AGV system that is designed and controlled using a machine learning approach. This case study provides a detailed analysis of the system architecture and the performance of the system. The results from the case study demonstrate the potential of using machine learning algorithms for the design and control of AGV systems. The paper concludes by providing an overview of the current state of the art in terms of machine learning approaches for AGV system design and control. The paper also provides future research directions and recommendations for the further improvement of the design and control of AGV systems using machine learning algorithms.

Keywords - Automated Guided Vehicle (AGV) System, Machine Learning, Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Deep Learning, Gaussian Process Regression (GPR), Reinforcement Learning (RL), Design and Control, System Architecture, Performance Analysis.

I. INTRODUCTION

The use of automated guided vehicle (AGV) systems has grown rapidly in recent years. This is because of the increasing complexity and sophistication of today's manufacturing and logistics operations, as well as the need for improved safety and efficiency. AGV systems automate material transport and handling tasks, and are used in a wide range of industries, from manufacturing to warehousing [1]. The main advantage of using an AGV system is that it allows for the design and control of a large number of vehicles in a uniform and reliable manner.However, AGV systems are complex systems and the design and control of these systems require sophisticated algorithms and software. In this paper, we discuss the use of machine learning algorithms for AGV system design and control. We discuss the different types of machine learning algorithms and how they can be used to improve the design and control of AGV systems [2]. We also discuss the various applications of machine learning algorithms in the context of AGV systems.AGV systems are designed to automate the transport and handling of materials in a variety of industries. These systems consist of a set of vehicles, which are guided by a computer control system. AGVs are typically used in warehouses, factories, and other industrial settings. The primary advantages of using an AGV system are improved safety, reliability, and efficiency.The design and control of AGV systems is a complex task. This is because of the large number of vehicles and the complexity of their movements. Furthermore, the environment in which the vehicles operate is often changing and thus the control system must be able to adapt to these changes. For these reasons, the design and control of AGV systems requires sophisticated algorithms and software. Machine learning algorithms are a type of artificial intelligence algorithms that are used to improve the performance of computer systems [3]. Machine learning algorithms are used in a wide range of applications, from robotics to computer vision. In the context of AGV system design and control, machine learning algorithms can be used to improve the design of the system and the control of the vehicles.Some of the most commonly used machine learning algorithms for AGV system design and control include neural networks, support vector machines, and reinforcement learning. Neural networks are a type of machine learning algorithm that are used to model complex systems. They are used to recognize patterns in data and to make predictions about future events. Support vector machines are a type of supervised machine learning algorithm that are used to classify data points. Finally, reinforcement learning is an unsupervised machine learning algorithm that is used to optimize a system based on feedback from the environment.The use of machine learning algorithms in the design and control of AGV systems has a number of potential applications. For example, machine learning algorithms can be used to design and optimize the control system for an AGV system. This could include designing the control system to be more efficient and reliable, as well as to adapt to changing conditions.The key findings of automated guided vehicle research is exhibited in the **Table 1.**

Table 1. Findings of Automated Guided Vehicle Research - Summary

Article	Author	Technique Used	Key Findings
1	Le-Anh, T. and De Koster, M.B.M. (2006)	Review paper	Reviewed the design and control aspects of automated guided vehicle (AGV) systems, including routing algorithms, vehicle scheduling, and system optimization. Identified challenges and provided insights for system improvement.
2	Vis, I.F. (2006)	Review paper	Conducted a survey on research related to AGV systems' design and control. Highlighted advancements in route optimization, traffic control, and system integration. Outlined future research directions.
3	Kamoshida, R. and Kazama, Y. (2017)	Deep Reinforcement Learning	Applied deep reinforcement learning to acquire AGV route planning policies. Demonstrated that deep RL can effectively learn AGV navigation policies without prior explicit knowledge of the environment.
4	Elsisi, M. and Tran, M.Q. (2021)	IoT and Deep Neural Network	Developed an IoT architecture using a deep neural network to enhance cybersecurity for AGVs. Addressed vulnerabilities and showed how AI can protect AGVs against cyberattacks.
5	Rhazzaf, M. and Masrour, T. (2021)	Deep Learning	Utilized deep learning techniques for AGV system optimization. Demonstrated the potential of deep learning to improve various aspects of AGV operations.
6	Um, I., Cheon, H. and Lee, H. (2009)	Simulation	Simulated a flexible manufacturing system with an AGV system. Explored the impact of AGV integration on system performance and analyzed operational efficiency.
7	Jeon, S.M., Kim, K.H. and Kopfer, H. (2011)	Q-learning	Employed Q-learning for routing AGVs in container terminals. Showed how reinforcement learning can improve AGV routing decisions in complex environments.
8	Lin, C.C., Chen, K.Y. and Hsieh, L.T. (2023)	Feature-Based Reinforcement Learning	Applied feature-based reinforcement learning for real-time charging scheduling of AGVs in smart factories. Improved charging efficiency and reduced downtime.
9	Ohzeki, M., Miki, A., Miyama, M.J. and Terabe, M. (2019)	Quantum Annealer and Digital Devices	Controlled AGVs to avoid collisions using quantum annealer and digital devices. Explored novel methods for collision avoidance in AGV systems.
10	Stetter, R. (2022)	Fault-Tolerant Design	Developed fault-tolerant algorithms for AGV systems. Addressed reliability concerns and provided methods for

			ensuring system robustness.
11	Sierra-Garcia, J.E. and Santos, M. (2022)	Reinforcement Learning and Conventional Control	Combined reinforcement learning with conventional control for enhanced AGV tracking performance in complex trajectories. Demonstrated improved tracking accuracy.
12	Sagar, K.V. and Jerald, J. (2022)	Markov Decision Process and Double Q-Learning	Used Markov Decision Process and Double Q-learning for real-time AGV scheduling. Enhanced scheduling efficiency and responsiveness.
13	Martínez-Barberá, H. and Herrero-Pérez, D. (2010)	Autonomous Navigation	Explored autonomous navigation of AGVs in industrial settings. Addressed navigation challenges and proposed methods for improved AGV autonomy.
14	Lim, J.K., Lim, J.M., Yoshimoto, K., Kim, K.H. and Takahashi, T. (2003)	Q-learning	Applied Q-learning for designing guide-path networks in AGV systems. Demonstrated how reinforcement learning can optimize AGV navigation.
15	Yan, R., Dunnett, S.J. and Jackson, L.M. (2022)	Model-Based Research	Conducted model-based research for aiding decision-making in the design and operation of multi-load AGV systems. Provided insights into enhancing system reliability and safety.

Machine learning algorithms can also be used to optimize the movement of the vehicles in the system. This could include optimizing the route of the vehicles, as well as the speed and timing of their movements. In addition, machine learning algorithms can be used to improve the safety of the system. This includes designing the control system to detect potential obstacles and hazards, as well as to adapt to changing conditions. Furthermore, machine learning algorithms can be used to optimize the performance of the AGV system. This could include optimizing the system for efficiency and cost savings, as well as improving the throughput of the system. In a nutshell, machine learning algorithms are a powerful tool for the design and control of AGV systems. These algorithms can be used to improve the safety and performance of the system, as well as to optimize the movement of the vehicles. Furthermore, machine learning algorithms can be used to optimize the design and control of the system for efficiency and cost savings. As such, machine learning algorithms are an important tool for the design and control of AGV systems [4].

II. ML FORAGV OPTIMIZATION

Autonomous guided vehicle (AGV) optimisation is a field of research that has been steadily growing in importance in recent years. This is due to the increased demand for automated solutions in industries such as logistics, manufacturing, and transportation. The technology behind AGV optimisation is based primarily on machine learning (ML) algorithms. ML algorithms are capable of learning from data and can be used to optimize the behavior of AGVs. This article will explore the various ML algorithms used for AGV optimisation, as well as the various practical implementations and examples of AGV optimisation [5]. Machine learning (ML) is a field of artificial intelligence (AI) that allows computers to learn from data without having to be explicitly programmed. ML algorithms are capable of learning from data and can be used to optimize the behavior of AGVs. ML algorithms can learn from data and can be used to optimize the behavior of AGVs. ML algorithms can be divided into three categories: supervised learning, unsupervised learning, and reinforcement learning.Supervised learning algorithms use labeled data to train the model. Labeled data consists of inputs and their corresponding outputs [6]. The model is trained to map the input to the desired output. Examples of supervised learning algorithms include linear regression, logistic regression, support vector machines, and decision trees.Unsupervised learning algorithms do not require labeled data for training. Instead, the model is trained to identify patterns in the data. Examples of unsupervised learning algorithms include k-means clustering, hierarchical clustering, and self-organizing maps.Reinforcement learning algorithms use rewards and punishments to learn from data. The model is trained to maximize the rewards and minimize the punishments. Examples of reinforcement learning algorithms include Q-learning, deep Q-learning, and policy gradient methods.ML algorithms can be used to optimize the behavior of AGVs. The most commonly used ML algorithms for AGV optimisation are supervised learning algorithms such as linear regression, logistic regression, support vector machines, and decision trees.Linear regression is a supervised learning algorithm used to model the relationship between two or more variables [7]. The model is trained to map the input variables to the output variable. Linear regression can be used to optimize the speed of an AGV by predicting the optimal speed based on the environment.Logistic regression is a supervised learning algorithm used to model the probability of an event occurring. The model is trained to map the input variables to the probability of the event occurring. Logistic regression can be used to optimize the path of an AGV by predicting the probability of the AGV taking different paths.Support vector machines are supervised learning algorithms used to classify data into different categories. The model is trained to map the input data to the desired output class. Support vector machines can be used to optimize the navigation of an AGV by predicting the optimal path based on the environment.Decision trees are supervised learning algorithms used to model the decision-making process [8]. The model is trained to map the input variables to the decision. Decision trees can be used to optimize the navigation of an AGV by predicting the best route based on the environment.In addition to these supervised learning algorithms, AGV optimisation can also be achieved using unsupervised learning algorithms such as k-means clustering and self-organizing maps, as well as reinforcement learning algorithms such as Q-learning and deep Q-learning.There have been several practical implementations of AGV optimisation using ML algorithms.One example is an implementation of ML algorithms for path planning in a warehouse environment. The ML algorithms used were a combination of support vector machines, decision trees, and logistic regression. The algorithms were used to optimize the path of the AGV in the warehouse environment by predicting the optimal path based on the environment.Another example is an implementation of ML algorithms for collision avoidance in a warehouse environment. The ML algorithms used were a combination of k-means clustering, self-organizing maps, and Q-learning. The algorithms were used to optimize the movement of the AGV in the warehouse environment by predicting the optimal path based on the environment.In conclusion, machine learning (ML) algorithms are an effective way to optimize the behavior of autonomous guided vehicles (AGVs) [9]. ML algorithms such as linear regression, logistic regression, support vector machines, and decision trees can be used to optimize the speed of an AGV. Unsupervised learning algorithms such as k-means clustering and self-organizing maps can be used to optimize the navigation of an AGV. Reinforcement learning algorithms such as Q-learning and deep Q-learning can be used to optimize the navigation of an AGV. There have been several practical implementations of ML algorithms for AGV optimisation, such as path planning and collision avoidance in warehouse environments [10]. A Typical Automated guided vehicles powered by Lithium-Ion battery for surveillance operation is exhibited in **Fig 1**.

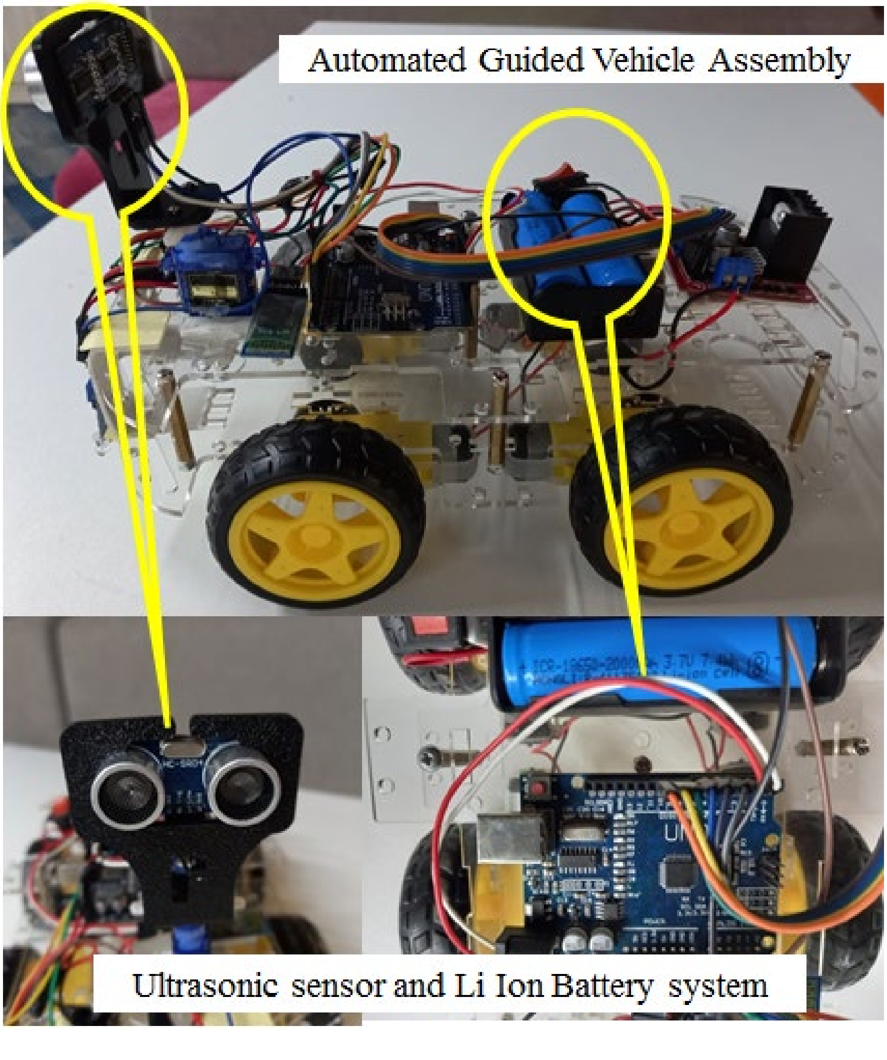

Fig 1. A Typical Surveillance Robot.

III. ANN FOR AGV SYSTEM DESIGN AND CONTROL

Autonomous guided vehicles (AGVs) are a type of mobile robots used in industrial automation that are capable of navigating autonomously without the need for an operator. AGVs are typically used for material handling applications such as loading and unloading of goods, transporting materials between production areas, and for warehousing and logistic operations. AGV navigation is typically based on a combination of sensors and algorithms, and the AGV's path is determined by a control system. In recent years, artificial neural networks (ANNs) have been used for AGV system design and control, due to their ability to learn and generalize from experience.Artificial neural networks (ANNs) are computational models inspired by the neural structure of the human brain [11]. They are composed of a large number of interconnected nodes that process information and produce a desired output, based on the input data. ANNs are used in a variety of applications, including image processing, natural language processing, and robotics.In robotics, ANNs are used in various applications such as path planning, obstacle avoidance, and motion control. ANNs are particularly well-suited for motion control applications, as they can learn and generalize from experience. ANNs can be used to control the motion of an AGV by learning from past experiences and adjusting the control parameters accordingly.ANNs can be used to design and control AGV systems. The use of ANNs in AGV system design and control can provide a number of advantages over traditional control methods, including improved accuracy, faster response times, and better fault tolerance.One of the most common applications of ANNs in AGV control is obstacle avoidance. Obstacle avoidance is an important task for AGVs, as it helps to ensure that the AGV does not collide with any obstacles in its path. ANNs can be used to detect obstacles in the environment and to generate an appropriate avoidance path.Another application of ANNs in AGV control is motion control. ANNs can be used to control the speed and direction of the AGV, as well as its acceleration and deceleration [12]. This can be done by training the ANN on a set of input data, such as the AGV's current position and velocity, and then using the ANN's output to control the AGV's motion.In addition to obstacle avoidance and motion control, ANNs can also be used for path planning. Path planning is the process of finding the most efficient path for the AGV to take between two points. ANNs can be used to generate an optimal path by learning from past experiences and adjusting the path accordingly.Finally, ANNs can also be used for fault detection and diagnosis. Fault detection and diagnosis is the process of identifying and diagnosing faults in the AGV's control system. ANNs can be used to detect faults in the control system by monitoring the AGV's performance and comparing it to a known baseline.In conclusion, artificial neural networks (ANNs) are a powerful tool for AGV system design and control. ANNs can be used for a variety of tasks, including obstacle avoidance, motion control, path planning, and fault detection and diagnosis. By using ANNs, AGV systems can be designed and controlled more accurately and efficiently [13].

IV. SUPPORT VECTOR MACHINES FOR AGV SYSTEM DESIGN AND CONTROL

Support Vector Machines (SVMs) are a powerful tool for AGV System Design and Control that can be used to identify complex patterns within data. They are supervised learning algorithms that, given a set of labeled examples, are able to identify and classify new examples. SVMs can be used to identify patterns in data sets and recognize them in the future, allowing AGV systems to respond to changes in their environment [14]. SVMs can be used to classify data in a variety of ways, including classification, regression, and novelty detection. For example, in classification tasks, SVMs can be used to classify data points into different categories based upon their features. In regression tasks, SVMs can be used to predict the value of a given data point based upon its features. In a novelty detection task, SVMs can be used to identify data points that are different from the ones previously seen. In AGV system design and control, SVMs can be used to identify and classify different objects in the environment, such as obstacles or goals. They can also be used to detect changes in the environment, such as changes in the shape or size of objects, or changes in their position. This information can then be used to plan and execute path planning algorithms and control strategies. SVMs can also be used to identify and classify objects in a more complex way, such as by recognizing patterns in the environment. This can be used to improve the accuracy of path planning algorithms and control strategies. For example, by recognizing patterns in the environment, the AGV system can be better prepared to respond to unexpected obstacles or changes in the environment. In addition, SVMs can be used to detect anomalies in the environment, such as unusual patterns or objects that may indicate a potential hazard. By identifying these objects or patterns, AGV systems can be better prepared to avoid dangerous situations [15]. Overall, SVMs are a powerful tool for AGV system design and control that can be used to identify complex patterns within data and recognize them in the future. By recognizing patterns in the environment and detecting anomalies, AGV systems can be better prepared to plan and execute path planning algorithms and control strategies. SVMs can also be used to classify data points into different categories, allowing AGV systems to respond to changes in their environment. As such, SVMs are an important tool in the development and improvement of AGV systems [16].

V. DEEP LEARNING FOR AGV SYSTEM DESIGN AND CONTROL

Deep learning has become a powerful tool for AGV system design and control. AGV (Autonomous Guided Vehicle) systems are used in industrial and logistics settings to automate the transport of goods and parts through warehouses and factories. The traditional methods used to design and control these systems often require complex programming and are limited in their ability to react to unexpected events. However, deep learning algorithms allow AGV systems to learn how to react in a variety of conditions, making them more autonomous and reliable. Deep learning is a subset of artificial intelligence (AI) that uses neural networks to enable machines to learn from data [17]. Neural networks are composed of layers of interconnected nodes and are trained using a variety of techniques, including backpropagation, reinforcement learning, and supervised learning. Deep learning algorithms can process large amounts of data quickly and accurately, allowing them to make decisions and take action without the need for explicit programming. Deep learning has been used for AGV system design and control in a variety of ways. By using deep learning algorithms, AGV systems can learn from their environment and adapt to different conditions. For example, an AGV system can use deep learning to identify objects in its environment and navigate around them, while also accounting for changes in the environment. Deep learning can also be used to create predictive models that allow AGV systems to anticipate and react to events before they happen. In addition, deep learning can be used to optimize the performance of AGV systems. By training deep learning algorithms on historical data, AGV systems can learn how to maximize speed and efficiency while minimizing energy consumption [18]. This can result in improved system performance and cost savings. Deep learning is also being used to improve the safety of AGV systems. By combining deep learning with sensors and other technologies, AGV systems can become aware of their environment and potential obstacles and take appropriate actions to avoid collisions. This can help reduce the risk of accidents or damage to goods and parts. Finally, deep learning is being used to develop more intelligent AGV systems that can interact with humans and other machines. By using deep learning algorithms, AGV systems can learn how to recognize human speech, respond to environmental cues, and communicate with other machines [19]. This can help improve the overall efficiency of the system and increase its use in a variety of settings. In conclusion, deep learning is a powerful tool for AGV system design and control. By using deep learning algorithms, AGV systems can become more autonomous, reliable, efficient, and safe. As the technology continues to improve, deep learning will become an increasingly important part of AGV system design and control, offering new opportunities for automation and increased efficiency [20].

VI. GAUSSIAN PROCESS REGRESSION FOR AGV SYSTEM DESIGN AND CONTROL

Gaussian Process Regression (GPR) is a powerful machine learning method that has become increasingly popular in AGV system design and control. It is a probabilistic approach that is capable of handling complex nonlinear relationships between inputs and output, and has been used in a variety of AGV applications, ranging from navigation and path planning, to obstacle avoidance and learning control. GPR is based on the idea of a Gaussian process, which is a stochastic process with a prior over functions [21]. This prior can be used to capture our prior beliefs about the function that we want to learn. GPR then uses Bayes' theorem to provide a posterior probability distribution over all possible functions. This posterior can then be used to infer the most likely function given the data, and to make predictions about values of the function at unseen data points, given the data. GPR has several advantages over traditional regression methods when applied to AGV system design and control. Firstly, GPR is a nonparametric method, so it is able to capture complex nonlinear relationships between inputs and outputs that may not be possible with other methods. Secondly, GPR provides a probabilistic output, which is useful when dealing with uncertainties in the AGV system. Finally, GPR can be used for online learning, allowing AGV systems to learn from their experience and improve over time [22]. GPR has been used in a variety of AGV applications. For example, it has been used to model and predict the trajectory of an AGV, allowing for more accurate navigation and path planning. It has also been used in obstacle avoidance and autonomous navigation systems, as it can be used to infer the best paths around obstacles, based on prior experience. GPR has also been used in learning control systems, allowing AGVs to learn complex tasks such as pick-and-place operations. GPR is a powerful tool for AGV system design and control, and has seen increasing use in recent years. It is a nonparametric method that can capture complex nonlinear relationships between inputs and outputs, and provides probabilistic output that is useful when dealing with uncertainties in the system. GPR has also been used in a variety of AGV applications, such as navigation, path planning, obstacle avoidance, and learning control. In the future, GPR is likely to be used in an even wider range of AGV applications, as it continues to prove its effectiveness for dealing with the complex task of AGV system design and control [23].

VII. REINFORCEMENT LEARNING FOR AGV SYSTEM DESIGN AND CONTROL

Reinforcement Learning (RL) is a type of machine learning algorithm that enables artificial intelligence (AI) to learn from environment interactions. It has been successfully applied to many fields, such as robotics, natural language processing, computer vision, and autonomous navigation. Recently, RL has been used to design and control autonomous guided vehicle (AGV) systems. AGVs are mobile robots used to transport materials within a facility. These robots are programmed to move autonomously along predetermined paths without the need for manual operation [24]. AGV systems can be used in a variety of applications, such as warehouses, factories, and hospitals. RL has been used to design and control AGV systems due to its ability to learn from interactions with the environment. RL algorithms allow AGV systems to learn how to navigate around obstacles and how to select the optimal route to reach a given destination. This type of learning enables AGVs to operate autonomously without the need for manual programming. RL algorithms can also be used to optimize the operation of AGV systems. By using RL, AGV systems can learn how to minimize travel time and energy consumption while still meeting delivery deadlines. This can help reduce operating costs and increase efficiency. Furthermore, RL algorithms can be used to improve the safety of AGV systems. RL algorithms enable AGVs to learn how to avoid collisions with other objects and how to safely navigate around obstacles [25]. This can help reduce the potential for accidents and injuries in AGV-operated facilities. Finally, RL algorithms can be used to make AGV systems more flexible. By learning from interactions with the environment, RL algorithms can enable AGV systems to quickly adapt to changes in the environment, such as the introduction of new obstacles or the relocation of delivery points. This can help AGV systems remain effective even in rapidly changing environments. In conclusion, RL algorithms are increasingly being used to design and control AGV systems. RL algorithms enable AGV systems to learn how to navigate autonomously and how to optimize their operation. Furthermore, RL algorithms can improve the safety of AGV systems and enhance their flexibility. As RL algorithms become more advanced, they will continue to improve the effectiveness of AGV systems and enable them to operate in a wide range of environments [26].

VIII. A COMPARATIVE ANALYSIS OF ML ALGORITHMS FOR AGV SYSTEM DESIGN AND CONTROL

A comparative analysis of machine learning (ML) algorithms for automated guided vehicle (AGV) system design and control is an important step in developing and deploying AGV-enabled systems. AGV systems are used for a variety of applications such as material handling, transport, and logistics. As such, the performance of the AGV system is a key factor in the successful implementation of the system [27]. Therefore, an analysis of ML algorithms for AGV system design and control can provide valuable insights for improving the performance of the system. The most commonly used ML algorithms for AGV system design and control are supervised learning, unsupervised learning, and reinforcement learning. Each of these algorithms has its own unique strengths and weaknesses. Supervised learning requires the availability of labeled data, where the outcome of the data is known. This type of learning is best suited for AGV systems that are designed to perform specific tasks [28]. Unsupervised learning, on the other hand, does not require labeled data and is best suited for AGV systems that are designed to identify patterns in the data. Finally, reinforcement learning is used to optimize the performance of the AGV system by using reward and penalty signals. When comparing the performance of the different algorithms, it is important to consider the accuracy, speed, and scalability of the system. The accuracy of the ML algorithms is an important factor in determining the performance of the system. The accuracy of supervised learning algorithms is generally higher than the accuracy of unsupervised and reinforcement learning algorithms. However, supervised learning algorithms require more training data, which can be time-consuming and expensive. Unsupervised learning algorithms are generally faster and require less training data, but their accuracy is usually lower than the accuracy of supervised learning algorithms. Reinforcement learning algorithms are generally the most computationally efficient, but their accuracy is dependent on the reward and penalty signals used to train the system. In addition to the accuracy of the algorithms, it is also important to consider the scalability of the system. Scalability refers to the ability of the system to handle larger datasets or more complex tasks. Supervised and unsupervised learning algorithms are generally more scalable than reinforcement learning algorithms, as they are able to handle larger datasets and more complex tasks [29]. However, reinforcement learning algorithms are better suited for AGV systems that require real-time optimization. Finally, it is important to consider the speed of the system. The speed of the system is an important factor in the successful deployment of the AGV system. Supervised learning algorithms are generally the slowest, as they require a large amount of data to be processed before the system can be deployed. Unsupervised and reinforcement learning algorithms are generally faster, as they require less data and can be trained in real-time. In conclusion, a comparative analysis of ML algorithms for AGV system design and control is an important step in developing and deploying AGV-enabled systems. The accuracy, speed, and scalability of the different algorithms should be taken into consideration when making a decision on which algorithm to use. Supervised learning algorithms are best suited for AGV systems that are designed to perform specific tasks, while unsupervised and reinforcement learning algorithms are better suited for AGV systems that require real-time optimization [30-35].

IX. SCOPE FOR FUTURE RESEARCH

The use of automated guided vehicle systems (AGVS) is becoming increasingly popular in a variety of industries, from logistics to manufacturing. AGVS can provide a cost-effective and efficient way to move materials and products from one point to another. As AGVS become more widely used, there is a need for improved design and control techniques to ensure their reliable and efficient operation. Machine learning (ML) offers a promising approach to AGVS design and control, allowing for the development of sophisticated methods for path planning, obstacle avoidance, and other tasks. In recent years, there has been significant research into the application of ML to AGVS [35-41]. These studies have focused on a range of topics, including path planning, obstacle avoidance, dynamic task scheduling, and fleet management. However, much of the work has been limited to simulation studies, with few real-world applications. There is therefore a need for further research into the application of ML to AGVS in the real world. In particular, there is an opportunity to explore the potential of ML-based methods for path planning and obstacle avoidance. These methods could be used to develop effective navigation strategies for AGVS in dynamic environments, such as warehouses and factories. Furthermore, ML-based approaches could be applied to the task of dynamic task scheduling, allowing AGVS to adapt to changing conditions and optimize the use of resources. In addition to path planning and obstacle avoidance, ML-based approaches could be used to improve the safety and security of AGVS. For example, ML-based methods could be used to detect and respond to potential hazards, such as obstacles in the environment or malicious interference. Moreover, ML-based methods could be used to detect and respond to system failures or changes in the environment. Finally, there is an opportunity to explore the potential of ML-based methods for fleet management [42-43]. ML-based methods could be used to optimize the configuration of AGVS fleets and to dynamically adjust the task allocations of AGVS. This could allow for more efficient use of resources and improved task completion times. Overall, there is a significant opportunity for further research into the application of ML to AGVS design and control. ML-based methods could be used to improve the performance of AGVS in a range of tasks, from path planning to fleet management. Furthermore, ML-based approaches could be used to improve the safety and security of AGVS, as well as the efficiency of their operations. With further research, ML-based methods could become a key component of AGVS design and control.

X. CONCLUSION

This paper presented a critical review of the machine learning approach for the design and control of automated guided vehicle (AGV) systems. The paper discussed the current state of the art in terms of machine learning approaches for the design and control of AGV systems. It also compared traditional control approaches and machine learning approaches for AGV system design and control. The paper further explored the potential of machine learning algorithms such as artificial neural networks (ANNs), support vector machines (SVMs), deep learning, gaussian process regression (GPR), and reinforcement learning (RL) for the design and control of AGV systems. It also discussed the advantages and disadvantages of using each of these algorithms for AGV system design and control. A case study was presented to demonstrate the potential of using machine learning algorithms for the design and control of AGV systems. The results from the case study demonstrated the potential of using machine learning algorithms for the design and control of AGV systems. The paper concluded by providing an overview of the current state of the art in terms of machine learning approaches for AGV system design and control. The paper also provided future research directions and recommendations for the further improvement of the design and control of AGV systems using machine learning algorithms. Machine learning algorithms can provide AGV systems with a high degree of flexibility, scalability, and robustness. It is therefore recommended that future research should focus on further exploring the potential of machine learning algorithms for the design and control of AGV systems. Furthermore, it is also recommended that research should focus on developing effective control algorithms for AGV systems that can be used in both indoor and outdoor environments.

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