Automated Guided Vehicles Challenges for Artificial Intelligence

Rafał Cupek
Silesian University of Technology
Gliwice, Poland
rcupek@polsl.pl

Jerry Chun-Wei Lin
Western Norway University of Applied Sciences, Bergen, Norway
jerrylin@ieee.org

J. H. Syu
National Taiwan University,
Taipei, Taiwan
f08922011@ntu.edu.tw

2022 IEEE International Conference on Big Data (Big Data) | 978-1-6654-8045-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/BigData55660.2022.10021117

Abstract **– The use of Artificial Intelligence (AI) to support the Automated Guided Vehicles (AGV) that are used by industry poses a number of challenges that are specific to smart internal logistics systems that are necessary for agile manufacturing. On the one hand, it might seem that experience with the autonomous navigation system that are used in autonomous vehicles can be easily transferred to AGV. However, in this paper, the authors highlight specific problems that are associated with the navigation system of AGV, which has to reflect its operation in an industrial environment with high level of interaction with other production systems and human staff. On the other hand, it may seem that the wealth of experience from using AI in smart manufacturing can be easily transferred to the use of AGV. However, the authors show that although AGV are production tools, the challenges that are associated with the use of AI can significantly differ from other smart manufacturing areas. The number of challenges that are specific to use of AI for AGV is also discussed. This paper systematizes these challenges and discusses the most promising AI methods that can be used for the internal logistics systems that are based on AGV.**

Keywords – Artificial Intelligence (AI), Automated Guided Vehicles (AGV), Smart Manufacturing, Internal Logistics, Explainable AI (XAI).

I. Introduction

Two of the terms that are most commonly used to describe the continuous changes in manufacturing are the fourth or fifth industrial revolution. Looking at the history of revolutions in industry, we can start with first commercially used steam engine, which was designed by James Watt in 1776 [1]. The second revolution is associated with mass production, which began when the movable assembly line for assembling Ford T automobiles was invented in 1913 [2]. The third revolution is associated with the use of computer control systems for discreet manufacturing and with the first use of a PLC (Programmable Logic Controller), which was installed on the GM Hydramatic automatic transmission assembly line in 1969 by Modicon [3]. The fourth revolution is associated with digitalization, the common use of wireless communication and the IT support services that enable agile and cooperative manufacturing services [4], while the fifth industrial revolution is associated with the idea of harmonious human-machine collaborations with a specific focus on the well-being of multiple stakeholders, i.e., society, companies, employees and customers [5].

Creating milestones is a feature of the human mind that facilitates their ability to describe and understand the world. In fact, James Watt's invention was simply a refinement of an earlier idea of the steam engine that was invented by Thomas Newcomen in 1710. The common use of steam engines was associated with social changes and economic processes such the rise of capitalism, the emergence of a middle class and the creation of an economy that was regulated by the markets: goods and services, labor and capital. Similarly, the movable assembly line is nothing more than a visible sign of the changes in the organization of work. At the beginning of the production of the Ford T (1908), the work cycle of the personnel was 514 minutes and during one shift, the employee performed operations associated with the assembly of large car components. Gradually, the operations performed by each employee became easier and therefore work was more effective. In 1913, even before the introduction of the mobile assembly line, the average turnaround time for a repetitive manufacturing operation was 2.13 minutes [2]. In the case of the third, fourth and fifth industrial revolutions, the milestones such as the introduction of computers, robots, wireless networks and artificial intelligence in manufacturing were not the reason for the changes in manufacturing, but they were rather well-applied tools that were available at a given stage of the development of production technology.

For this reason, when considering the use of artificial intelligence (AI) in industry and particularly the use of AI for Automated Guided Vehicles (AGV), we should start from an analysis of the needs and then determine which AI mechanisms can be used to assist in solving the challenges that are posed with the increasing use of AGV for agile manufacturing. The growing popularity of AGV is not only due their technical features but primarily because of the ongoing changes in manufacturing that can by characterized by [6] an increasing degree of flexibility, which is required in order to cope with customers' orders that frequently change, low material buffers and agile production technologies. Moreover, production is often performed by robotic production stations that can execute many different variants of technological operations.

AGV are not stand-alone technological solutions; they have to cooperate with and become a part of highly advanced technical systems and have to perform successive steps in the production chain. This means that AGV have to cooperate with other production tools and management systems in order to effectively support the production tasks by automatically cooperating with production stands in the way that is based on Machine-to-Machine communication [7]. AGV also have to be equipped with self-diagnostic tools, which are necessary for predictive maintenance and also have to support the new information architectures that are characterized by a high level of autonomy as well as the distribution of the decision-making processes in manufacturing.

Artificial Intelligence (AI) was inspired by the desire to stimulate the brain, model human problem solving, formal logic, large databases of knowledge and imitate animal behavior [8]. AI is used for knowledge processing, pattern recognition, machine learning and natural language processing. In the area of its use in manufacturing systems, it has been used for automatic programming, expert systems, knowledge systems and intelligent robots [9]. AI-driven analytics is one of the domains that plays a significant role in maintaining a fleet of AGV and the production cycle. It includes the development and use of ML algorithms to analyze the behavior of AGV and for detecting any anomalies early in order to reduce the incidents of future problems or failures using predictive maintenance. Predicting power consumption is necessary for the optimal use of an AGV fleet and includes both the need to dynamically fulfill a constantly changing list of transportation tasks and to ensure an optimal charging schedule for the AGV that are used in an internal logistics system.

The problem of AGV navigation in an industrial environment requires a special approach because of the specificity of the layouts of production areas and operating at the shopfloor level with continuous and sometimes unforeseen interactions with personnel, machines or other AGV. The AI that is used for the AGV that are used in manufacturing have to consider collective and distributed tasks that have both central processing parts that are performed at the system level and also edge computing routines that are performed directly on an AGV. On the one hand, an AGV can be characterized by high level of autonomy when operating in warehouses and production environments. In such a case, an AI can support the accident-free operations of AGV under different conditions. On the other hand, AGV are part of the internal material transport system and have to work in a collective and cooperative way in order to ensure manufacturing efficiency.

AI algorithms should support the fleet management system with the goal of the global optimization of transportation tasks. At the shopfloor level, AGV have to be integrated with collaborative robots and other production tools in a flexible way in order to blur the line between the transportation and production tasks. At this level, the use of AI should support cooperation with the industrial equipment and production staff. AI should also support the integration of AGV and a Manufacturing Execution System (MES) during operational scheduling, tracking and performance analysis in order to achieve the optimal and flexible manufacturing system that covers the entire production process that is composed of many manufacturing operations including the transportation tasks that are performed by AGV.

The rest of this paper is organized as follow: section two focuses on the most common problems that are associated with the AI application for AGV that are used in the internal logistics systems that are dedicated for agile manufacturing. The authors focus on challenges that are associated with navigating in a manufacturing environment including route planning and navigation assistance, and on cooperation with other production systems. Next the multiplicity and non-repeatability of data generated by AGV is analyzed. Finally, the problem of transparent data exchange between many source streams and number of AI alghoritms is discussed. The third section focus on the AI tools that can support dealing with challenges mentioned in section two including various machine learning (ML) algorithms, deep learning (DL), reinforcement learning (RL) and Explainable AI (XAI). The main focus is on predictive maintenance and power consumption prediction issues. The conclusions and future works are presented in the final section.

II. AGV as an Autonomous and Cooperative Production Tool

Autonomous Guided Vehicles (AGVs) are production tools (considering internal logistics system as a part of manufacturing system) that have a high level of autonomy. Ther tasks that are performed by AGVs are defined at higher level of manufacturing support tools such as a Manufacturing Execution System (MES) or Transport Management System (TMS). An AGV is selected, e.g., by a TMS, which uses an internal logistics optimization algorithm for a given transportation task that is has to perform in an autonomous way while trying to solve route problems and avoid unexpected obstacles without supervision from humans or external computer systems. Although the logistics tasks are performed by AGVs in an autonomous manner, the data that describes the progress in executing them must be cyclically delivered to the master systems in order to allow the operational management of manufacturing process.

A. The problem of route planning and navigation assistance

A number of methods have been developed for AGV navigation in an industrial environment [10]. The simplest but the least flexible solution is magnetic or electromagnetic navigation in which electromagnetic sensors that are installed on an AGV keep to a route that is designated by a magnetic or electromagnetic strip. The navigation strip is also used in vision-based systems where it is detected by a camera that works on the image processing principle [11]. More flexible navigation systems use triangulation positioning via UWB (Ultra-Wideband) technology, which is based on a nanosecond narrow pulse to transmit data and enables the position of an AGV to be estimated based on the distance from the tag on the AGV body to the surrounding anchors, which are measured by the time of flight (TOF) ranging algorithm [12]. The actual coordinates of an AGV are calculated with high positioning accuracy up to 5-10cm using the trilateral centroid localization algorithm. Another option is AGV navigation that is based on GPS (Global Position System) where the position of an AGV is tracked and guided by satellite [13]. However, a significant disadvantage of GPS navigation is its low level of accuracy, especially in closed areas of factory shopfloors.

For the purpose of this research, the authors considered a 2D lidar-based natural navigation system [14]. The environment of an AGV is recognized by front and rear laser sensors that continuously send laser beams and scan the surroundings by detecting the reflections from walls, the other equipment and human staff visible by lidars. The image that is obtained from lidars is compared with a map on which the location of walls, permanent obstacles and virtual paths on which the AGV can move are marked. In order to make such comparison possible, the approximate position of the AGV has to be known and therefore the process is repeated cyclically. The distance that has been traveled by the AGV is calculated based on the signals that are generated by encoders, which are installed on right and left wheels, after which the next new estimated position of the AGV is calculated. Then, the new approximate position is compared with the map and

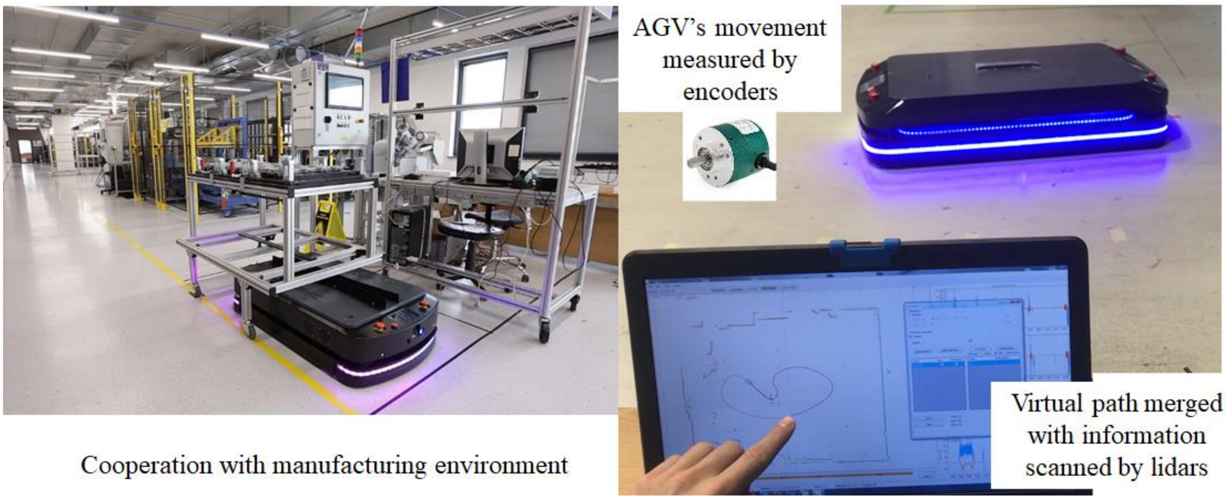

Fig.1 Natural navigation for AGV based on odometry and map location by lidars

an image of the surrounding environment that is created by the 2D lidars and the location of the AGV is updated (Fig.1).

The downside of such a natural navigation system is the limited confidence in the location of the AGV, which results from the possibility of the occurrence of new objects, e.g., human staff or other AGV that are not indicated on the map but are detected by the lidars. Another problem is missing some of the points that are indicated on the map that are obscured by new objects. Another source of an inaccuracy is caused by the lidar working principle, where precision decreases with the distance between an AGV and any objects that are detected as well as with problems that can be caused by the high absorption of the laser beams by an environment with low reflectivity. If the certainty of AGV's location drops below the minimum threshold, no further automatic navigation is possible. The accuracy of the location of an AGV can be improved by installing additional highly reflective markers in the work area.

The natural navigation system is based on a map that can be created during an AGV's trip in accordance with the SLAM (simultaneous localization and mapping) principle. However, in industrial applications, because AGV work in fixed environment, the most common solutions are based on the prior scanning of the manufacturing area in which an AGV is expected to move. Then, the map has to be improved by removing any temporary elements and leaving only permanently visible objects in the environment in which the AGV will work. When there is a lack of natural characteristic points or obstacles that enable the position of AGV to unambiguously be determined based on lidar scanning, e.g., when it is driving along a long wall without any characteristic points, additional reflective markings should be installed before the map is prepared.

A natural navigation system usually consists of a part that is installed onboard an AGV and an external navigation system that coordinates the movement of an AGV through the industrial environment. The local part is responsible for determining the current location using lidars, for updating position of the AGV on the map and for controlling the movement of the AGV via the direct or indirect control of the drives to keep the designated path smoothly. The external part of the navigation system has a route planning module, which sends a map to an AGV that is required for work in a specific location and sets the path on which the AGV should move. The route can be determined statically by the external part of the navigation system e.g., based on the data on the occupancy of segments of the by other AGVs or information about the presence of obstacles or dynamically based on current information collected by the AGV. In the second case, an AGV can modify its path during a transportation task. In the first case, an unexpected obstacle on the route can cause an AGV to be stopped and wait until the obstacle is removed. In the second case, an obstacle avoidance algorithm can be run in an automatic way.

A special case of natural navigation is the precise docking to a production station. In this case, the accuracy that is required is usually higher than is required to pass between waypoints [14]. This can be achieved through additional measurement systems that are installed on an AGV or an external guidance system that is based on external measurements of the location of an AGV and the transmission of control information. AGV docking can be supported by additional sensors, e.g., an optical ruler or ultrasound. Based on these measurements, the angle and distance from the docking point can be measured [15]. However, this requires using methods that permit the data that is obtained from a sensor to be selected with the highest accuracy or using data fusion methods to obtain the highest accuracy from several sensors. If a horizontal position is required after docking, an AGV can be checked by an inclinometer and if necessary can be improved by adjusting location of the AGV. Both the information about the vertical and horizontal position of the AGV and information shared with the cooperating production station make the docking process unrepeatable and more difficult to support than in other navigation system applications.

B. *The problem with the non-repeatability of the data that is generated by an AGV*

The change of the production model from mass manufacturing to mass-customized manufacturing and short-series production creates new challenges that are associated with the unrepeatability of manufacturing operations [16]. For the classical mass-production systems, the production technology and manufacturing operations schedule were based on the optimal setup parameters that were selected for the production tools or for fixed transportation systems. In these systems, the manufacturing operations were more stable and the transportation tasks were more repeatable. In the case of short series production, the technology is changes often, the production tools have to be adjusted to specific production variants and materials, the transport of semi products or finished products are supported by an internal logistics system and an AGV must follow these changes in order to avoid or reduce any losses resulting from non-productive time gaps. Research results show that trade-offs are not only made between the time, quality and expense but also that trade-offs are necessary when additional development expenses are incurred, including cross-functional integration such as the integration of an AGV with a collaborative robot, which substantially impacts the profitability of a product via a mix of direct and mediated effects [17, 18].

The above-mentioned factors also mean that the data analysis methodology that are used for AGV should take into account the diversity of the variants of the transportation tasks that are provided by an AGV, which reflect the frequently changing requirements that are typical for contemporary manufacturing systems. Therefore, it is no longer possible to prepare large sets of data that is based on repeatable operations that are performed in similar conditions but rather AI algorithms must work with the data from different variants of the transportation tasks that are being performed by an AGV. Contemporary AGV should follow short-series production needs and should be self-adaptive in order to support the changes in the manufacturing environment. AGV have to provide flexible and open transportation services that interact with the physical production system. On the one hand, an AGV performs repetitive tasks by overcoming the transport paths of materials, semi-finished products and finished products. In the case of short-series production, the repetitive variants are intertwined with each other and successive routes differ between each other. Due to the autonomous decisions of the onboard navigation system, the way in which a given transportation task is performed can also differ depending on the environmental conditions. An AGV can follow different paths, perform unexpected stops or run routines in order to avoid obstacles.

The tasks that are performed by an AGV cannot be grouped and compared based on the information that is processed by management systems such as an AGV fleet management system, a TMS or an MES. The implementation of the same logistics orders (from the point of view of the master system) can be performed by a transportation task that can be quite different depending on the environmental conditions and the degree of the autonomy of the navigation system of an AGV (route selection via navigation). The logistics order can suddenly be disrupted because of an interaction with the environment or technical problems on the AGV. The difference can also result from systematic changes in an AGV, e.g., a decrease in the battery capacity, wheel wear degradation or mechanical problems. Other sources of differences can be associated with the periodic changes in the production environment, e.g., increased intensity of staff traffic because of the time of day or with interferences that are caused by the parallel implementation of a series of production tasks with a large number of transportation orders, which can occur in a unique way and can increase the probability of interactions between AGVs that are operating in the same area).

Because of the nondeterministic behavior of the navigation system of AGV, the same transportation task can be performed using different paths and different transportation tasks can also be performed by an AGV in a very similar way.

One such example is presented Figure 2. The factory floor layout, which has transportation paths that intersect at right angles, must be taken into account. Transportation tasks A and B can be performed in the same way (from the point of view of an AGV). On the other hand, when the path is planned based on its minimal length, the A1 and A2 or B1 and B2 transport paths seem to be the same. Although they are the same length, they differ significantly for an AGV when the travel time and the energy that is used are compared. The path in option 1 consists of only one turn and can be completed faster and with less energy consumption than in the case of the same distance when traveled by an AGV using path 2. From the point of view of the transportation task of an AGV, A1 is more similar to B1 than to A2. The above example is only a trivial illustration of the problem. In fact, environmental factors can make comparing routes more complicated and route planning is very difficult in an analytical way due to the lack of information about unpredictable events that can occur during its implementation. Therefore, navigation remains nondeterministic and the AGV routes (although repetitive) can differ even for similar transport tasks.

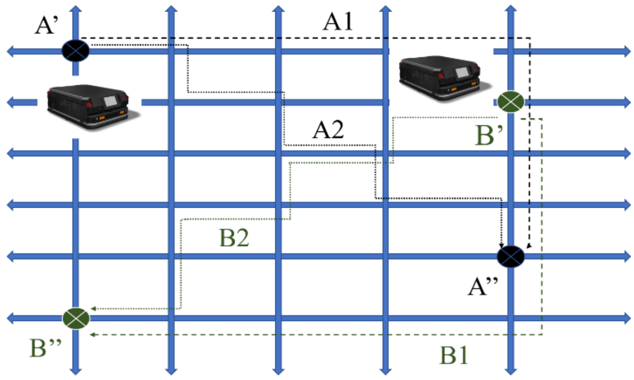

Fig.2. Similarity (A1 & B1 and A2 &B2) and difference (A1 & A2 and B1 & B2) of transportation orders dependents not only on the target location

Not only is the non-repeatability of a transportation tasks but the ability of an AI system to learn during the normal operation of an AGV a critical feature. A characteristic feature of short-series production is the emergence of new production variants, which result in the appearance of new variants in the transportation tasks that must be performed by an AGV. Considering the non-determinism of a navigation system, deciding whether the unusual way of traveling route that must be traveled by an AGV, it can be an anomaly associated with maintenance problems or environmental conditions or it can be caused by a new production variant. Because of this ambiguity, decisions about any anomalies that are detected must be made in any interactions with the staff that is overseeing the operation of the internal logistics system. This creates an additional challenge associated with the way data is represented. Anomalies are usually detected by AI on data that is processed to increase the efficiency or to improve the efficiency of a system. This type of data cannot be analyzed by a human. For this reason, the technologist and AI algorithms have to cooperate based on the presentation of the results of the AI analysis in a way that refers to the technological parameters that can easily be understood by an operator. This problem requires replacing the classic AI algorithms with Explainable AI (XAI) algorithms that produce additional data representation in a way that is understandable for a human.

C. The problem with the multiplicity of AI algorithms that process the AGV data that is used by manufacturing systems

The AI-based analysis of the data that is collected from AGVs and their environment enables for both the support of an AGV that is considered to be a transportation tool as well as for the functional support of the entire internal logistics system. AI can be used to detect technical problems early, e.g., increased energy consumption due to mechanical problems, which enables the availability of an AGV to be increased by using the self-diagnostics and predictive maintenance routines. AI can process the information about manufacturing environment and use it to dynamically select a path during navigation, e.g., to avoid areas with increased traffic or such information can be used at the system management level for reducing the areas of congested traffic by selecting alternative transportation paths. AI can be used to optimize energy consumption as an onboard routine of an AGV for smart motion control but it can be also used in a holistic way as a part of transportation task planning and scheduling by cooperating with the production scheduling that is prepared by an MES. AI can also be supportive in making decisions about merging or breaking down production orders. which enables the better use of the production facilities while it also helps to avoid the bottlenecks that can be caused by the limited availability of internal logistics system that is based on an AGV.

The broad applicability of AI for the many possible areas that are associated with AGV support in smart manufacturing leads to the problem of providing and sharing the optimal data for different AI algorithms. On the one hand, different kinds of AI algorithms require different forms of input data for their effective use. On the other hand, this may lead to the multiplication of data, data inconsistency and system overload, in particular, when AI routines are operating on edge devices. In order to make AI more effective and efficient, the streams of data that come from different sources can be grouped and annotated according to their technical meaning and the context of their use, including information that is supported by different sensors, data from the control systems or environmental data that is collected by an AGV. This data transformation creates transparent data sources that can be used by the AI that is operating on the data on an AGV. It can be performed by communication middleware by exposing both data and data models in order to support the data processing of an AGV by a number of AI algorithms.

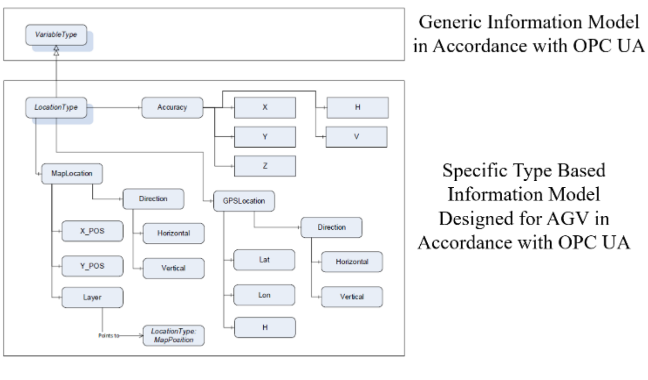

Fig.3. An ontology-based information model for AGV reflects environment context of its use

The communication middleware, e.g., OPC UA standard [19] forms a bridge between the raw process data that is used by an AGV and the annotated and structuralized information that can be used by the AI algorithms. This approach makes it possible for the AI routines to properly select the data source by, reduces the number of data streams used in system and also supports the conversion from a raw data format into a format that is more suitable for AI and also for a format that is understandable by human staff. An ontology-based information model [19] can adapt the information about an AGV and its environment to the context of its use (see Fig. 3). This unifies the access to the information that is produced by the control system, the technological data that is exchanged with an MES and the information that can support Business Intelligence or other systems. Object oriented data models enable the interoperability between the various machines, technologies and also support the production staff. Such an approach supports an unambiguous data representation for the cooperating AI algorithms regardless of the kind of data source, e.g., machines, sensors, systems, production staff and other AI services.

Model-based communication middleware also supports feature scaling, which is often a necessary condition for AI input. The raw information from an AGV is in the binary format that is used by control systems. The format is device specific and it is difficult to compare one data source with another even when describing the same or similar information, e.g., the distance to an obstacle that is measured by ultrasound sensors and an optical ruler. The communication middleware converts the raw data format into its representation in engineering units and therefore enables the information to be compared among different sources. The model can also describe the range of a given signal, which supports the normalization of the input data for AI processing. Moreover, the model provides the information about the technological significance of the individual parameters that should be taken into account when creating the AI input vector.

Another important approach that supports AI working with AGV is data aggregation. Data can be aggregated in order to create new information that reflects the statistically important features [20]. This step combines the external engineering knowledge that is used to define the aggregates with the current information that is being collected from the transportation system. In this way, the streams of data from AGVs can be transformed into discreet production records that are created by the aggregation functions. Aggregation routines can produce one (aggregated) value according to the aggregation model that is defined by communication middleware. On the one hand, the information that is collected in one production record comes from different sources, e.g., sensors, control signals, machine states, messages transmitted from the parent system, independent security systems, etc., while on the other hand, each information source can be used many times by the different aggregation functions (different points of view on the same data source).

The fusion of the aggregates can form a new information record, which describes a segment of the transportation path or an entire transportation task. The aggregated data includes the technological knowledge that is used to create the aggregates and therefore is a convenient data source of information for the AI algorithms. Examples of the aggregates can be the difference between the values at the beginning and at the end of a transportation segment, e.g., for the energy consumption measurement; the integral of a physical parameter, e.g., the current consumption over time or virtual sensors, which can generate new information based on one or more information sources by using additional knowledge about the production technology.

III. LANDSCAPE FOR THE AI METHODS THAT SUPPORT AGV

Besides their use in AGV, AI methods are also widely used in industry and manufacturing. Over the past decade, the meteoric rise of information and communications technology has been a driving force in accelerating the development of smart industry, smart manufacturing and Industry 4.0 [4, 21, 22]. Among the AI methods, the Internet of Things (IoT), data mining, machine learning, deep learning, reinforcement learning (RL) and distributed learning are powerful techniques that are used in smart industry and AGV.

By using IoT devices and other forms of advanced communications technology the Internet of Things (IoT) techniques are intended to facilitate the connections between machines and humans and between machines and other machines. IoT techniques enable the real-time monitoring and automatic control of an AGV without the need for human intervention. IoT devices refer to the research into edge computing, fog computing and cloud computing [23], which deal with the computation load shift and balance between a local device and online server. Additionally, due to its use in real-time, the advanced communication of 5G, 6G and Wi-Fi 6 are being widely studied in the IoT communication.

After data is collected and preprocessed from the Internet-of-Things devices, data mining algorithms can be adapted to analyze the patterns in industrial environments and the AGV situations. These patterns can serve as the basis for diagnoses and decisions and furthermore, self-monitoring [24, 25] and improved efficiency [26] can also be achieved.

Various machine learning (ML) algorithms, which are subfields of artificial intelligence that learn from data, build models and make predictions, have been developed in order to achieve higher levels of predictability. The success of ML in a number of industrial applications has been demonstrated in the published literature. Both Sharp et al. [27] and Kotsiopoulos et al. [28] indicated that ML has the potential to improve the energy efficiency and agility of manufacturing systems, in addition to further optimizing the production process. Traditional machine learning algorithms can provide lightweight models with a low level of computational complexity and computation time. These algorithms include regression, support vector machines, decision trees, random forests and others [29]. However, the computational capacity of an AGV and edge devices would be limited.

Deep learning (DL) algorithms are attracting the attention of a growing number of researchers due to the exponential growth of computing capacity and cloud computing. These algorithms are effective in robust feature extraction and accurate prediction. Recurrent Neural Networks (RNN) and Convolutional Neural Networks are two of the most important branches of the Deep Learning algorithm family. RNN are capable of storing and analyzing the temporal behavior of input data. Among the best known RNN models are the Gated Recurrent Unit (GRU) and the Long Short-Term Memory (LSTM). Both models are practical and are used extensively in smart industry and for time-series-based AGV data. Essien and Giannetti [30] have developed a novel autoencoder that uses deep convolutional LSTM neural networks to predict machine speed. This autoencoder uses a sliding window approach to reconstruct input sequences in a supervised learning framework. Wang et al. [31] proposed a hybrid prediction scheme for smart manufacturing that consists of a novel deep heterogeneous GRU model and a local feature extraction mechanism.

CNN are unique in their ability to extract features from a variety of scales and filters using a shared weight architecture. They have excelled in image processing and computer visioning [32] and are suitable for use in the environment sensing and obstacle detection of AGVs. Melinte and Vladareanu [33] used a number of CNN-based networks for facial expression recognition in human-computer interactions. These networks include VGG, Inception, ResNet and Faster R-CNN. A CNN-based image detection model for unmanned aerial vehicles was developed by Luo et al. [34] and Benjdira et al. [35]. However, there is a possibility that industry and AGV do not provide correct and deterministic answers and the training also lacks complete data.

In contrast to supervised and unsupervised learning, reinforcement learning (RL) algorithms enable intelligent agents to learn between the environment and the agents using trial and error. As a result, these intelligent agents can eventually learn the patterns and take appropriate actions to maximize the rewards. Moreover, RL algorithms can be generated and trained under an infinite number of training conditions in a simulated environment, which makes them suitable for use in AGV research. This is true even when only a small amount of training data is available. A multi-agent RL-based model for online scheduling in smart factories was proposed by Zhou et al. [36]. An approach to model unknown fields for autonomous ground vehicles, which and is based on reinforcement learning, was developed by Faryadi and Mohammadpour Velni [37].

In a smart factory, the limited computational capacity of AGVs and edge devices makes distributed learning algorithms a potential candidate for real-world implementation. Learning tasks are distributed across multiple devices and multiple computers by distributed learning algorithms, which also train the model in this way. The fact that they are decentralized, have a high level of parallelism, preserve user data privacy and are secure makes them suitable for use in smart factories. The main subfields of distributed learning are federated learning and shared learning; this is also the area in which most of the cutting-edge research on smart manufacturing can be found. Zhang et al. [38] proposed a real-time tuning architecture with a two-level deep federated learning and a mechanism for real-time automatic configuration tuning. In this architecture, local servers accumulate experience and share it with cloud servers. The cloud servers then aggregate the knowledge to create a robust federated model.

Explainable AI (XAI) is a combination of tools and architectures that can help learners or users develop and build interpretable, integrative machine learning models [39]. XAI has three characteristics: developing interpretable inclusive AI, rapidly deploying AI and creating simplified model management. XAI can be divided into three categories: Deep Explanation – while the model outputs the decision result, it also outputs the explanation behind the decision; Interpretable Models – the models themselves can be interpreted and Model Induction – this is used to find an explanation for the black box model. The method can be used to describe the behavior of AI models or to analyze the neural network-like architecture and hyperparameters of the AI models [40]. This XAI approach and visualization is currently the most widely used research approach in that is used to interpret deep learning models. Therefore, the use of XAI for AGV in order to support machine learning and deep learning algorithms can also support the accuracy of predictive models by creating a visualized tool to explain the AI decision. XAI can also support increasing the performance of AGV AI development, especially when only short data series are available. XAI can be used to develop a transportation scheduling algorithm, power consumption prediction models and agent-based simulations for various software components that are to be tested.

To summarize, AGV are an evolving research topic in intelligent industry and research in this area is currently in its early stages. The artificial intelligence (AI) techniques and literature we have reviewed are evidence of the viability of smart industry and the potential of AGV research. The most practical applications for an automated guided vehicle (AGV) system are predictive maintenance and energy consumption prediction, both of which are discussed in more detail in the following sections.

A. *Predictive Maintenance*

Anomaly detection and predictive maintenance are two important issues that have to be addressed in industry and in the field of AGVs. The goal of the research area that is known as predictive maintenance is to monitor the current state of production in order to detect potential irregularities (atypical conditions) and to provide early warning of any problems that could have a significant impact on quality, efficiency and even safety. In addition, predictive maintenance should ensure that the life of the production equipment (AGV) is fully utilized, that planned downtime is kept to a minimum and that unplanned downtime is avoided at all costs [41]. Predictive maintenance should monitor the battery level of an AGV and warn the system when it needs to be charged. Because the charging time for an AGV should be determined and planned, it is associated with predictive maintenance. Ideal maintenance would ensure a longer AGV battery life while simultaneously reducing downtime and increasing efficiency.

Conventional approaches to predictive maintenance rely Conventional approaches to predictive maintenance rely on either the passage of time or the accumulated wisdom of humans; however, these approaches can benefit greatly from the use of AI technologies. It is common practice to improve the effectiveness of predictive maintenance through the use of IoT sensors [41, 42], web platforms [43] and machine learning models [44, 45]. In their study on anomaly detection in automated vehicles, Javed et al. [45] used the Ensemble, Attention, RNN and CNN methods. Malawade et al. [46] developed neuroscience-inspired algorithms for predictive maintenance. These algorithms used hierarchical temporal memory and were evaluated using the Numenta Anomaly Benchmark (NAB).

B. *Power Consumption Prediction*

Predicting how much power will be consumed is essential for managing smart factories in order to organize tasks and charge driverless transportation systems. Prediction accuracy depends heavily on data collection and analysis. A short-term energy prediction system], which collects, relays, processes and predicts data, was developed by Luo et al. [47. Data mining technology was used by VE et al. [48] to predict energy consumption in the steel industry. Along with data mining for the Internet of Things devices, feature engineering and model selection also play an important role in predicting power consumption. Cheng et al. [49] discussed feature engineering that is based on deep learning for a small area of a building. They also discussed the effectiveness of different types of recurrent neural networks [50].

With more and more electric vehicles and unmanned vehicles now on the road, estimating the power consumption of vehicles is becoming an increasingly important issue. Niri et al. [51] analyzed the lithium-ion battery load using the wavelet Markov model and Xing et al. [52] further analyzed driving behavior to obtain a personalized prediction model. Both studies can be found here [52]. Research on unmanned vehicles includes ground, air and surface vehicles [53, 54, 55] and predicts the energy requirements for a variety of tasks and driving distances.

IV. Summary

This research study provides an overview of the most important challenges that are associated with the use of Artificial Intelligence (AI) for the Automated Guided Vehicles (AGV) that are used in industrial internal logistics systems. The authors indicated the specific features that are associated with the work of AGVs in agile production systems, which make it impossible to directly transfer the AI methods that are used in autonomous cars or other areas of smart manufacturing. The authors stress the problem of the non-repeatability of the transportation tasks and the need for them to cooperate with different production stands, production staff and a number of manufacturing production systems, which all present challenges to using AI for AGV. Another problem is the variety of goals that have to be achieved when using AI and the problem of multiplication of input data and limited resources in the case of edge computing.

The main research contribution of this paper is the comprehensive review of contemporary AI methods, which is presented in section three and is supported by a critical analysis of those features, which may be helpful in solving the specific challenges of AGV that are associated with their use in flexible internal logistics as is presented in section two.

Acknowledgment

The research leading to these results received funding from the Norway Grants 2014-2021, which is operated by the National Centre for Research and Development under the project “Automated Guided Vehicles Integrated with Collaborative Robots for Smart Industry Perspective” (Project Contract no.: NOR/POLNOR/CoBotAGV/0027/2019 -00.

References

[1] Dickinson, H. W. (2010). “James Watt: craftsman and engineer”, Chapter V: PARTNERSHIP WITH MATTHEW BOULTON. PERIOD OF STRUGGLE 1774-1781, Cambridge University Press. pp.86-122.

[2] Womack, J. P., Jones, D. T., & Roos, D. (1990). Machine that changed the world.Chapter: The rise and fall of mass production; pp.21-47 Simon and Schuster

[3] Jones, C. T.. Programmable logic controllers: the complete guide to the technology. 1-6 A Tour of PLC Evolution; pp17-23; Patrick-Turner Publishing Company Atlanta Philadelphia 1996

[4] . Wan, Yi Minglun, Li Di, C. Zhang, S. Wang, and K. Zhou, (2016), “Mobile services for customization manufacturing systems: an

example of industry 4.0," IEEE Access, vol. 4, pp. 8977-8986, Nov. 2016.

[5] Noble, S. M., Mende, M., Grewal, D., & Parasuraman, A. (2022). The Fifth Industrial Revolution: How harmonious human–machine collaboration is triggering a retail and service [r] evolution. Journal of Retailing.

[6] Cupek, R., Ziebinski, A., Drewniak, M., & Fojcik, M. (2019). Knowledge integration via the fusion of the data models used in automotive production systems. Enterprise Information Systems, vol. 13, nr 7-8, pp. 1094-1119.

[7] Cupek, R., Drewniak, M., Fojcik, M., Kyrkjebø, E., Lin, J. C. W., Mrozek, D., ... & Ziebinski, A. (2020, June). Autonomous guided vehicles for smart industries–the state-of-the-art and research challenges. In International Conference on Computational Science (pp. 330-343). Springer, Cham.

[8] McCorduck, P., & Cfe, C. (2004). Machines who think: A personal inquiry into the history and prospects of artificial intelligence. CRC Press..

[9] Zhang, C., & Lu, Y. (2021). Study on artificial intelligence: The state of the art and future prospects. Journal of Industrial Information Integration, 23, 100224.

[10] Zhou, S., Cheng, G., Meng, Q., Lin, H., Du, Z., & Wang, F. (2020, June). Development of multi-sensor information fusion and AGV navigation system. In 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC) (Vol. 1, pp. 2043-2046). IEEE.

[11] Liu, S., Xiong, M., Zhong, W., & Xiong, H. (2020, October). Towards Industrial Scenario Lane Detection: Vision-Based AGV Navigation Methods. In 2020 IEEE International Conference on Mechatronics and Automation (ICMA) (pp. 1101-1106). IEEE.

[12] Hu, X., Luo, Z., & Jiang, W. (2020). AGV localization system based on ultra-wideband and vision guidance. Electronics, 9(3), 448.

[13] Yadav, A., Gaur, A., Jain, S. M., Chaturvedi, D. K., & Sharma, R. (2020). Development Navigation, Guidance & Control Program for GPS based Autonomous Ground Vehicle (AGV) using Soft Computing Techniques. Materials Today: Proceedings, 29, 530-535.

[14] Villagra, J., & Herrero-Pérez, D. (2011). A comparison of control techniques for robust docking maneuvers of an AGV. IEEE Transactions on Control Systems Technology, 20(4), 1116-1123.

[15] Ziebinski, A., Mrozek, D., Cupek, R., Grzechca, D., Fojcik, M., Drewniak, M., ... & Biernacki, P. (2021, June). Challenges associated with sensors and data fusion for AGV-driven smart manufacturing. In International Conference on Computational Science (pp. 595-608). Springer, Cham.

[16] Cupek, R., Ziebinski, A., Huczala, L., & Erdogan, H. (2016). Agent-based manufacturing execution systems for short-series production scheduling. Computers in Industry, 82, 245-258.

[17] R.C. McNally, M.B. Akdeniz, R.J. Calantone, New Product Development Processes and New Product Profitability: Exploring the Mediating Role of Speed to Market and Product Quality: The mediating role of speed to market and product quality, J. Prod. Innov. Manag. 28 (2011) 63–77. doi:10.1111/j.1540-5885.2011.0086

[18] D'Souza, F., Costa, J., & Pires, J. N. (2020). Development of a solution for adding a collaborative robot to an industrial AGV. Industrial Robot: the international journal of robotics research and application, 47(5), 723-735.

[19] Maka, A., Cupek, R., & Rosner, J. (2011, November). OPC UA object oriented model for public transportation system. In 2011 UKSim 5th European Symposium on Computer Modeling and Simulation (pp. 311-316). IEEE.

[20] Steclik, T., Cupek, R., & Drewniak, M. (2022). Automatic grouping of production data in Industry 4.0− the use case of internal logistics systems based on Automated Guided Vehicles. Journal of Computational Science, 101693.

[21] Haverkort, Boudewijn R., and Armin Zimmermann. "Smart industry: How ICT will change the game!." *IEEE internet computing* 21.1 (2017): 8-10.

[22] Wang, Baicun, et al. "Smart manufacturing and intelligent manufacturing: A comparative review." *Engineering* 7.6 (2021): 738-757.

[23] Qi, Qinglin, and Fei Tao. "A smart manufacturing service system based on edge computing, fog computing, and cloud computing." *IEEE Access* 7 (2019): 86769-86777.

[24] Bergweiler, Simon. "Intelligent manufacturing based on self-monitoring cyber-physical systems." *UBICOMM 2015* 121 (2015).

[25] Syu, Jia-Hao, et al. "Self-Management Portfolio System with Adaptive Association Mining: A Practical Application on Taiwan Stock Market." *Mathematics* 9.10 (2021): 1093.

[26] Meng, Yuquan, et al. "Enhancing sustainability and energy efficiency in smart factories: A review." *Sustainability* 10.12 (2018): 4779.

[27] Sharp, Michael, Ronay Ak, and Thomas Hedberg Jr. "A survey of the advancing use and development of machine learning in smart manufacturing." *Journal of manufacturing systems* 48 (2018): 170-179.

[28] Kotsiopoulos, Thanasis, et al. "Machine learning and deep learning in smart manufacturing: The smart grid paradigm." *Computer Science Review* 40 (2021): 100341.

[29] Pranckevičius, Tomas, and Virginijus Marcinkevičius. "Comparison of naive bayes, random forest, decision tree, support vector machines, and logistic regression classifiers for text reviews classification." *Baltic Journal of Modern Computing*5.2 (2017): 221.

[30] Essien, Aniekan, and Cinzia Giannetti. "A deep learning model for smart manufacturing using convolutional LSTM neural network autoencoders." *IEEE Transactions on Industrial Informatics* 16.9 (2020): 6069-6078.

[31] Wang, Jinjiang, et al. "Deep heterogeneous GRU model for predictive analytics in smart manufacturing: Application to tool wear prediction." *Computers in Industry* 111 (2019): 1-14.

[32] O'Shea, Keiron, and Ryan Nash. "An introduction to convolutional neural networks." *arXiv preprint arXiv:1511.08458*(2015).

[33] Melinte, Daniel Octavian, and Luige Vladareanu. "Facial expressions recognition for human–robot interaction using deep convolutional neural networks with rectified adam optimizer." *Sensors* 20.8 (2020): 2393.

[34] Luo, Xin, et al. "Fast automatic vehicle detection in uav images using convolutional neural networks." *Remote Sensing* 12.12 (2020): 1994.

[35] Benjdira, Bilel, et al. "Car detection using unmanned aerial vehicles: Comparison between faster r-cnn and yolov3." *2019 1st International Conference on Unmanned Vehicle Systems-Oman (UVS)*. IEEE, 2019.

[36] Zhou, Tong, et al. "Multi-agent reinforcement learning for online scheduling in smart factories." *Robotics and Computer-Integrated Manufacturing* 72 (2021): 102202.

[37] Faryadi, Saba, and Javad Mohammadpour Velni. "A reinforcement learning-based approach for modeling and coverage of an unknown field using a team of autonomous ground vehicles." *International Journal of Intelligent Systems*36.2 (2021): 1069-1084.

[38] Zhang, Yilei, Xinyuan Li, and Peiyun Zhang. "Real-time automatic configuration tuning for smart manufacturing with federated deep learning." *International Conference on Service-Oriented Computing*. Springer, Cham, 2020.

[39] Lin, D. J., Chen, M. Y., Chiang, H. S., & Sharma, P. K. (2021). Intelligent Traffic Accident Prediction Model for Internet of Vehicles With Deep Learning Approach. IEEE Transactions on Intelligent Transportation Systems.

[40] Zhang, T., Zhao, Y., Jia, W., & Chen, M. Y. (2021). . IEEE Transactions on Intelligent Transportation Systems

[41] Pech, Martin, Jaroslav Vrchota, and Jiří Bednář. "Predictive maintenance and intelligent sensors in smart factory." *Sensors*21.4 (2021): 1470.

[42] Chehri, Abdellah, and Gwanggil Jeon. "The industrial internet of things: examining how the IIoT will improve the predictive maintenance." *Innovation in medicine and healthcare systems, and multimedia*. Springer, Singapore, 2019. 517-527.

[43] Aksa, Karima, et al. "Developing a web platform for the management of the predictive maintenance in smart factories." *Wireless Personal Communications* 119.2 (2021): 1469-1497.

[44] Cho, Sangje, et al. "A hybrid machine learning approach for predictive maintenance in smart factories of the future." *IFIP International Conference on Advances in Production Management Systems*. Springer, Cham, 2018.

[45] Javed, Abdul Rehman, et al. "Anomaly detection in automated vehicles using multistage attention-based convolutional neural network." *IEEE Transactions on Intelligent Transportation Systems* 22.7 (2020): 4291-4300.

[46] Malawade, Arnav V., et al. "Neuroscience-inspired algorithms for the predictive maintenance of manufacturing systems." *IEEE Transactions on Industrial Informatics* 17.12 (2021): 7980-7990.

[47] Luo, Haidong, et al. "A short-term energy prediction system based on edge computing for smart city." *Future Generation Computer Systems* 101 (2019): 444-457.

[48] Sathishkumar, V. E., et al. "An energy consumption prediction model for smart factory using data mining algorithms." *KIPS Transactions on Software and Data Engineering* 9.5 (2020): 153-160.

[49] Fan, Cheng, et al. "Deep learning-based feature engineering methods for improved building energy prediction." *Applied energy* 240 (2019): 35-45.

[50] Fan, Cheng, et al. "Assessment of deep recurrent neural network-based strategies for short-term building energy predictions." *Applied energy* 236 (2019): 700-710.

[51] Niri, Mona Faraji, et al. "State of power prediction for lithium-ion batteries in electric vehicles via wavelet-Markov load analysis." *IEEE Transactions on Intelligent Transportation Systems* 22.9 (2020): 5833-5848.

[52] Xing, Yang, et al. "Energy oriented driving behavior analysis and personalized prediction of vehicle states with joint time series modeling." *Applied Energy* 261 (2020): 114471.

[53] Chan, C. W., and T. Y. Kam. "A procedure for power consumption estimation of multi-rotor unmanned aerial vehicle." *Journal of Physics: Conference Series*. Vol. 1509. No. 1. IOP Publishing, 2020.

[54] Sadrpour, Amir, Jionghua Jin, and A. Galip Ulsoy. "Mission energy prediction for unmanned ground vehicles using real-time measurements and prior knowledge." *Journal of Field Robotics*30.3 (2013): 399-414.

[55] Büchi, Giacomo, Monica Cugno, and Rebecca Castagnoli. "Smart factory performance and Industry 4.0." *Technological Forecasting and Social Change* 150 (2020): 119790.