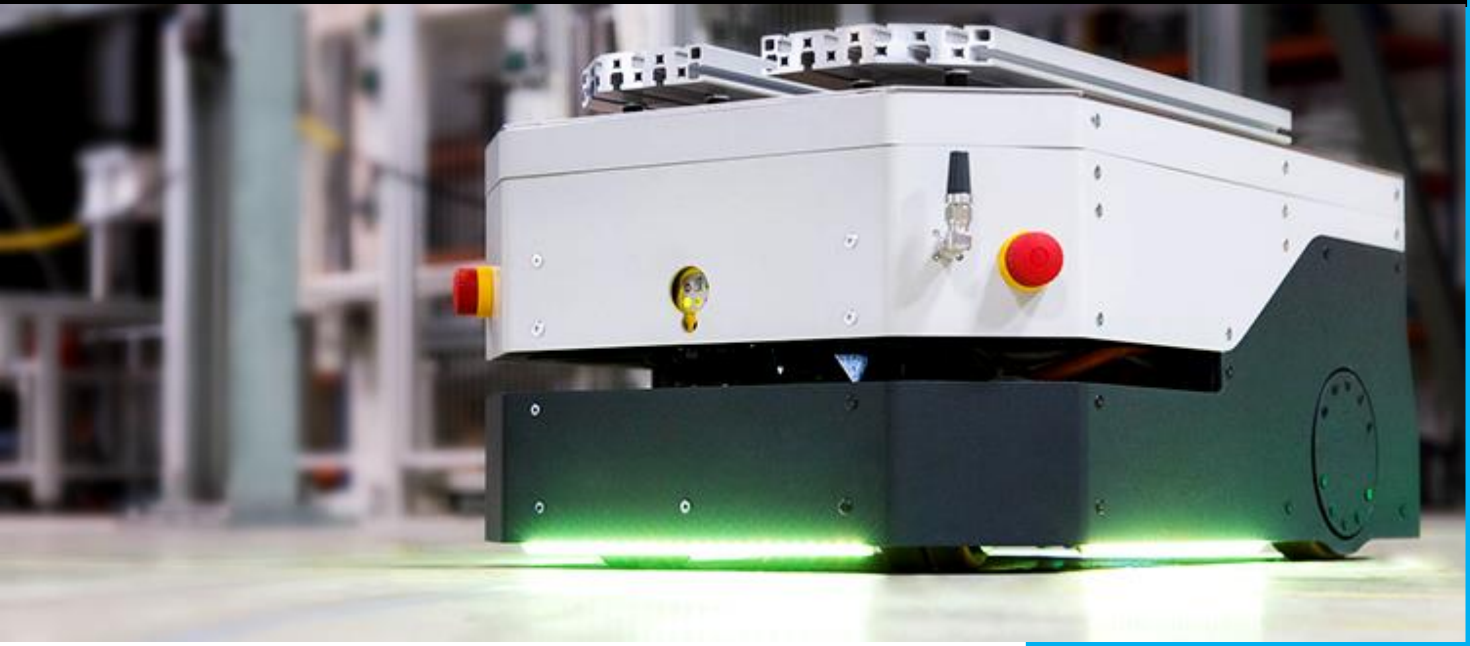
Dynamic AGV routing depending on sensor-based collision avoidance: A case for the light metal & forging industry



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ME54035 – Master Thesis
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Dynamic AGV routing depending on sensor-based collision avoidance: A case for the light metal and forging industry

By

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To fulfil the Master thesis under Theme 2 – Intelligent Control for Transport Technology at the Delft University of Technology

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Preface

The following report is a documentation of the MSc graduation project, titled, "*Dynamic AGV routing depending on sensor-based collision avoidance: A case for the light metal and forging industry*". The graduation project forms a major part of the Mechanical Engineering MSc in the Transport Engineering & Logistics track at the Delft University of Technology. This project has been conducted in association with GLAMA Maschinenbau GmbH, which has been a reliable supplier of innovative solutions for the material handling and production of steel, copper and light metal industry since 1961.

To begin with, I would like to thank ir. Maarten Meijer, who is the Sales Manager at GLAMA Maschinenbau GmbH, for providing me with the opportunity to work on this project. I would also like to mention that I received immense support and valuable inputs from him during the period of this project and I am certain that the industry experience will help me in my future endeavours. Further, I would like to extend my gratitude to Dr. Frederik Schulte, who supervised me throughout this project. I truly appreciate the fact that he was always available at short notice and his valuable support and inputs throughout the research has ensured that I successfully completed the project. Subsequently, I would like to thank Dr. ir. Henk Polinder, who as the chair of my MSc thesis committee has been extremely supportive throughout this period, by ensuring that the content of the work was up to the standards of the university requirements. Lastly, I would also like to thank Santhosh Shetty, for assisting me with the Python code.

Furthermore, I would like to take this opportunity to thank Dr. ir. Yusong Pang and ir. Mark Duinkerken for their guidance and support throughout my Master's study at the Delft University of Technology. Lastly, I would like to mention that the constant support from my family and friends during this period has been invaluable.

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Abstract

AGVs have seen an upward trend in development over the last 60 years. The technology has developed from mechanical bumpers and guided wire navigation to contactless sensors and free navigation technique in the current age. Further, the control on AGVs has moved from central control system to local intelligence which opens up various possibilities with respect to operations as well as applications. The growing trend of AGVs has been due to the sudden growth in digital technology and the ever-increasing demand to reduce human intervention in operations. This has resulted in increased research regarding the implementation of intelligent AGVs in areas of application that have not yet been explored, namely, light metal and forging industry. The major reasons for indulging in autonomous equipment are, increased productivity, reliability and safety since human involvement is either eliminated or largely reduced.

However, a major share of the research about intelligent AGVs has been confined to warehouses and port logistics. Therefore, through this research, another area of application is investigated, namely, the light metal and forging industry, and more specifically, the potroom of an aluminium smelter. Hence, the objective of the research is as stated: *With the introduction of intelligent AGVs, stochastic behaviour needs to be addressed, that is, how would these AGVs react to disturbances created by such random human behaviour and process interference?* Therefore, the research focusses on the routing problem in such situations which are dynamic in nature. The research aims to provide a planning approach in terms of dynamic AGV routing under the assistance of a sensor based system that can detect obstacles.

The dynamic re-routing of AGVs is addressed using a mathematical formulation as well as a graphical representation. In order to solve the problem at hand, the graphical approach is followed and the objective has been simplified for research purposes. It is simplified as: *For instance, if a certain pathway is blocked in the potroom of an aluminium smelter due to such stochastic behaviour, how would the AGV find the optimal path?* An algorithm is devised in order to answer the above research question and further implemented in Python. Various scenarios of stochastic disturbances is analysed and evaluated accordingly. Therefore, this research develops an algorithm and a subsequent model that is implemented using Python which is used to evaluate the routing of an AGV in the presence of stochastic behaviour. It acts as a proof of concept for the problem at hand as it restricts the work to a simplified situation of a single AGV operation.

Although this research uses the case of a light metal and forging industry, the same can be applied to industries with similar challenges such as, cement industry, power generation industry, aerospace, construction and so on. Cement, construction and power generation industry deal with environments similar to the light metal and forging industry. Further, in all these application areas, the use of AGVs for material handling would improve productivity and reliability, while improving safety of operations as well. This research focusses on a simplified situation, however, the basis of this work can be further extended to solve a more detailed real world scenario with a fleet of AGVs, and this can be done by the use of advanced heuristics.

Contents

1 Introduction

AGVs have been under constant development since early 1960s. AGVs have seen a shift from mechanical bumpers to contactless sensors, guided wire navigation to free navigation and emergency stops to obstacle avoidance. The control strategy has also moved from central intelligence to local intelligence, and this equips the AGV to handle situations independently. The following chapter provides a brief overview of the research. To begin with, *section 1.1* provides a short background into AGVs and it addresses the areas of concern for this research. Further, it refers to the current standard of research on which the following work needs to be built upon. Subsequently, *section 1.2* defines the objective of the research and the research question by specifying the gap in literature. Further, *section 1.3 and 1.4* presents the contribution of this research and the approach to be followed in the research respectively. Finally, *section 1.5* presents the structure of the research report.

1.1 Background

An Automated Guided Vehicle (AGV) is a mobile robot used for various purposes in manufacturing, warehouses and inventory management. They are mainly material handling equipment which significantly reduce operational times and the need for humans by introducing automation. Efficient transport and logistics are a significant challenge for any industry. This has led to extensive research and development in the field of AGVs. The major reasons for indulging in autonomous equipment are, increased productivity, reliability and safety since human involvement is either eliminated or largely reduced. AGVs have been under development for a number of decades and they have also been implemented successfully in certain areas of interest, namely, warehouse, ports and factory assembly lines to name a few. In recent years, research in this sector has extended to more challenging environments like underground mining, aerospace and rescue operations. According to Ullrich (2015a), the 60 years of AGV history can be divided into 4 separate eras, and these are distinguished by the technology available and the emotional attitude towards these systems, as seen in *figure 1*.

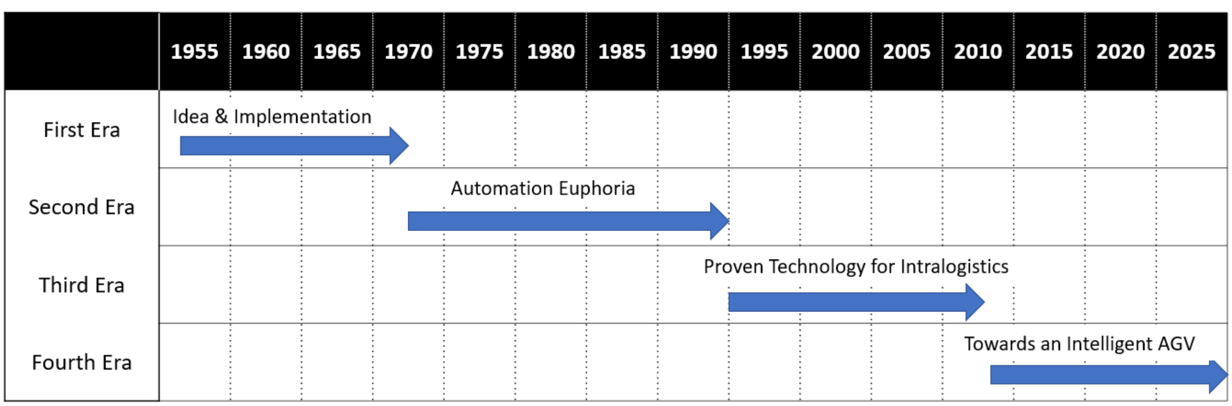

Figure 1 History of AGV Development

The initial era of AGVs began in America in the year 1953 with the idea of replacing drivers on a tractor used for transporting goods. This era was referred to as idea and implementation as per Ullrich (2015a). Although it began in America, it was popular quite quickly in Europe and the first era of AGVs lasted about 20 years. In terms of technology, it was limited to a simple track-guided system with sensors such as mechanical bumpers and emergency switches. Subsequently, inductive guidance were used for navigation purposes. There were also companies that deployed coloured strips on the floor which could be recognized by an optical sensor and hence assist in the navigation of an AGV. Starting 1960s, transistor based electronics were being used and these improved the steering and guidance flexibility of AGVs. The first era of AGVs were restricted to regular factories and warehouses, and the range of vehicles were also restricted to towing vehicles and forklifts.

The second era of AGVs was between the years 1970 and 1990 and it was referred to as automation euphoria as per Ullrich (2015a). This period witnessed the introduction of electronics at a large scale. Microprocessors and PLCs were used for the purpose of positioning and guidance of AGVs and this improved precision. Automatic battery charging systems were introduced for such AGVs and active inductive track guidance became the norm. Infrared and radio signals were being used for data transfer. Material handling processes became increasingly automated and hence they were fully integrated into the production process and most importantly, assembly lines of automotive industries.

The third era of AGVs ranges between mid-1990s and 2010 and it was widely regarded as the proven technology for intralogistics as per Ullrich (2015a). This era witnessed AGVs with electronic guidance and contact-free sensors. The AGVs are controlled by powerful PCs and the AGV contains either an SPS or a microprocessor. Conductive cable guidance has been replaced by free range technologies such as magnetic and laser navigation. Data transfer occurs through WLAN. These developments have ensured faster AGVs in terms of driving, manoeuvring and material handling. It has also meant new areas of application, such as, bulk-storage warehouses, lean production factories, hospitals and so on.

The fourth era of AGVs will not effectively replace the previous one, but build on the developments of the previous era. Few of the functional demands of the future AGVs include, truly autonomous driving, obstacle avoidance, ability to recognize disturbances, adaptability in terms of material handling, traffic and battery usage (Ullrich, 2015b). The technological advancements are due to various reasons such as, new, low-cost and intelligent sensors, as well as developments in the internet domain. It is quite evident that the automotive industry has seen dramatic technological advancements over the years and this is greatly down to the fact that safety is at times the ultimate responsibility of the driver, however, this is not the case in an industry like the aluminium smelter. Certain advancements in the area of mapping, localization, navigation and obstacle avoidance is required to achieve an intelligent AGV. Intelligence in an AGV allows the discussion on dynamic situations during operations as they are equipped to handle such cases, unlike the earlier eras of AGVs.

1.2 Problem statement

It is evident from the literature study conducted that, most of the research in the field of AGVs and most importantly, intelligent AGVs confined its applications to warehouses and port logistics. There is very limited research applicable to significantly harsh environments like, the light metal and forging industry. These industries have unique operating challenges such as extremely dynamic environments, uneven and old flooring, as well as high operating temperatures and magnetic fields. As the operating environment that is under consideration is highly dynamic, it is crucial that the AGV is intelligent enough to react to such dynamics in the environment. The fourth era of AGVs are capable of dealing with dynamic surroundings. There has been some research conducted in how intelligent AGVs would react to dynamic changes with regard to the process involved, that is, customer demands, manufacturing schedules and so on.

However, a crucial aspect of dynamics in the form of human interference to such AGVs has not been studied so far. Intelligent AGVs are expected to work in conjunction with various human operators and this would result in situations wherein the human would interfere in AGV operations. This interference which would result in a passageway being blocked. In the current standard, one can observe that the factory floor has been segregated into areas where the AGV can travel with some traffic rules and few other confined areas for humans. A segregation of this manner would mean reduced flexibility for the AGV and this has known to cause bottlenecks in operation which could last hours before being resolved.

Therefore, it is important to have a workspace where the AGV is allowed to move freely in the presence of human operators, as this results in increased flexibility and productivity as the probability of bottlenecks are reduced. An intelligent AGV can readily deal with the first situation as they are equipped to react dynamically to such obstacles during operation. However, if an entire passageway has been blocked, it would result in disruptions with regard to the tasks to be completed as well. There has been no research conducted with regard to the impact of human stochastic behaviour in terms of blocked passageways on a certain AGV operation. Hence, based on the conditions mentioned, the objective of the research is as stated below: *With the introduction of intelligent AGVs, stochastic behaviour needs to be addressed, that is, how would these AGVs react to disturbances created by such random human behaviour and process interference?* For the purpose of this research the question to be answered is simplified in the following manner: *For instance, if a certain pathway is blocked in the potroom of an aluminium smelter due to such stochastic behaviour, how would the AGV find the optimal path?*

1.3 Research contribution

This research develops an algorithm and a subsequent model implemented using Python which is used to evaluate the routing of an AGV in the presence of stochastic behaviour. The literature review showed that over the years AGV technology has seen significant improvements with respect to sensors and control strategy. This has led to advancements in the field of mapping & localization, navigation, obstacle avoidance and routing.

The introduction of natural navigation solved the problem of fixed AGV routing. Further, the introduction of obstacle avoidance technology allowed an AGV to be able to move around an obstacle and not just come to a stop and wait for the obstacle to be moved. However, there has been limited research into dynamic AGV routing in challenging environments such as the light metal and forging industry and especially under the consideration of stochastic behaviour. Advancements in the field of AGV technology has paved the way for research into dynamic AGV routing due to stochastic behaviour in the specific case of a light metal and forging industry and hence, this work contributes to the scientific domain by filling these research gaps.

This research acts as a proof of concept for the problem at hand as it restricts the work to a simplified situation of a single AGV operation. Although this research uses the case of a light metal and forging industry, the same can be applied to industries with similar challenges such as, cement industry, power generation industry, aerospace, construction and so on. Cement, construction and power generation industry deal with environments similar to the light metal and forging industry. Further, in all these application areas, the use of AGVs for material handling would improve productivity and reliability, while improving safety of operations as well. This research focusses on a simplified situation, however, the basis of this work can be further extended to solve a more detailed real world scenario with a fleet of AGVs, and this can be done by the use of advanced heuristics.

1.4 Approach

The research starts with a literature review of AGV technologies with regard to mapping & localization, navigation, obstacle avoidance and dynamic routing strategies. Then, a brief understanding of the research area, specifically the case of light metal and forging industry in the form of an aluminium smelter is addressed. Furthermore, various technological requirements in order to achieve an intelligent AGV are analysed. Then, an algorithm is developed, followed by an implementation of the code in Python, which helps analyse the dynamic routing of AGVs in the presence of stochastic behaviour. Finally, some experiments are conducted on the model by studying certain scenarios which further helps the research understand the problem at hand and the subsequent results are tabulated.

1.5 Structure of the report

The research report consists of 8 chapters in total and two separate appendices. Initial section of the report focusses on the motivation of the study and some background information. The report begins with a preface and abstract, followed by *Chapter 1*, which is the introduction section of the report. The first section of this chapter provides a brief account of the history, followed by the problem statement, contribution of the research and the approach to be followed. Subsequently, an appropriate literature study is conducted to focus on the aspects of the research and hence identify the research gap. Based on this, the objective of the study and the research question is formulated. This is followed by the *Chapter 2,* which presents the literature review that has been conducted for the purpose of this research. *Chapter 3* focusses on the analysis of requirements to move from the current standard of AGVs to an intelligent AGV, and these include, mapping and localization, navigation and obstacle avoidance. It also introduces the case that is being analysed.

The latter section of the report presents the system and the dynamic routing model. *Chapter 4* presents the model to be analysed. *Chapter 5* presents the dynamic AGV model used in this research, that is, it includes the methodology to be adopted, followed by the description of the algorithm devised and the code which has been implemented for this case. As the algorithm and the code based on it is implemented in Python, the study will analyse the results as per the four different scenarios which are considered in this research. *Chapter 6* presents the results of the model implemented and they are subsequently discussed. The penultimate chapter of the report, *Chapter 7,* provides the conclusion of the research followed by *Chapter 8,* which provides future recommendations based on the work carried out in this particular research. Appendix A of the report presents a research paper format for the study conducted and Appendix B provides the code that has been formulated as part of the research.

2 Literature review

Chapter 1 of the research report focussed on the motivation for the study as well as provided background information about AGV development, research area and the various aspects involved in the study. This chapter documents the literature study conducted during the research that helps identify the gap in the scientific domain and hence formulate the main research question. Further, it also helps the research form an overview of the current standard of AGV technology with respect to mapping & localization, navigation, obstacle avoidance and dynamic routing. *Section 2.1* describes the dynamic routing of AGVs as per the current literature. Further, *section 2.2* presents an overview of the obstacle avoidance aspect of an AGV. Subsequently, *section 2.3* describes the technology of an AGV with respect to navigation in the current literature and finally, *section 2.4* focusses on the mapping and localization aspects of an AGV.

2.1 Dynamic AGV routing

Research about dynamic AGV routing has been mostly relevant to indoor, well-structured warehouses and to port logistics. Most of the scientific study borrows techniques from autonomous driving vehicles which operate on road, however, the safety claim on these vehicles are totally the driver's responsibility. This cannot be the case for an industrial environment as certain safety standards need to be met for the functioning of AGVs capable of dynamically re-routing themselves around obstacles, both static and dynamic. Research as per, Duinkerken, et al., (2006), Ahmadi-Javid & Seddighi (2013), Secchi, et al., (2015), Zhang, et al., (2015) and Vivaldini, et al., (2009) present their work on dynamic or free ranging AGVs around operating environments.

Duinkerken, et al., (2006), presents an algorithm for dynamic free ranging of AGVs. It is based on the microscopic pedestrian behavioural model. The current standard in the research does not offer efficiency and optimal paths. Therefore, the proposed algorithm ensures free ranging trajectory for AGVs while avoiding static obstacles and collisions with other operating AGVs. Ahmadi-Javid & Seddighi (2013), focusses on a routing problem in a supply chain network. The disruptions considered in this case include, production irregularities and vehicles being disrupted randomly. The problem has been formulated as a mixed-integer linear program, followed by a two-stage heuristic based on simulated annealing (Ahmadi-Javid & Seddighi, 2013). In this above case, the disruptions modelled can be classified as process interferences, however, the disruptions due to human interference also needs to be studied and this has not yet been done in the scientific domain.

Similar to the previous work, Zhang, et al., (2015), focuses on capacitated location-routing problem in which depots are stochastically disturbed. This work provides a scenario based mixed-integer programming model in order to optimize the situation and further, a metaheuristic algorithm has been developed. Heuristic results showed that the model was successful enough by balancing the operating and failure costs of such disturbances (Zhang, et al., 2015). Secchi, et al., (2015), proposes an algorithm for dynamic routing of AGVs in automatic warehouses. The routing algorithm in this research is based on the expected dynamic behaviour of the traffic in the warehouse. It has been formulated for a single AGV and it can further be expanded to a fleet of AGVs. The research mainly aims at optimizing the dynamic behaviour of AGV traffic (Secchi, et al., 2015). This research goes a step further by trying to analyse the dynamic disturbances due to traffic, but still fails to address the impact of human events. The importance of human-robot interaction in a work space is provided by Bauer, et al., (2008). As mentioned, it focusses on the importance of collaboration between humans and robots in various applications, namely, space, healthcare, rescue operations and so on. The article stresses on the point that the robots should not just concentrate on the safety aspects while working in an environment with humans involved, but it is also extremely crucial that the focus is also on collaboration between the two. This is important in order to achieve efficiency in operations including safety (Bauer, et al., 2008).

Literature study about dynamic AGV routing strategies has led to the following conclusions:

- Majority of the research has been limited to well-structured indoor warehouses and port logistics.
- Some of the research borrowed techniques from the automotive industry, however this cannot be applied directly to an industry such as light metal and forging.
- There has been research based on production irregularities and vehicle disruptions in ports. However, stochastic human behaviour has not been studied for the application under concern in this research.

2.2 Obstacle avoidance

The other significant factor that needs to be considered is obstacle avoidance. In order to accomplish this, the first step is to select scenarios of interest, followed by a perception system and finally work towards making the perception system reliable and robust. For instance, obstacles can be of varied nature, namely, static and dynamic. Further, they can of different shape, size, colour and texture. Today's AGVs navigate along until the safety sensor has been triggered. This method is sufficient for regulated settings, that is, with trained personnel. However, in situations wherein, pedestrians or even trained personnel being less cautious, such a system would result in the AGV coming to a stop and in some cases, it can result in bottlenecks. An intelligent AGV should be capable of thinking like a human and therefore, adjust to dynamic changes in the operating environment accordingly (Ullrich, 2015b).

Kar, et al., (2016) provides solution for AGV navigation in an unguided (normal) and guided environment with obstacle avoidance strategies. The approach used in this research is two-fold, that is, an artificial potential function can be used to navigate the AGV in an unguided environment. Attractive and repulsive forces approach is useful in avoiding obstacles in an unguided environment. However, the limitations to this approach is the fact that obstacles are assumed to be spherical in nature and the fact that the algorithm fails in the presence of a saddle point.

There has been extensive work done in the use of depth cameras and ultrasonic sensors for obstacle detection by Kar, et al., (2016) and Shaholia (2016). The sensor is capable of detecting the obstacle by setting a threshold distance. Depth camera or ultrasonic sensor detects an obstacle the AGV stops and moves back to the previous node. It then recalculates the optimal path by eliminating the edge where the obstacle is present, and it reiterates until it reaches the destination. This is done using Dijkstra's algorithm (Kar, et al., 2016). As per, Shaholia (2016), localisation of mobile robots using ultrasonic sensors can be done by a genetic algorithm for obstacle avoidance in an indoor semi-structured environment. This method is based on the iterative non-linear filter which matches between the geometric beacons that are visible to the locations of the beacons on the priori map. This helps the vehicle to correct the position and orientation of the vehicle. It is seen from the results that this approach has some drawbacks such as reflection problems and low angular resolution. The author also states that if the obstacle resides between unfavourable angles then it may not be detected. Another approach that uses the same ultrasonic sensors, but different method is using a decision tree method. In this method to avoid obstacles in robots that can freely move around which in this case is the humanoid intelligent robot using ultrasonic sensors. Based upon the readings from the ultrasonic sensors the robot is given three different types of movement: move forward, turn left and turn right. This approach uses a method called as decision tree, which can be interpreted as a flow chart. Ultrasonic sensors are preferred because they do not depend on optical reflectivity, colour or surface finish of the object in front of them. They also possess high repeat sensing accuracy which means it is possible to ignore immediate background objects at long distances since switching hysteresis is low. Their data transfer rate is quick enough to receive data every second and their power consumption is low (Shaholia, 2016).

Further, there has been research about obstacle avoidance using vision sensors by Bostelman, et al., (2005), Bernini, et al., (2014), Pinggera, et al., (2015), Guo, et al., (2006), Mukhtar, et al., (2015) and Bichsel & Borges (2016). These scientific studies present the use of vision based sensors for the purpose of obstacle avoidance. Bostelman, et al., (2005), evaluates the performance of an obstacle detection and segmentation algorithm for an AGV using a 3D real-time range camera. The 3D range camera is based on the Time-Of-Flight (TOF) principle and it has the ability to simultaneously produce high intensity images and range information of targets in indoor environments. However, this is not the most ideal solution for an outdoor environment due to bright lighting conditions on a sunny day (Bostelman, et al., 2005). Bernini, et al., (2014), presents a brief survey about obstacle detection techniques based on stereo vision for ground vehicles. Each obstacle detection system has been classified mainly into 4 categories, namely, probabilistic occupancy map, digital elevation map, scene flow segmentation and geometry based cluster. Pinggera, et al., (2015) present a method for joint detection and localization of distant obstacles using stereo vision system has been presented. This study focusses on passive sensors for the purpose of collision avoidance and path planning. Obstacle detection has been formulated as a statistical hypothesis testing problem and since it operates on image data it provides excellent detection performance and localization accuracy for long distances (Pinggera, et al., 2015).

Guo, et al., (2006), is focused on using simple video cameras as a sensor device and it describes a new machine learning approach for drivable surface detection which automatically combines a set of rectangular features and histogram back projection based image segmentation algorithm. However, this research addresses a scenario wherein, the vehicle stays in a particular area that does not change often. This is not the ideal representation of the problem that is being analysed in this particular research since the operating environment is highly dynamic. Bichsel & Borges (2016), proposes a real-time algorithm for detection of low obstacles by merging 2D and 3D information from stereo imaging. The algorithm proposed in the study relies on three inputs, that is, a dense 3D point cloud from the stereo vision system calculated with Efficient Large-Scale Stereo (ELAS) matching algorithm, a rectified image from one of the cameras and any odometry information. A few assumptions have been made for low obstacles in this study (Bichsel & Borges, 2016).

Mukhtar, et al., (2015), presents a survey about the various on-road vision-based vehicle detection and tracking systems for collision avoidance. Some of the common approaches to detect vehicles using active sensors are, radar and laser or lidar based. Passive sensors include acoustic and optical sensors, like cameras. Optical sensors are known to be more effective than active sensors when it comes to detecting approaching or preceding vehicles. The approach of fusing sensors is expected to have a positive impact in terms of reliability when compared to a single sensor. Active sensors are known to perform well in various weather conditions and in low lighting conditions. Camera sensors lack dynamic range and they have a narrow field of view, further, high resolution cameras lead to increased processing time. In addition to this, development of algorithms is quite challenging in itself as they need to be reliable and robust in all operating conditions (Mukhtar, et al., 2015).

Additionally, the closest scientific work that would be relevant to this particular research is the use of 2D/3D laser scanners for the purpose of obstacle management. There are also cases where laser scanners are used in conjunction with other type of sensors for better results. Hussein, et al., (2016), Hedenberg (2014) and Romero, et al., (2016). Hussein, et al., (2016), presents a fusion system for stereo-vision and laser-rangefinder for outdoor obstacle detection. Due to various limitations of the laser range finder and stereo vision approach, they are combined to obtain better results. In this research, path planning is done using the simulated annealing approach (Hussein, et al., 2016). Hedenberg (2014), aims to identify the objects that are difficult to detect with the existing 2D sensors and hence propose better models for them. Further, to investigate if there are 3D perception systems, like cameras which can be used for this purpose. This study aims to go beyond the previous literature which considers just humans, box or cylindrical type of objects as obstacles in the industrial working environment. A few examples of other important obstacles to consider include, a protruding bar, suspended objects, a ladder and so on. The working environment can usually be classified as, partially observable, stochastic, sequential, dynamic, continuous and multi-agent. The results also show that for all vision sensors, illumination conditions and placement of camera plays a significant role in obstacle detection. The TOF camera and Kinect device are known to get in trouble during daylight or when specular reflections take place (Hedenberg, 2014) (Hedenberg & Astrand, 2008a) (Hedenberg & Astrand, 2008b) (Hedenberg & Astrand, 2011) (Hedenberg & Jan-Baerveldt, 2004).

Romero, et al., (2016), discusses how prior knowledge of the environment can help improve the quality of sensor fusion, hence increasing the performance of an obstacle detection system. The work shows that in regions where sensor behaviour changes within the map, it is possible to automatically select an adequate sensor configuration which improves detection capabilities. The experiments also show that this results in better performance when compared to single sensor configuration (Romero, et al., 2016). The research specific to 2D/3D laser scanners is by, Mendes, et al., (2004). It presents a method of detection and tracking of moving objects using a laser range finder. It has three modules, scan segmentation, object classification and object tracking. The purpose of scan segmentation is to identify segments defined by several lines hence fitting the points that represent each object. In order to achieve this, the process involves grouping all the scan measures into several clusters based on the distance between consecutive measures followed by line fitting of the points of each cluster. Further, the object classification consists of three submodules with different purposes. This research also deals with object tracking by using a Kalman filter while assuming an object model with constant velocity and white noise acceleration, considering different maximum accelerations for each object type (Mendes, et al., 2004).

Finally, Sivakumar & Mangalam (2014), presents the utilization of RADAR technology for obstacle avoidance in automobiles. The proposed vehicle collision avoidance system is an improvement on the current cruise control system seen in automobiles. This system uses radar technology to detect vehicles in its path and hence slow down or stop accordingly. The proposed system is also capable of detecting obstacles like walls, trees, people and so on and hence its applications can be extended (Sivakumar & Mangalam, 2014).

The literature review about obstacle avoidance methodology in AGVs has led to the following conclusions:

- Some of the earlier research focussed on emergency stop options on the AGVs in the event of an obstacle interrupting operations. However, this is known to create bottlenecks and hence reduced productivity.
- There has also been research about the use of vision based sensors for the purpose of obstacle avoidance, but this is suitable for areas of application where the lighting is good and the environment is structured. However, this is not the case in light metal and forging industry wherein the lighting is usually poor and there is a lot of dust in areas of operations, in addition to obstructed view.
- Combination of active sensors, such as, laser scanners or RADAR based scanners and vision sensors is known to be effective in difficult operating environments.

2.3 Navigation

Some of the early technology involved the AGVs following a guided rail system, furthermore, guided wire or painted line solutions on the floor of the working environment were developed as seen in *figure 2*. As technology developed, AGVs started using reflective tapes in the environment in conjunction with a rotating laser for the purpose of navigation. In addition to reflective tapes in the environment, few other methods of navigation that were explored in the earlier days include, odometry or dead-reckoning. An important limitation of dead-reckoning method is its susceptibility to errors due to various reasons, which include, wheel slippage, tire wear and floor quality. Such an error can accumulate over time and it needs to be corrected by using an absolute positioning system. With such a method there is a huge reliance on floor conditions and hence it is not the best approach for navigation (Beliveau, et al., 1996).

As per, Beliveau, et al., (1996), various beacon-based systems have also been developed for navigation purposes. The general idea behind such a method is to have laser, optical or ultra-sound scanners on top of the AGV which is capable of scanning the environment and looking for beacons around the operating environment. The beacons will reflect a signal and by determining the angle of reflection from at least 3 fixed beacons, the pose of the AGV can be determined and hence its heading. This system is very reliable and suitable for a factory environment with flat and smooth floors, wherein the required speed of operation is low and most significantly, the environment is not subjected to constant changes for long periods of time as only this would justify the high installation and maintenance costs of such a system. There are several issues with such a system, namely, limited range of scanning systems, accuracy is majorly dependent on the accuracy with which beacons are installed in the operating environments, beacons can be obstructed due to various reasons and beacons are affected by external conditions, such as, dust and light.

Figure 2 Representation of an AGV under guided navigation

There has been extensive research of autonomous vehicles in the domain concerning underground mining and construction by Roberts, et al., (2000) and Beliveau, Fithian, & Deisenroth, (1996) respectively and this is quite interesting for our research as the operating environment is slightly similar in the fact that it is unpredictable, dynamic and harsh. However, both these studies do not help us solve the problems of the environment under concern. The challenges in this industry include, mapping, navigation and obstacle avoidance. The work by Kar, et al., (2016), Roberts, et al., (2000), Beliveau, et al., (1996) and Schadler, et al., (2014) mainly focusses on navigation of autonomous vehicles. Kar, et al., (2016) proposes the use of Dijkstra's algorithm for navigation planning when there are better alternate and reliable solutions. Roberts, et al., (2000) proposed an absolute and reactive navigation technique for autonomous vehicles and these are known to have multiple limitations from the tests that have been conducted. The research by Beliveau, et al., (1996) concentrates on using laser transmitters with a trivial path planning system and finally, Schadler, et al., (2014) uses 2.5D surfel map and A* algorithm for the purpose of navigation, however, the tests conducted were in an environment completely different to the environment under concern.

The choice of sensors for the purpose of autonomous functioning are also significant. Shaholia, (2016) presents the use of ultrasonic sensors, however, these sensors have limitations with regard to reflection and resolution. Similarly, Sivakumar & Mangalam, (2014) have proposed the use of RADAR, which have multiple limitations in the considered environment for research. Work carried out by Bostelman, et al., (2005), Hussein, et al., (2016), Murphy & Chelberg, (2014) and Pinggera, et al., (2015) suggest the use of vision based sensors for autonomous operations. These sensors are known to have limited field of view, they require certain lighting conditions and they could possibly be blinded by the high temperature environments in various industries. Garcia-Favrot & Parent, (2009) propose a sensor system based on 2D laser scanners, however the tests have been conducted in an environment completely different to the one under concern and 2D scanners are known to be insufficient. Additionally, Fang, et al., (2018), Surmann, et al., (2003), Bosse & Zlot, (2009), Droeschel, et al., (2017) and Schadler, et al., (2014) present a system of 3D laser perception using 2D laser range finders with the help of a spinning platform. This is achieved by using a motor which could possibly fail in the environment under concern.

The tests conducted in all the above research do not consider these factors. Majority of the above research that has been conducted is validated by tests in either indoor office-like environments or outdoor. Both these cases do not reflect the high temperature and altered magnetic field, in addition to dust, unpaved floor and a dynamic environment, which are relevant for the following industries, light metal and forging, cement industry, oil and gas industry, industries dealing with power generation and chemical industries. There has been limited research about autonomous vehicles in the area of research that is our concern, specifically by Duff, et al., (2002), Pradalier, et al., (2008) and Pfrunder, et al., (2017). Duff, et al., (2002), presents the implementation of an autonomous navigation system onto a 30 tonne Load-Haul-Dump (LHD) truck with a 2D laser scanner as the primary sensor. Reactive navigation is known to be more effective and robust than absolute navigation and opportunistic localization has been found to be sufficient to navigate underground (Duff, et al., 2002). Pradalier et al., (2008), presents a study which proves that vision can be used as a primary sensor to locate and load aluminium. This study addresses the challenge of using vision based sensors in an outdoor environment, by using artificial visual fiducials and by creating a novel landmark. The crucible handle is accurately located and tracked by using a particle based filter and it was enhanced further by using a PTZ camera, which increased accuracy and robustness. However, this study has not addressed low lighting conditions and 3D maps (Pradalier, et al., 2008). Pfrunder, et al., (2017), presents a waypoint navigation framework for unmanned ground vehicles. In this research, the authors redesign a 6DOF LiDAR SLAM algorithm to achieve 3D localization on the base map, including real-time vehicle navigation. Low-frequency, high precision SLAM updates is fused with high-frequency, odometric local state estimates from the vehicle. The navigation costmap is a 2D grid which has been computed from a 3D base map. This system has been shown that it works reliably in a dynamic environment (Pfrunder, et al., 2017).

The basic requirements for free ranging navigation include, an AGV, a PC for navigation and calculations and a laser-based scanner. These can be referred to as intelligent or fully autonomous AGVs, and are as seen in *figure 3*. Now, the PC receives position information from the scanner. The PC will then compute and compare the desired and actual trajectories, followed by, computing the information that needs to be sent to the AGV for updating the trajectory and finally this information will be communicated (Beliveau, et al., 1996). Most of today's AGVs are controlled centrally, that is, a central system controls the AGVs in the ground. If the aim is to move towards an intelligent AGV, the system should be able to make decisions and for this to occur, the AGV should have access to all necessary information. Additionally, there should be communication between all the facilities and between AGVs themselves (Ullrich, 2015b).

Figure 3 Representation of free ranging AGVs

The literature review about navigation in AGVs has led to the following conclusions:

- Some of the earlier research focussed on guided navigation for AGVs, either in terms of magnetic wires on the floor, painted flooring or beacons in the operating environment. However, this is known to cause bottlenecks and it is quite expensive in terms of installation and maintenance.
- Further, there has been research about the use of laser sensors and RADAR technology for navigation purposes. But, majority of such studies confined their application areas to structured indoor warehouses or port logistics.
- There has been research which concentrates on SLAM for navigation purposes in addition to 6 DOF LiDAR. Such advancements resulted in more application domains such as underground mining, and this is quite similar to the area of research under concern.
- Fourth generation of AGVs as per Ullrich (2015b), are equipped with free navigation technologies, although they are under operations only in well structured environments.

2.4 Mapping & localization

According to Fairfield (2009), mapping is the problem of collecting and correlating a multitude of sensor measurements into a common map representation. There are two distinct type of map representations, namely, feature-based maps and featureless metric maps. Feature based maps are those which lists the various features and related information of the area being mapped, whereas, featureless metric maps represent just the geometry of the environment. Fairfield (2009) defines localization as using sensor measurements in order to estimate the robot’s pose, that is, position and orientation, relative to a map.

Both mapping and localization are interdependent and they should be able to deal with sensor noise and uncertainty. The current standard for the above working environment consists of an AGV with a 2D scanning solution which following reflective tags installed in the factory. This also means the factory needs to be mapped, which is a tedious process with the technology being employed and various traffic rules need to be defined, which does not always end up giving the most effective and efficient solution. In addition to this, working with reflective tags would mean high installation and maintenance costs.

Hence, use of Simultaneous Localization and Mapping (SLAM) technique is suggested. Cadena, et al., (2016) defines SLAM as simultaneous estimation of the state of the robot equipped with on-board sensors, and the construction of map of the environment which the sensors are perceiving. The importance of mapping is mainly due to two reasons. First, it is used to support other tasks such as path planning or for visualization purposes. Second, it helps in reducing the error of robot state estimation. In earlier cases, localization was calculated based on wheel odometry approach since the vehicle is equipped with optical encoders and a compass module. It uses the incremental number of ticks per revolution from the encoder, transform them into distance by taking into consideration the wheel outer circumference. Then, this is transformed into X and Y coordinates taking into account the current heading of the vehicle. This provides a local localization and in order to have a global localization the GPS module is utilized (Hussein, et al., 2016). If dead-reckoning is used for localization purposes, the robot can drift over time, however, using a map would mean that robot can re-set its localization by referring to the landmarks in the map generated. Hence, SLAM is quite helpful when a prior map is not present and it needs to be built.

The emergence of SLAM is due to the increased functionality of AGVs in indoor applications. Indoor applications rule out the possibility of using GPS to cater for the localization errors. Further, SLAM presents a valuable alternative for user built maps and proves that AGV operation is possible without ad-hoc localization infrastructure (Cadena, et al., 2016). SLAM can be applied for both 2D and 3D motion and it includes the following, landmark extraction, data association, state estimation, state update and landmark update (Riisgaard & Blas, 2003). Riisgaard & Blas (2003) also stresses on the importance of considering the hardware on the AGV for implementing SLAM. One of the important parameters to consider is the odometry performance of the robot. This measures how well the robot can estimate its own position with the help of wheel rotation. The range measurement device can be laser scanners, sonar or vision. Laser scanners are the most widely used range measurement as they are precise, efficient and it requires very little computation. Sonar has comparatively bad measurements and their advantages lie in underwater operation. Vision has been traditionally intensive when it comes to computations and they are quite error prone as it depends completely on light. However, in recent years there have been developments in this field and with advances in algorithms, computation power is becoming less of a concern.

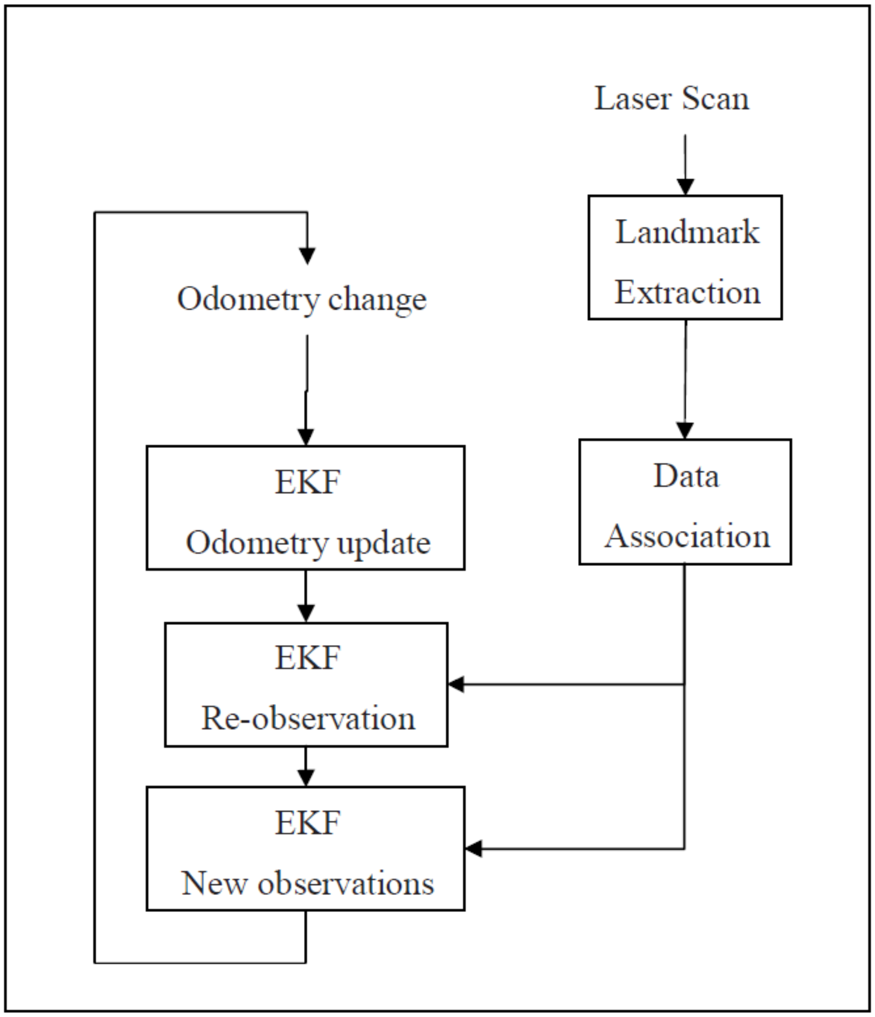

Figure 4 Overview of the SLAM process

As per Riisgaard & Blas (2003), the objective of the SLAM process is to use the environment to update the position of the robot. As the odometry of the robot is not flawless, laser scanners are used to correct the position of the robot. This is done by extracting landmarks from the environment and observing the robot movement. An extended Kalman filter (EKF) is the heart of the SLAM process. It updates the position of the robot based on landmarks. When the odometry changes because the robot moves, the uncertainty with respect to new position is updated in the EKF using odometry update. This is followed by the landmarks being extracted from the environment with regard to the new position and then the robot tries to associate these landmarks to the ones previously seen. Re-observed landmarks are used to update the position in the EKF and the landmarks which were not seen previously will be added to the EKF. The basic algorithm is as seen in *figure 4*.

Landmarks are very important to SLAM. These are features which can be easily re-observed and distinguished from the environment. Robots use landmarks to localize itself. The landmarks should therefore be visible for detection from different angles and positions. Few other important pointers to consider for landmarks are, landmarks should be distinct from one another, they should be plentiful in the environment and they should be stationary. Once the landmarks have been decided upon, a robot should be able to reliably extract these landmarks from the sensory inputs. The issue with data association is to reliably match observed landmarks with one another. Some of the issues that arise with data association are, landmarks might not be re-observable in every time step, a landmark might be observed at one point, but it might not be recognized as one at a later stage and one can wrongly associate a landmark to a previously seen landmark (Riisgaard & Blas, 2003).

Additionally, as per, Riisgaard & Blas (2003), the Extended Kalman Filter (EKF) determines the state (position) of the robot from odometry data and landmark observations. After landmark extraction and data association, SLAM process includes the following steps, update the current state estimate using odometry data, update estimated state from re-observing landmarks and add new landmarks to the current state. The first step of updating the current state estimate with the help of odometry data is quite simple as it is just an addition of the controls of the robot to the old state estimate. In the second step, the re-observed landmarks are considered and the uncertainty of each observed landmark is also updated in order to reflect the changes. In the third step, new landmarks are added to the robot map using the information about the current position and by adding information about the relationship between the new landmark and old landmarks. Further, Garcia-Fervot & Parent (2009) defines SLAM approach as the duality between creating consistent maps and localizing itself within this map. It is important to note that more the information the map has about the surrounding, it works better. An important conclusion to be drawn from this is the fact that having a sensor monitoring the direction opposite to the movement works best. The algorithm proposed in this paper is suitable to generate an accurate map over 100m of our vehicle in order to extract various relevant information. For loss of localization, open spaces is the major bottleneck. Hence, the robustness of the algorithm is directly proportional to the laser scan range and the field of view. The other possible source of error is moving objects. The field of view is quite significant when choosing a laser scanner and 270 degrees is sufficient to deal with (Garcia-Favrot & Parent, 2009).

There has been numerous work based on this idea of using 2D scanners in order to project a 3D map of the operating environment. Fang, et al., (2018) delivers a real-time and low-cost 3D perception and reconstruction system suitable for autonomous navigation and large-scale environment reconstruction. This particular 3D mapping system is based on a 2D planar laser scanner which rotates due to the help of a motor and is suitable for continuous mapping. The 3D scanner developed using these methods is tested successfully in an indoor and office-like environment (Fang, et al., 2018). Further, research on a 2D laser range finder which has been mounted on a spinning platform to generate a 3D point cloud and it spins about the centre scan line of the sensor has been conducted by Bosse & Zlot (2009). Due to symmetry, one half of a spin revolution is enough to cover the entire space that is visible to the sensor and hence, it tries to match the scan. The spinning platform is less sensitive to timing errors which can arise with complex motion. Experiments have been conducted on a flat, paved surface as well as an off-road terrain and they have been relatively successful (Bosse & Zlot, 2009).

Throughout the years, mapping technology has seen improvements and the most advanced stage is the use of 3D laser scanners for the purpose of mapping the operating environment. Use of such technology is mostly warranted when the operations to be handled are indoor, since, the use of GPS becomes void. Subsequently, SLAM can be used in various ways to map the surrounding as the algorithms are various and their efficiency depends on numerous factors. Surmann, et al., (2003), presents a study which digitizes indoor environments at a relatively fast pace reliably without any intervention and solves the SLAM problem. The 3D laser range finder acquires 3D scans at given poses and an ICP algorithm is used to register the 3D scans and localize the robot. However, in this research, robot self-localization has not been addressed (Surmann, et al., 2003). Although the research by, Fang, et al., (2018), Bosse & Zlot (2009) and Surmann, et al., (2003) have provided exceptional results, the application areas are mostly confined to indoor environment and areas where there are no harsh operating conditions, such as, high temperatures and static magnetic fields.

The literature review about mapping & localization in AGVs has led to the following conclusions:

- There has been research about the use of SLAM methodology for the purpose of mapping and localization and this is known to be effective. However, it has not been tested in the operating environment under concern in this research.
- The use of 2D scanners with modifications to project 3D images has also been studied and this is helpful as 3D imagery is known to be more representative of the operating environment.
- Mapping technology has seen significant improvements and the most advanced stage is the use of 3D laser scanners for the purpose of mapping the operating environment. However, the use of such technology is mostly warranted when the operations to be handled are indoor, since, the use of GPS becomes void.

3 System description

The previous chapter of the report helped identify the research gap, both in terms of the overall objective as well as the various aspects involved in the study, such as, dynamic routing strategies, obstacle avoidance, navigation and mapping & localization. This chapter focusses on the various physical elements involved in the research. To begin with, *section 3.1* presents a short description about the requirements of an intelligent AGV. This is then followed by *section 3.2* which presents a relatively detailed description of the intelligent AGV used at GLAMA Maschinenbau GmbH for the purpose of proof of concept. The final *section 3.3* discusses the case at hand, that is the aluminium smelter.

3.1 Intelligent AGVs

It is important to understand the difference between a standard AGV and an intelligent AGV as it has a direct impact on the manner in which operations are performed. The fundamental attribute of an intelligent AGV is its ability to make decisions on its own, with reference to navigation, obstacle management and task management. On the other hand, a standard AGV basically obeys simple orders from a higher level of control structure and they tend to be constrained in terms of navigation and obstacle management since they do not have the ability to adapt to changes or disruptions in the operating environment. An intelligent AGV is known to be a lot more sophisticated and equipped with sensors and powerful on-board computers which assist the AGV in decision making and adaptability. For a fully autonomous system, the vehicle should be aware of the following:

- Where am I? This is answered through localization of the AGV.
- Where am I going? This is answered through path planning technique employed by the AGV.
- How do I get there? This is answered through navigation strategy adopted by the AGV.

An intelligent AGV should be equipped with software that can generate maps of the environment either on-site or through pre-loaded drawings. It uses the sophisticated set of sensors and scanners to then localize itself and then plan a path efficiently. Once the path has been defined, it should be intelligent enough to navigate itself to the destination from the point of origin and perform assigned tasks. While navigating through the operating environment, the AGV should be equipped enough to not just stop when an obstacle occurs, but also be able to dynamically navigate around it, in order to ensure high productivity and reliability.

Finally, another vital aspect of an intelligent AGV is obstacle management. An intelligent AGV should be capable of adapting to disruptions in the operating environment by dynamically re-routing itself around obstacle. A basic illustration of a situation wherein an intelligent AGV is faced with an obstacle can be as seen in *figure 5*. The origin and destination points are defined by the yellow and blue circles respectively. Before the operation begins, the AGV will generate a path between the two and this is depicted by the black line. The AGV starts its operation and the black circle indicates its current position. At this moment, the sensors on the AGV will detect the obstacle in front of it and will react to it by re-routing itself around the obstacle instead of coming to an emergency stop and waiting for the obstacle to be cleared. The dotted red line indicates the new path taken by the AGV to reach its destination.

Further, as per literature and subsequent analysis, various attributes of an AGV over the years is as tabulated in *table 1*. Based on the *table 1* and market research, GLAMA Maschinenbau GmbH decided to use the incubed IT smart shuttles. This was done in order for the shuttle to act as a proof of concept, not just for GLAMA Maschinenbau GmbH, but also for its various clients. The shuttle was tested for a period of time, albeit in indoor office-like operating conditions, with the intention of modifying it further based on the requirements of the smelter and then testing it in that particular environment.

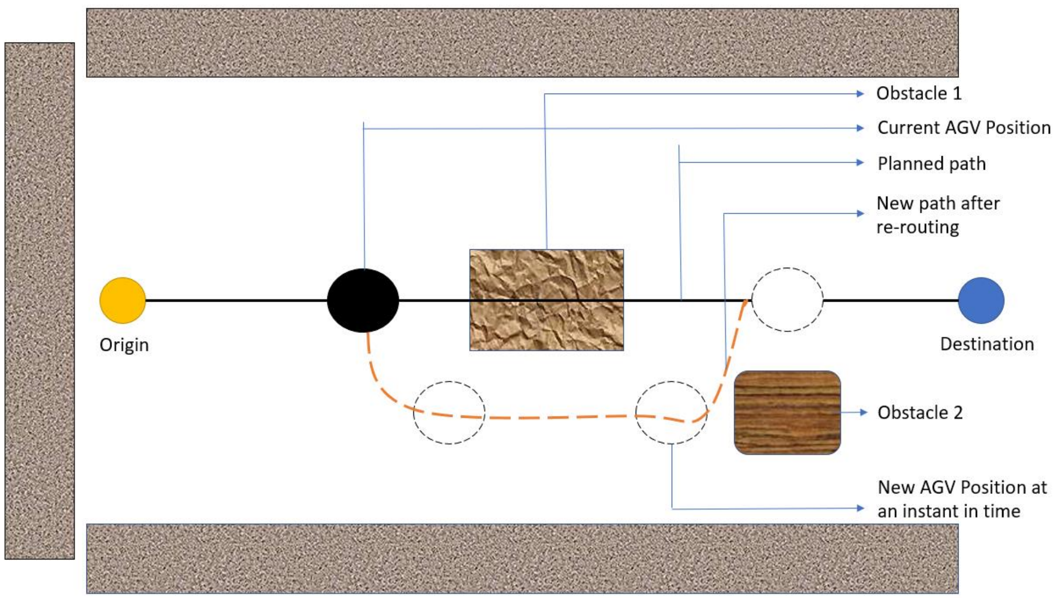

Figure 2 Illustration of Obstacle Management

Table 1 Technological roadmap of an AGV

Mapping and Localization	Navigation	Obstacle Avoidance
Global Positioning System (GPS)	Artificial potential function & Dijkstra's algorithm	Attractive & Repulsive force approach
Global Navigation Satellite System (GNSS)	Reactive navigation	Ultrasonic sensors
Odometry	Simultaneous Localization & Mapping (SLAM)	RADAR
Inertial Navigation System (INS)		Vision sensors
Beacons		2D laser scanners
Simultaneous Localization & Mapping (SLAM)		3D laser scanners

3.2 incubed IT shuttle

This section of the report provides a brief overview of the important concepts with regard to the incubedIT platform. Smart shuttles produced by incubedIT are known for their intelligent and autonomous navigation, as seen in *figure 6*. A decision was made at GLAMA Maschinenbau GmbH to use the shuttle to perform some simple tests. The shuttle was tested for a few days in the office space and it responded quite well, hence proving the concept of autonomous navigation of such a shuttle, including automatic re-routing around obstacles.

The shuttle is equipped with numerous sensors which assist in the process of navigation and localization and these include, wheel odometry sensors, inertial measurement unit, 2D laser scanners mounted on the front, rear and on the sides of the shuttle, as well as a few optional sensors. The laser scanners which are mounted on the shuttle provides dynamic safety fields (incubed IT System Documentation). When an obstacle is detected in that particular field, an emergency stop will be activated. These safety fields should be defined based on the shuttle's linear speed. The shuttle developed by incubed IT features a differential drive with 2 DC motors, hence it is capable of turning on the spot. The shuttle has a maximum forward velocity of 2m/s and a maximum reverse velocity of 0.3m/s (incubed IT System Documentation). The shuttle software is capable of autonomous and intelligent behaviour. It is capable of controlling the shuttle hardware functionality, localization, path planning, dynamic navigation which includes, obstacle avoidance and path re-routing and finally, the process of executing orders autonomously.

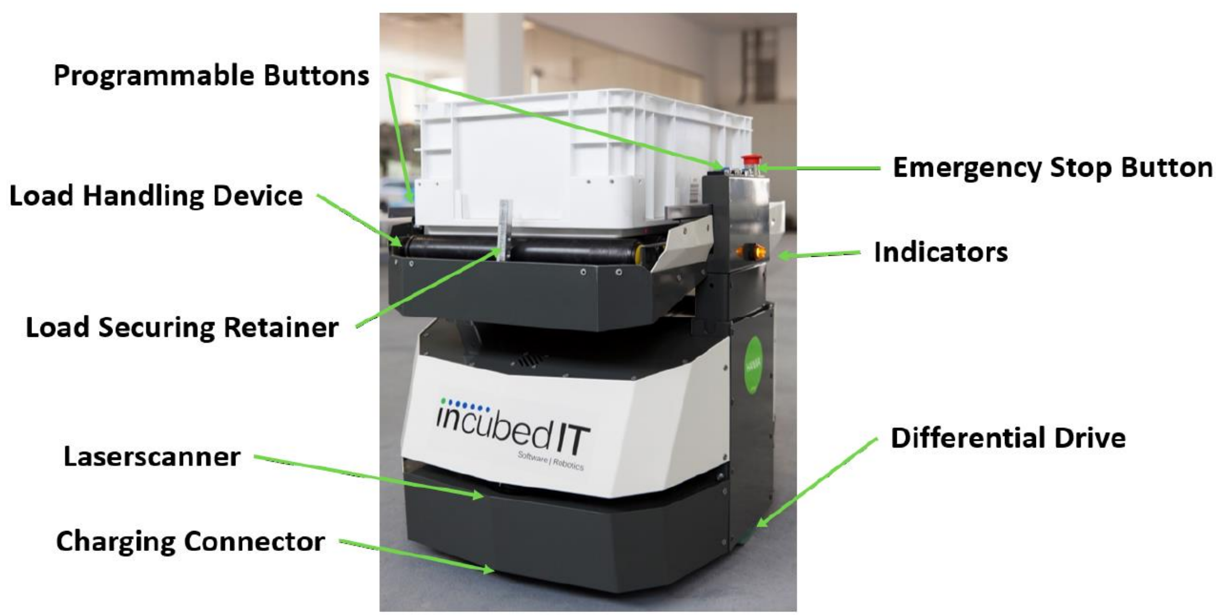

Figure 3 incubed IT smart shuttle and its components

3.3 Case description: Aluminium smelter

The research focusses on the light metal and forging industry, specifically, an aluminium smelter. The production of primary aluminium is done by two independent energy-intensive processes in order to transform the ore, bauxite, to aluminium by electrolytic reduction. First process is referred to as the Bayer process where thermochemical digestion is used to convert bauxite to alumina. This is followed by the Hall-Heroult process, which uses electrolytic reduction to produce molten aluminium (Kvande, 2014). A smelter has three important blocks, namely, the carbon area, potline and the castroom, as shown in the *figure 7*. The manufacturing of carbon anodes are done in the carbon area, production of liquid aluminium takes place in the potline and in the castroom the liquid metal is poured into moulds.

Figure 4 Aluminium smelter layout

Further, the research specifically focusses on the potline. The area housing the cell lines are referred to as a potline or potroom. In large smelters, these potrooms are more than 1km in length, 50m wide and about 20m high. The potroom is usually equipped with close to 100 electrolytic cells, each of them being 10 to 15m in height. The design of potrooms in various smelters around the world is quite similar, as seen in *figure 8* (Kvande, 2014). The movement of materials inside the smelter complex is done inside covered passageway or on external roads. The internal passageways are mainly asphalt pavement. The potroom floor is concrete and these surfaces have wear, cracks and some chipping. External roads are asphalt pavement. Materials are also being transported inside potrooms where there is a presence of magnetic field, and this can be up to 400 Gauss in some areas. The magnetic field is stronger in the axis along the potroom and close to the pot. The passageway has limited lighting and they are relatively dusty. A Wi-Fi network is available inside the potroom. The facility is also equipped with dedicated pedestrian walkways and they are separated by concrete walls. In the potroom area, the mobile equipment circulate amongst plant operating personnel and pedestrian-vehicle interface is a crucial factor to be considered in AGV operations.

Figure 5 A modern potroom in an aluminium smelter (Kvande, 2014)

Furthermore, the aluminium smelting process is far from being fully automated. Cranes are moved back and forth for transportation and changing of anodes and for removing aluminium from the cells. Large vehicles are used for transporting the metal out of the potline building and they bring the metal to the cast house for further treatment and casting of aluminium products. There is a very high ambient temperature in the potroom due to the heat emitted from the cells and therefore, heat exposure is a serious problem. It is important for the operators have a strict regime to avoid heat stress and exhaustion. Additionally, the high electric current flowing through each cell creates a strong static magnetic field (Kvande & Drablos, 2014).

4 Model description

The following chapter is built upon the previous sections of the research, more specifically based on the characteristics of an intelligent AGV and the operating conditions to be studied. The importance of an intelligent AGV has been addressed and obstacle avoidance plays a major role. This is because it enables the AGV to be able to dynamically react to disturbances in the operating environment and not come to an abrupt stop. Hence, under the assumption of an intelligent AGV, the remainder of the research is conducted. *Section 4.1* describes a mathematical approach to solving dynamic routing problems and an example formulation has been presented. *Section 4.2* focusses on the approach to be followed in this study, that is, a graphical approach. Therefore, the final section presents the case at hand in the form of a graph with nodes and edges. It includes the representations and the fact that the problem has been simplified for the purpose of this research. It also addresses the various assumptions considered and the problem is hence solved accordingly.

4.1 Dynamic routing formulation

Dynamic situations in vehicle routing can arise from various situations, namely, in the form of customer arrivals, demand expectations, travel times and so on. A varied range of techniques have been developed over the years to report the dynamic routing problems. Dynamic methods can generally be categorized as non-anticipative and anticipative. Non-anticipative methods are more in line with dynamic vehicle routing as they react to updates in the data. They are normally a direct adaptation from static methods such as, integer programming, neighbourhood search, tabu search, genetic algorithm and so on. One such method, that is integer programming-based formulation for time windows has been discussed. The article, *the vehicle routing problem with time windows and temporal dependencies*, by Dohn, Rasmussen, & Larsen (2011), presents a mathematical formulation for vehicle routing with time windows and temporal dependencies. To begin with, a mixed integer programming formulation is presented, followed by a time indexed formulation.

The objective with a traditional vehicle routing problem with time windows is to find the optimal set of routes, optimal being the cheapest, for a set C of n customers. The fleet of vehicles are denoted as V, and they are located in a central depot, which has a start depot location, 0, and an end depot location, n +1. All of these above variables form a set, N. The capacity of each vehicle is given by q and each customer i has a demand, d_i. The time window for service is given by $[\alpha_i, \beta_i]$, where, α_i represents the earliest service time and β_i represents the latest possible time of service. Similarly, $[\alpha_0, \beta_0]$, represents the scheduling horizon, where, α_0, represents start time of vehicles from the depot and, β_0, represents the latest return time of the vehicle to the end depot. τ_{ij} gives the total travel time between two points i and j, and this includes the service time. Cost of travel between these two points is given by c_{ij}. An assumption is made such that, q, d_i, α_i, β_i and c_{ij} are nonnegative integers. Further, it is also assumed that τ_{ij} is a positive integer. These variables, in addition to a few others are further summarized in the following table for easier representation.

Table 2 Variables used in the formulation

Variable	Description
C	Set of n customers
V	Set of vehicles
q	Capacity of each vehicle
d_i	Customer demand
α_i	Earliest service time
β_i	Latest possible service time
α_0	Start time of vehicles from the depot
β_0	Latest return time of vehicles to the end depot
τ_{ij}	Total travel time between i and j
c_{ij}	Cost of travel between i and j
x_{ijk}	Decision variable for routing
s_{ik}	Decision variable for servicing

The mathematical formulation is as follows, wherein, x_{ijk} is a binary variable and if it is equal to 1, it means that vehicle k drives directly from customer i to customer j. Further, s_{ik} is a continuous variable, and is defined as the start time for service at customer i, if serviced by vehicle k. The model also fixes, s0k = α_0 and $s_{n+1,k} = \beta_0$.

$$\min \sum_{i\in N} \sum_{j\in N} \sum_{k\in N} c_{ij} x_{ijk} \qquad (1)$$

$$\sum_{j\in N: j\neq i} \sum_{k\in V} x_{ijk} = 1 \qquad \forall i \in C \qquad (2)$$

$$\sum_{i\in C} d_i \sum_{j\in N} x_{ijk} \leq q \qquad \forall k \in V \qquad (3)$$

$$\sum_{j\in N} x_{0jk} = 1 \qquad \forall k \in V \qquad (4)$$

$$\sum_{i\in N} x_{ihk} - \sum_{j\in N} x_{hjk} = 0 \qquad \forall h \in C, \forall k \in V \qquad (5)$$

$$\sum_{i\in N} x_{i,n+1,k} = 1 \qquad \forall k \in V \qquad (6)$$

$$s_{ik} + \tau_{ij} - M(1 - x_{ijk}) \leq s_{jk} \qquad \forall i, j \in N, \forall k \in V \qquad (7)$$

$$\alpha_i \sum_{j\in N} x_{ijk} \leq s_{ik} \leq \beta_i \sum_{j\in N} x_{ijk} \qquad \forall i \in C, \forall k \in V \qquad (8)$$

$$x_{ijk} \in \{0,1\} \qquad \forall i, j \in N, \forall k \in V \qquad (9)$$

The objective here is to minimize the total costs of travel over the edges and this is represented by the objective function (1). The objective function is further subject to the constraints (2) – (9). (2) ensures that all the customers are visited by exactly one vehicle and (3) indicates the capacity constraints. (4), (5) and (6) ensure that the routes are not segmented, that is, a vehicle which arrives at a customer also leaves the customer eventually. (7) ensures that there is enough time for travel between the visits when it has to serve two customers between points i and j. Constraint (8) is present to ensure that the time windows are obeyed, additionally it also ensures that $s_{ik} = 0$ when the vehicle k does not visit customer i. (9) represents the integral constraints for the model.

Further, temporal dependencies can be expressed by generalized precedence constraints. A new parameter δ_{ij} is introduced at this stage and it denotes the minimum difference in time from customer i to j. The set Δ defines the customer pairs (i,j) for which temporal dependency exists. The generalized precedence constraints are formulated as,

$$\sum_{k \in V} s_{ik} + \delta_{ij} \leq \sum_{k \in V} s_{jk} \quad \forall (i, j) \in \Delta \qquad (10)$$

4.2 Graphical model: Aluminium potroom

The following AGV model aims at replicating the situation in the potroom at an aluminium smelter. The need for automation in aluminium smelters is justified as majority of the operations are still conducted manually. If automated, the operations can be more productive, reliable, effective and efficient. Another important reason for automation is the fact that humans are exposed to dangerous working environment which could prove to be fatal for their health. The initial part of the research concentrated the shift from the current standard of AGVs to a significantly more intelligent AGV for operations in the aluminium smelter, that is, a naturally navigating technology coupled with 3D safety laser scanners for obstacle avoidance.

When there is more than one AGV sharing the workspace and involved in operations, the process of motion planning and subsequent avoidance of obstacles becomes challenging. In most cases, this leads to bottlenecks. Therefore, AGVs should be able to coordinate with one another to achieve the final outcome, which could either be minimum time or distance, depending on the application. Another reason for deadlocks is the presence of narrow and/or blocked passageways. There are various methods known to solve this kind of a situation. The potroom can be represented as a graph with nodes and edges. The nodes in the graph indicate the start and end points, including the areas where the AGV is expected to stop. The edges represent the free space and where the AGV is expected to travel in order to reach its destination. *Figure 9* presents a brief graphical network representation of the potroom logistics in an aluminium smelter. It represents a potroom with 10 cells, indicated by rectangular blocks. Black coloured oval nodes represent the AGVs available for operation, which are 3 in this case. Additionally, an automated overhead crane has been represented by a blue coloured oval node as it is involved in material handling operations in the potroom as well. Various nodes in the graph are represented by yellow circled nodes and these are connected to one another to form a layout through blue coloured edges.

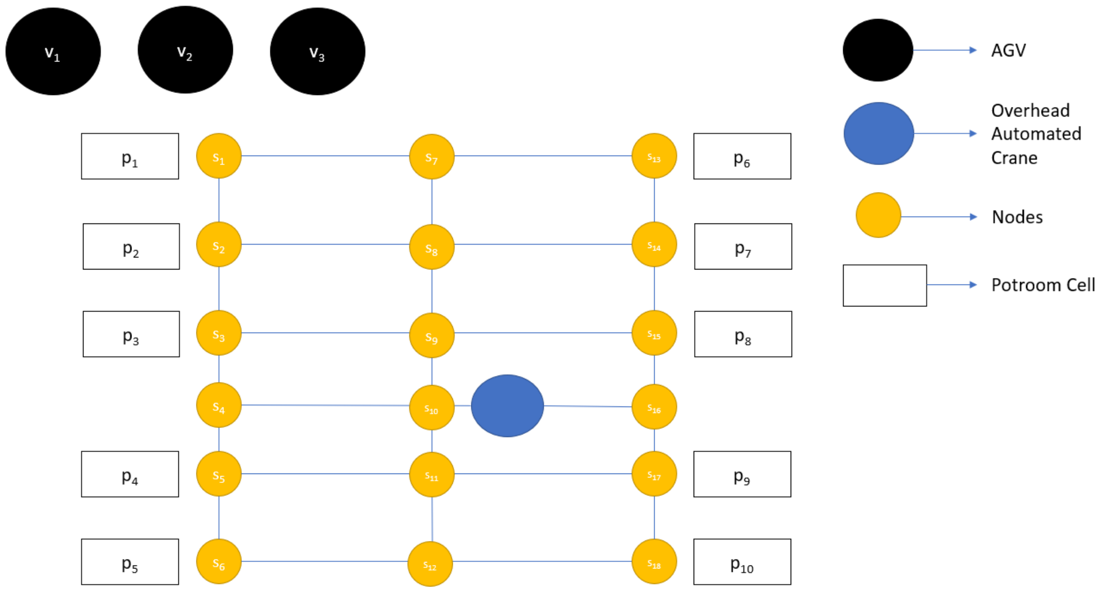

Figure 6 Graphical network representation of potroom logistics

The following assumptions are necessary to be made about the AGV and the graphical representation:

- The designated graph is known to be finite, connected and it represents free space.
- The graph is undirected, that is, a path exists from vertex a to b and vice versa.
- The starting and end positions of the AGV are represented in the graph and are well known.
- AGV can only stop at predefined loading or unloading stations.
- AGV should be able to reach their destination through various paths.
- Operation schedule is known.
- Sensor information is assumed to be available to the AGV.

Furthermore, in this research, for analysis purpose, the graphical representation used will be reduced to a more concise version as shown in *figure 10*. It is a simple and scaled down graphical representation of the potroom in an Aluminium smelter with the help of nodes and edges. This is due to the fact that the research aims to provide a proof of concept, which can be built upon further to extend it to a more detailed model with metaheuristics. Therefore, in this research, only one AGV is considered, and the black oval represents the AGV available for operation. The number of pot cells have been reduced to 5 and they are referred to as p_1, p_2, p_3, p_4 and p_5. Another important consideration made is the fact that the initial point as well as the delivery point of the AGV are the same, denoted by node s_1. The nodes s_2 to s_6 represent the pot cells and denote the nodes to be served by the AGV. Since, the aim of the research is to investigate the influence of stochastic human behaviour in the manner of blocked passageways, *figure 11* depicts one such situation, where the edge 2-3 is blocked.

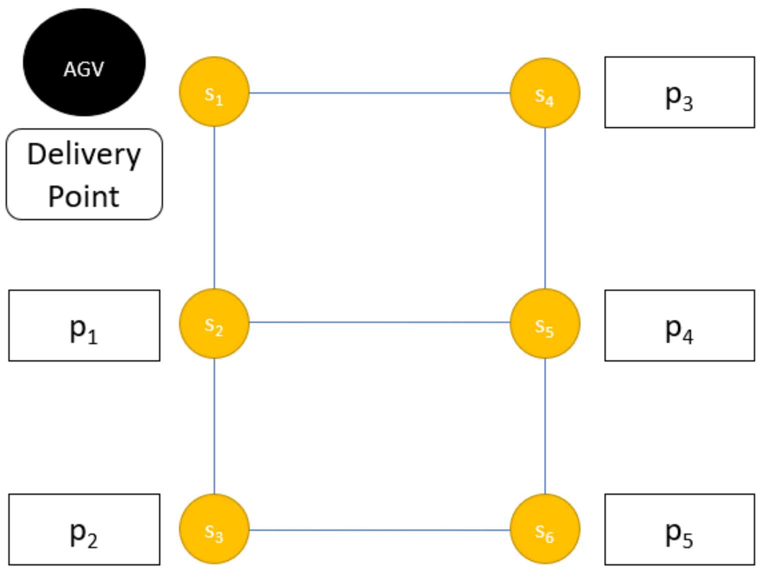

Figure 7 Graphical representation of normal potroom logistics

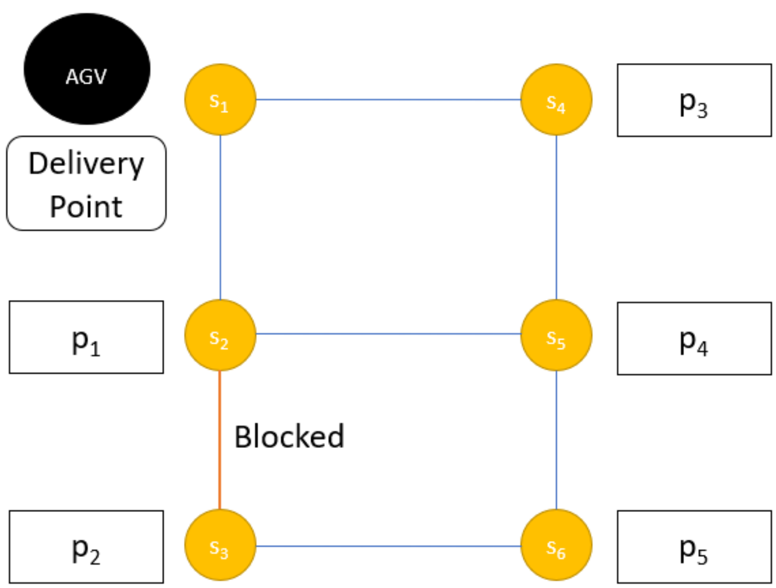

Figure 8 Graphical representation of potroom logistics with blocked path

5 Dynamic routing model

The following chapter focusses on the solution approach, which is in terms of a model. In this research, a simple algorithm has been devised to analyse the dynamic routing behaviour of an intelligent AGV in the potroom of an aluminium smelter. This is further built into a model and it represents the proof of concept for such a case. Therefore, this work can be further extended to a more detailed and expansive model, as well as to other applications. The chapter is organized as follows, *section 5.1* describes the methodology adopted to answer the research question. *Section 5.2* introduces the algorithm employed to solve the problem at hand and finally, *section 5.3* presents a brief description of the code.

5.1 Methodology

The objective of the research is to examine the routing behaviour of an intelligent AGV when faced with stochastic human disturbance, in the form of blocked passageways. In this research, an algorithm based approach has been chosen to solve the problem. The other straightforward option for such a problem would be a mathematical formulation. However, a formulation has its limitations in the fact that the constraints that need to be defined are not always an accurate representation of the real world situation and models with numerous variables would mean large computation time for the solver. An algorithm based solution tends to portray a more accurate version of the real world situation and such a model can always be extended to a more detailed and advanced metaheuristics based model in the future.

Since this model acts as the proof of concept for this case, the problem at hand has been simplified to a single AGV routing problem serving 5 potroom cells in an aluminium smelter. For such a case, an algorithm has been formulated. It includes the stochastic human behaviour in the form of blocked passageways. This has been modelled in the form of a probability distribution for one of the edges being blocked. Further, based on the algorithm that has been formulated, a Python code has been written. The code helps us evaluate the research problem at hand in the most simplest manner and it is a proof of concept which can further be extended to a more detailed model. A detailed model with advanced metaheuristics would lead to a better understanding of the functioning of an intelligent AGV and potroom logistics.

5.2 Algorithm

In this particular section, the algorithm used to derive the optimal path in terms of minimum time taken to complete all the tasks has been described, as well as the optimal path when one of the edges has been randomly blocked. The following assumptions have been made about the model,

- At the start of the operation there is no occurrence of an event.
- Distance values between the nodes are fed into the AGV, which is then translated into an array of task costs.
- The same applies when an edge has been blocked, since it is fair to make an assumption that the entire factory is connected, and information can be shared.

With regard to the model built, the AGV is located at its initial position s_1, which also happens to correspond to the delivery point. In this model, the AGV will serve each and every cell in the potroom, further delivering it at the assigned node. The model aims to achieve the optimal path for such a case by minimizing the time taken to serve all the pots. In addition to this, an event-based disturbance is added to the model, wherein, the model considers one of the paths to be inaccessible based on a probability distribution. This is an indication of one of the paths being blocked due to stochastic human disturbances at the potroom. For this additional case, the model aims to achieve the optimal path.

The basic algorithm can be seen in *figure 12*. It begins with creating the layout of operation through a graphical representation. This is then followed by an optimization process of the sequence of tasks to be performed and the routing decision. Finally, in order to understand the behaviour of the model in the presence of stochastic human behaviour, an event in the form of one of the paths being blocked is generated, and the process repeats with the aim being optimization.

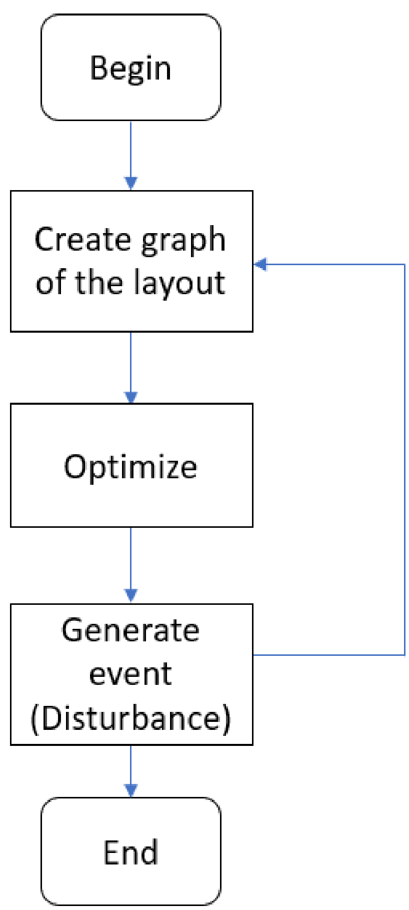

Figure 9 Basic algorithm

Furthermore, a detailed description of the algorithm can be seen in *figure 13*. The first step in the process is generation of the network of operation in the manner of a graph with nodes and edges. Subsequently, costs with regard to assignment of tasks and routing needs to be initialized. The model then optimizes the sequence of tasks to be performed. This is followed by the model generating all the possible paths from the initial point of the AGV to the pot cell which needs to be served. With the help of this information, the model can optimize the route that needs to be chosen.

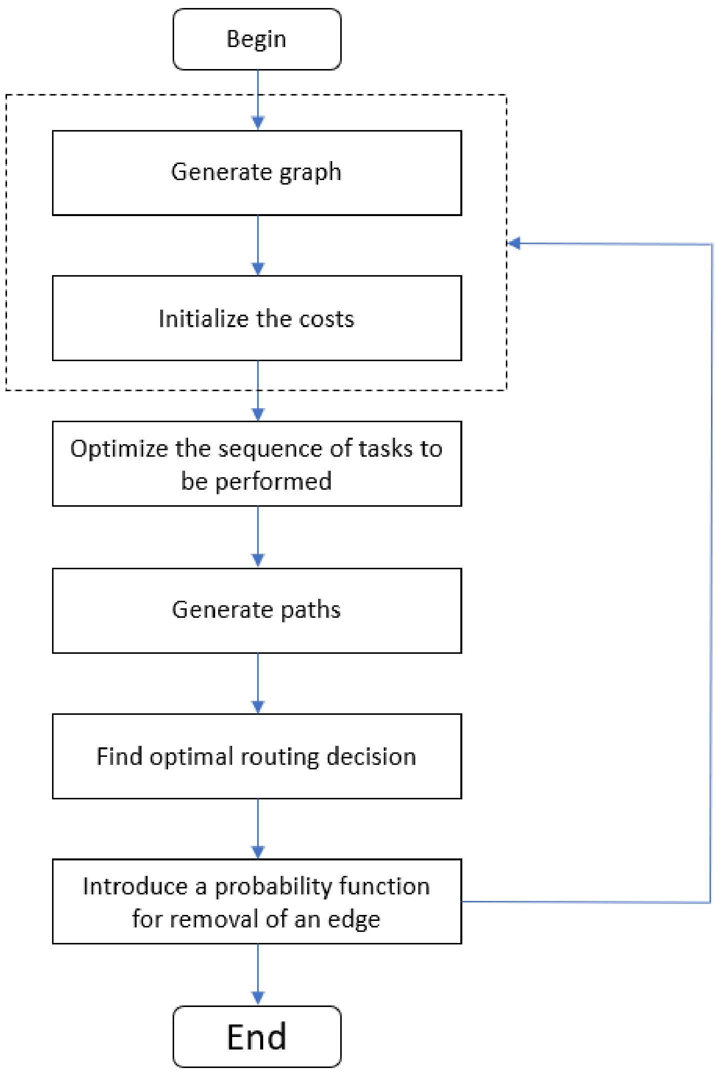

Figure 10 Detailed representation of the algorithm

At this instance of time, the AGV is aware of the order in which the tasks need to be served as well as the optimal path to be chosen for each task. The model also incorporates the human stochastic behaviour at the workspace by blocking one of the edges from operation. This can be seen as a representation of a part of the AGV passageway being blocked in reality due to human interference. Therefore, the algorithm introduces a probability function which will result in the removal of an edge. Once this occurs, the graphical representation and the cost initialization functions will be modified accordingly. Furthermore, the same process of optimization of task sequence and routing decision will be carried out until all the tasks are served.

5.3 Code description

As per the devised algorithm, a code has been written in Python for the model described in *section 5.3*, and it can found in *Appendix B*. This code acts as a proof of concept and it can be further extended to a larger model which would represent the entire potroom logistics in an aluminium smelter. To begin with, various libraries used in the code include, NumPy, node, RenderTree, search, defaultdict, random, time and operator. Libraries are basically a collection of functions and methods which allows one to perform actions without writing that part of the code. This is followed by initializing the various associations of the nodes in the model and further, initializing the costs of travel between two nodes.

The function AGV_Output determines the sequence of tasks to be performed as per the cost initialization matrix by optimization. This functions returns the sequence of tasks as output. Subsequently, the next function create_nodes generates all possible paths as per the sequence of tasks to be performed. The function cost_calculator calls the function cost_from_route in order to calculate the costs for the required paths between two nodes. Further, cost_calculator will optimize the path to be taken by considering the calculated costs per path. The output from cost_calculator will be the minimum path and the associated cost.

The function cost_task_updater is used to update the initialized costs to a larger number when that particular has been completed. This function helps the model keep track of the tasks that have been completed during operations. The output from this function is progress_array and this is an array of completed tasks and it is checked throughout the code. In order to represent the stochastic human behavior in terms of blocked passageways randomness is introduced in the code. If a certain edge is removed at random, the code checks the progress_array for already completed tasks and accordingly re-initializes the costs. The entire process is then repeated until all the tasks are complete.

6 Results

This chapter provides the results of the research in quantitative form and as illustrations. The Python code as per the algorithm devised helps in the analysis of a situation when there is stochastic human behaviour in the form of blocked passageways. Since the idea was to provide a proof of concept which could be further extended to a more detailed model, the AGV model generated is of the most simplified form. The human stochastic behaviour has been represented in the form of a probability distribution through the code. Since the model is simplified, there are only 3 scenarios of blocked edges for which the AGV routing is dynamically changed and these are reported accordingly. For the purpose of demonstration, the results have been tabulated by manually blocking a edge. However, the model constantly checks for disturbance based on the probability distribution and routes the AGV accordingly. There are 4 distinct scenarios for which the results have been tabulated and illustrated further,

- Scenario 1 : When all the paths are available for operation
- Scenario 2 : When edge 1-2 is blocked
- Scenario 3 : When edge 1-4 is blocked
- Scenario 4 : When edge 2-3 is blocked

6.1 Scenario 1: No path is blocked

The following situation is when the operations in the potroom have not begun yet or have just begun, as seen in *figure 14*. In such a situation, all the paths are usually available for operation. Based on this assumption, the sequence of tasks are assigned and further, the AGV route is optimized to ensure it takes the least amount of time to serve all the tasks.

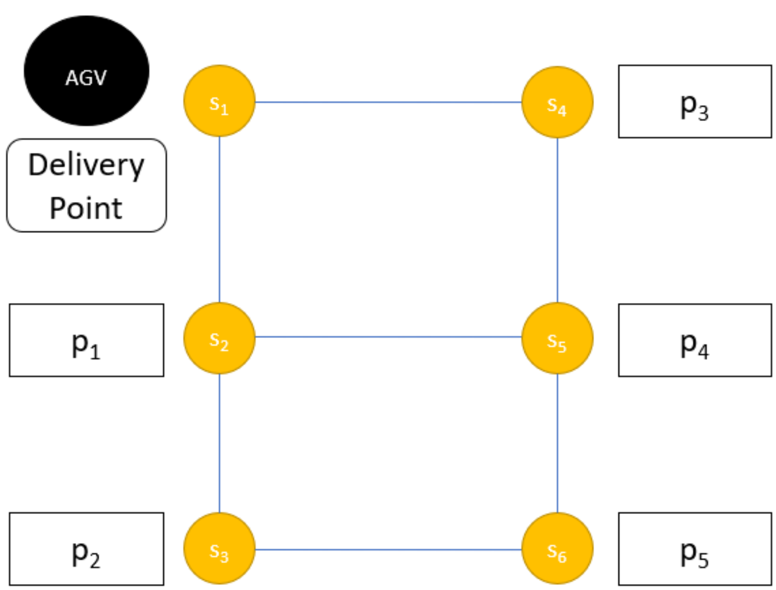

Figure 11 Representation of potroom layout : Scenario 1

To begin with, the input costs needs to be initialized based on the distance between nodes. Since the layout is assumed to be symmetric, the costs can be tabulated as shown in *table 3*. Based on the cost initialization, sequence of tasks to be served can be optimized. For this particular case, the sequence of tasks are : 2-4-3-5-6.

Table 3 Initial Cost Matrix

Edge cost	1	2	3	4	5	6
1	1000	5	1000	5	1000	1000
2	5	1000	5	1000	5	1000
3	1000	5	1000	1000	1000	5
4	5	1000	1000	1000	5	1000
5	1000	5	1000	5	1000	5
6	1000	1000	5	1000	5	1000

Table 4 Summarized Output : Scenario 1

Tasks	Possible Paths	Optimal Path	Associated Cost
2	1-2 1-4-5-6-3-2 1-4-5-2	1-2	10
4	1-4 1-2-5-4 1-2-3-6-5-4	1-4	10
3	1-2-3 1-4-5-2-3 1-2-5-6-3	1-2-3	20
5	1-2-5 1-4-5 1-2-3-6-5	1-2-5	20
6	1-2-3-6 1-4-5-2-3-6 1-2-5-6 1-4-5-6	1-2-3-6	30

Based on the sequence of tasks to be served, the AGV path for each task from the initial position of the AGV will be explored, followed by optimization in order to ensure least time. For tasks 2, 4, 3 and 5 there are 3 different possible routes from the initial position of AGV, which is node 1 to the node of the tasks. Additionally, for the final task 6, there are 4 possible paths between the initial node and node 6. The total costs of serving all the tasks is 90 units. These results are tabulated above and subsequently, illustrations for the same are provided in *figure 15*.

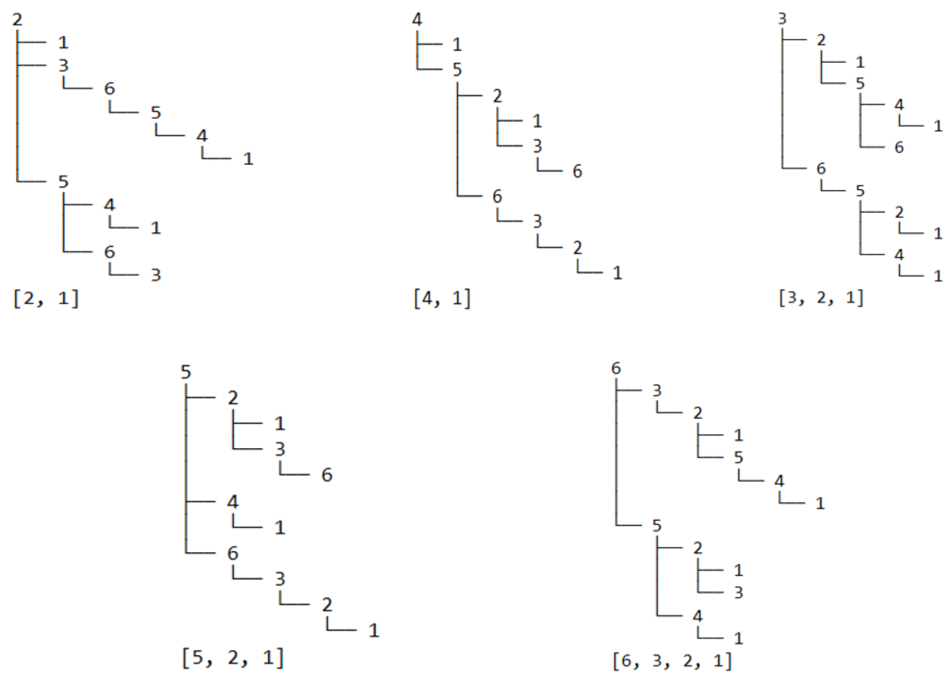

Figure 12 Possible AGV paths : Scenario 1

6.2 Scenario 2: Path 1-2 blocked

The following situation is when the operations in the potroom have begun and the probability distribution included in the code removes an edge at random as seen in *figure 16*. This can be seen as a real world representation of the path 1-2 being blocked due to random human disturbance. In such a situation, all the paths except 1-2 are available for operation. Based on this assumption, the sequence of tasks are assigned and further, the AGV route is optimized to ensure it takes the least amount of time to serve all the tasks.

To begin with, the input costs needs to be re-initialized based on the distance between nodes and the edge removed. Since the layout is assumed to be symmetric, the costs can be tabulated as shown in *table 5.* The costs 1-2 and 2-1 are the ones that are re-initialized due to the edge 1-2 being blocked. Based on the cost initialization, sequence of tasks to be served can be optimized. For this particular case, the sequence of tasks are : 4-3-5-2-6.

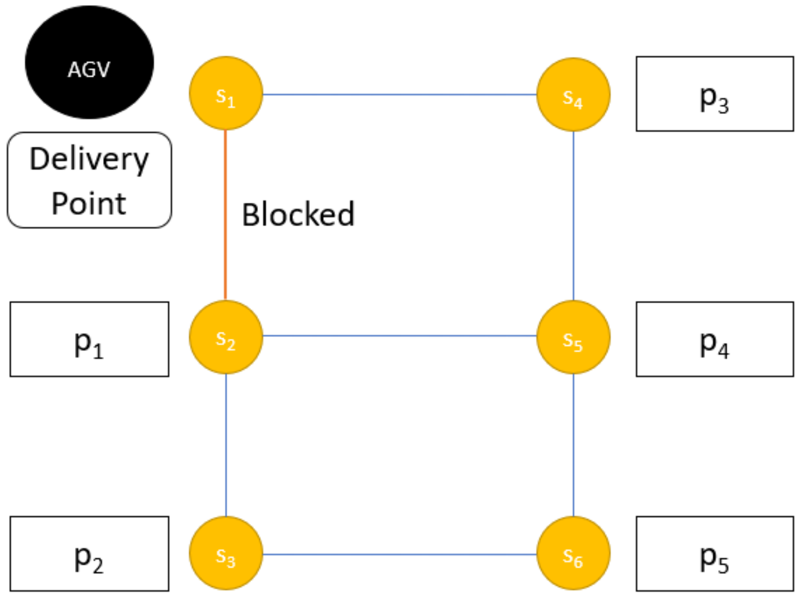

Figure 13 Representation of potroom layout : Scenario 2

Table 5 Re-initialized cost matrix

Edge cost	**1**	**2**	**3**	**4**	**5**	**6**
1	1000	1000	1000	5	1000	1000
2	1000	1000	5	1000	5	1000
3	1000	5	1000	1000	1000	5
4	5	1000	1000	1000	5	1000
5	1000	5	1000	5	1000	5
6	1000	1000	5	1000	5	1000

Table 6 Summarized Output : Scenario 2

Tasks	Possible Paths	Optimal Path	Associated Cost
4	1-4	1-4	10
3	1-4-5-2-3 1-4-5-6-3	1-4-5-2-3	40
5	1-4-5	1-4-5	20
2	1-4-5-6-3-2 1-4-5-2	1-4-5-2	30
6	1-4-5-2-3-6 1-4-5-6	1-4-5-6	30

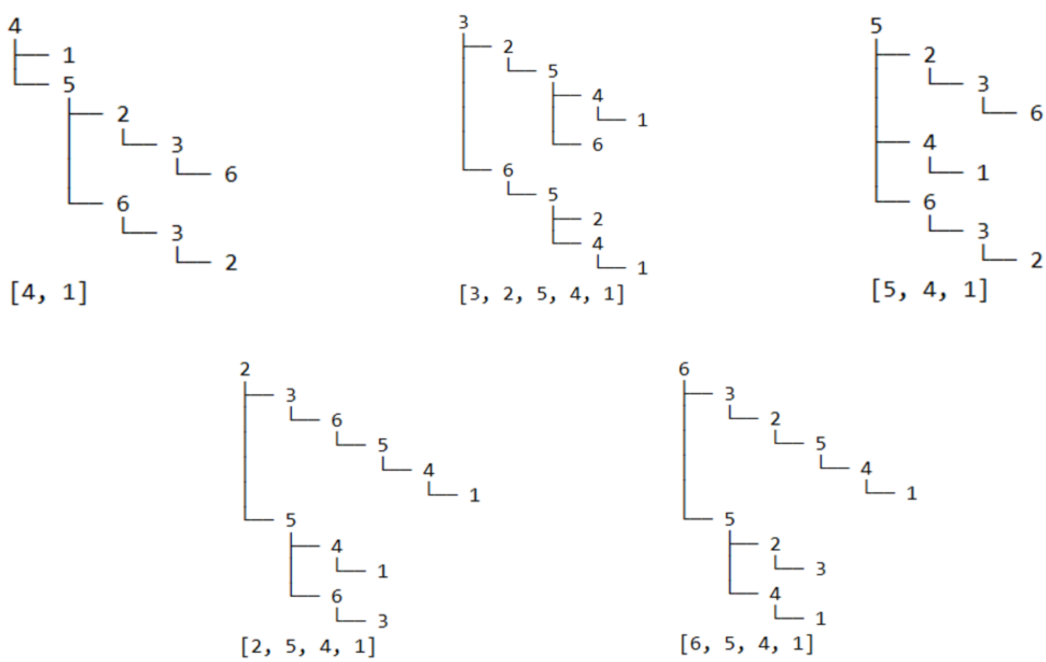

Figure 14 Possible AGV paths : Scenario 2

Based on the sequence of tasks to be served, the AGV path for each task from the initial position of the AGV will be explored, followed by optimization in order to ensure least time. When paths are being explored, one can notice that the code ensures that edge 1-2 is not in the options available. Due to this reason, the number of possible paths available will be relatively lesser when compared to case 1. For task 4 and 5 there is only one possible path that the AGV can follow. For the remaining 3 tasks there are 2 possible paths each from the initial point to the node where the task needs to be served. The total costs of serving all the tasks is relatively greater than case 1 at 130 units. These results are tabulated above and subsequently, illustrations for the same are provided in *figure 17*.

6.3 Scenario 3: Path 1-4 blocked

The following situation is when the operations in the potroom have begun and the probability distribution included in the code removes an edge at random as seen in *figure 18*. This can be seen as a real world representation of the path 1-4 being blocked due to random human disturbance. In such a situation, all the paths except 1-4 are available for operation. Based on this assumption, the sequence of tasks are assigned and further, the AGV route is optimized to ensure it takes the least amount of time to serve all the tasks.

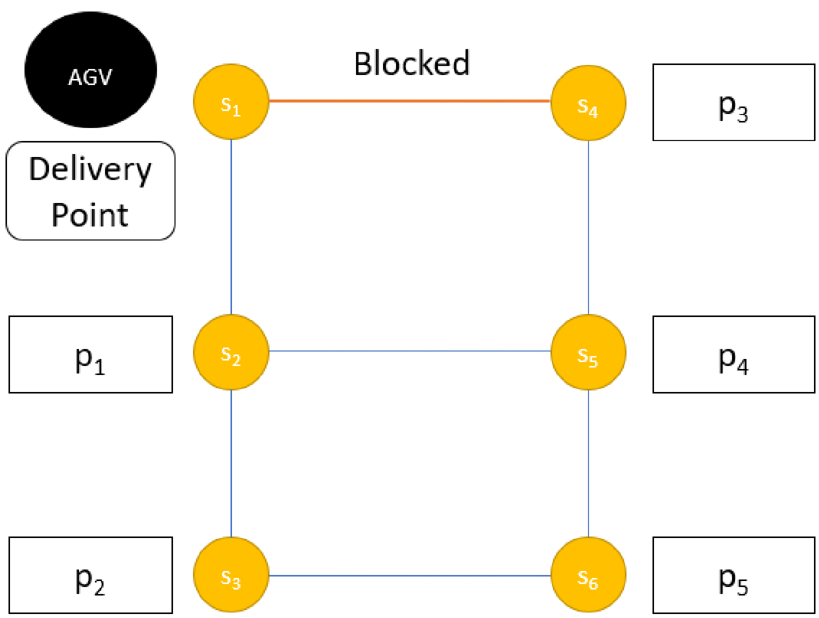

Figure 15 Representation of potroom layout : Scenario 3

To begin with, the input costs needs to be re-initialized based on the distance between nodes and the edge removed. Since the layout is assumed to be symmetric, the costs can be tabulated as shown in *table 7*. The costs 1-4 and 4-1 are the ones that are re-initialized due to the edge 1-4 being blocked. Based on the cost initialization, sequence of tasks to be served can be optimized. For this particular case, the sequence of tasks are : 2-3-5-4-6.

Table 7 Re-initialized cost matrix

Edge cost	1	2	3	4	5	6
1	1000	5	1000	1000	1000	1000
2	5	1000	5	1000	5	1000
3	1000	5	1000	1000	1000	5
4	1000	1000	1000	1000	5	1000
5	1000	5	1000	5	1000	5
6	1000	1000	5	1000	5	1000

Table 8 Summarized Output : Scenario 3

Tasks	Possible Paths	Optimal Path	Associated Cost
2	1-2	1-2	10
3	1-2-3 1-2-5-6-3	1-2-3	20
5	1-2-5 1-2-3-6-5	1-2-5	20
4	1-2-5-4 1-2-3-6-5-4	1-2-5-4	30
6	1-2-3-6 1-2-5-6	1-2-3-6	30

Based on the sequence of tasks to be served, the AGV path for each task from the initial position of the AGV will be explored, followed by optimization in order to ensure least time. When paths are being explored, one can notice that the code ensures that edge 1-2 is not in the options available. Due to this reason, the number of possible paths available will be relatively lesser when compared to case 1. For task 4 and 5 there is only one possible path that the AGV can follow. For the remaining 3 tasks there are 2 possible paths each from the initial point to the node where the task needs to be served. The total costs of serving all the tasks is relatively greater than case 1 at 110 units. These results are tabulated above and subsequently, illustrations for the same are provided in *figure 19*.

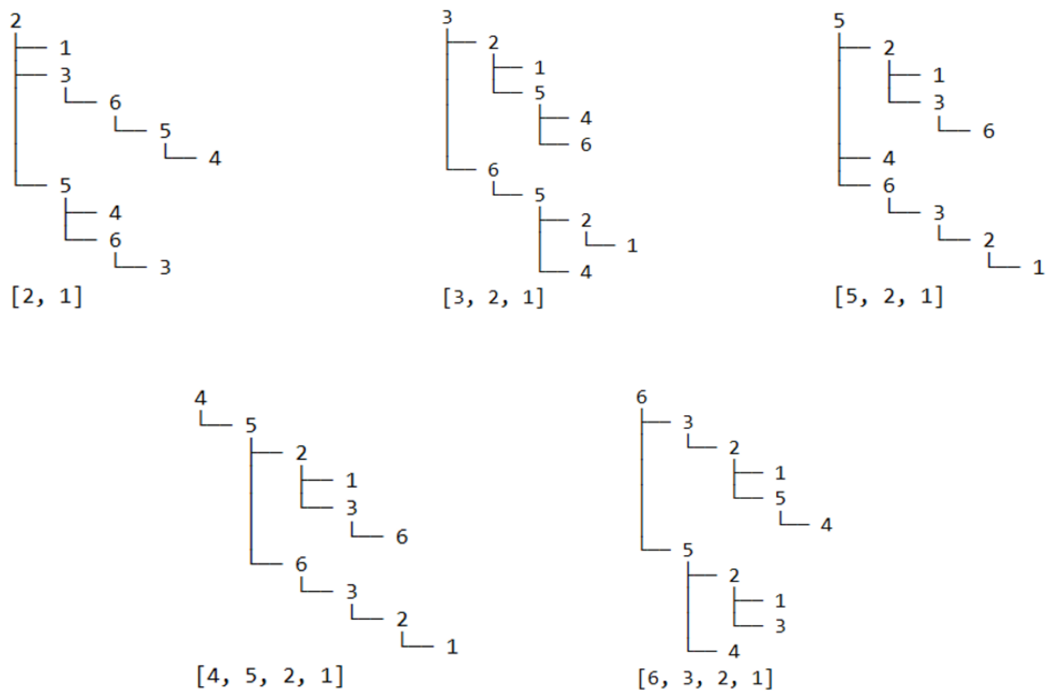

Figure 16 Possible AGV paths : Scenario 3

6.4 Scenario 4: Path 2-3 blocked

The following situation is when the operations in the potroom have begun and the probability distribution included in the code removes an edge at random as seen in *figure 20*. This can be seen as a real world representation of the path 2-3 being blocked due to random human disturbance. In such a situation, all the paths except 2-3 are available for operation. Based on this assumption, the sequence of tasks are assigned and further, the AGV route is optimized to ensure it takes the least amount of time to serve all the tasks.

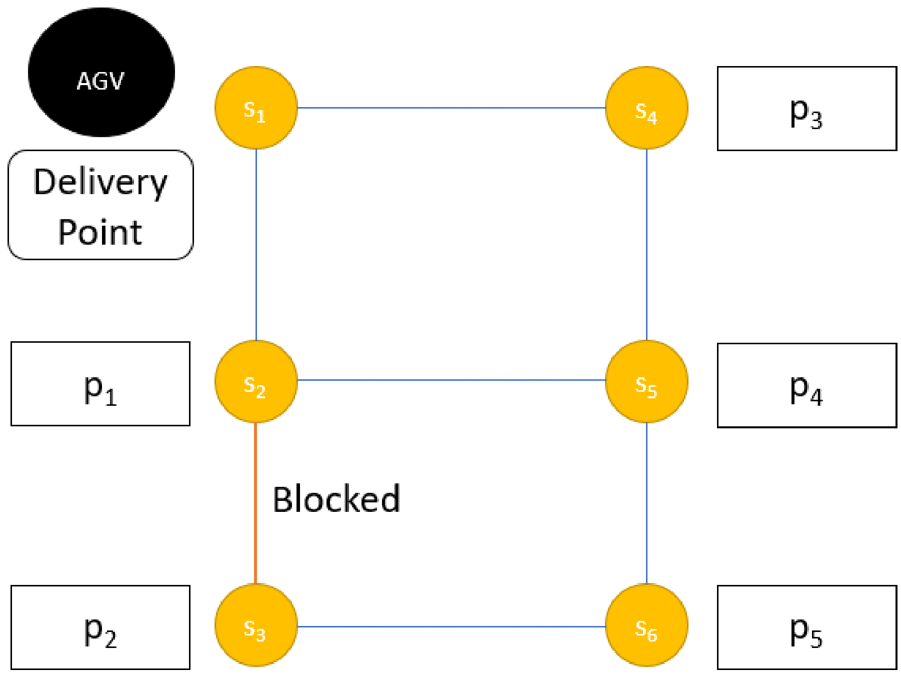

Figure 17 Representation of potroom layout : Scenario 4

To begin with, the input costs needs to be re-initialized based on the distance between nodes and the edge removed. Since the layout is assumed to be symmetric, the costs can be tabulated as shown in *table 9*. The costs 2-3 and 3-2 are the ones that are re-initialized due to the edge 2-3 being blocked. Based on the cost initialization, sequence of tasks to be served can be optimized. For this particular case, the sequence of tasks are : 2-4-5-6-3.

Based on the sequence of tasks to be served, the AGV path for each task from the initial position of the AGV will be explored, followed by optimization in order to ensure least time. When paths are being explored, one can notice that the code ensures that edge 2-3 is not in the options available. Due to this reason, the number of possible paths available will be relatively lesser when compared to case 1. For all the five tasks there are only two possible routes from the initial position of AGV, which is node 1 to the node of the tasks. The total costs of serving all the tasks is relatively greater than case 1 at 110 units. These results are tabulated above and subsequently, illustrations for the same are provided in *figure 21*.

Table 9 Re-initialized cost matrix

Edge cost	1	2	3	4	5	6
1	1000	5	1000	5	1000	1000
2	5	1000	1000	1000	5	1000
3	1000	1000	1000	1000	1000	5
4	5	1000	1000	1000	5	1000
5	1000	5	1000	5	1000	5
6	1000	1000	5	1000	5	1000

Table 10 Summarized Output - Scenario 4

Tasks	Possible Paths	Optimal Path	Associated Cost
2	1-2 1-4-5-2	1-2	10
4	1-4 1-2-5-4	1-4	10
5	1-2-5 1-4-5	1-2-5	20
6	1-2-5-6 1-4-5-6	1-2-5-6	30
3	1-2-5-6-3 1-4-5-6-3	1-2-5-6-3	40

```
2
├── 1
└── 5
    ├── 4
    │   └── 1
    └── 6
        └── 3
[2, 1]
```

```
4
├── 1
└── 5
    ├── 2
    │   └── 1
    └── 6
        └── 3
[4, 1]
```

```
5
├── 2
│   └── 1
├── 4
│   └── 1
└── 6
    └── 3
[5, 2, 1]
```

```
6
├── 3
└── 5
    ├── 2
    │   └── 1
    └── 4
        └── 1
[6, 5, 2, 1]
```

```
3
└── 6
    └── 5
        ├── 2
        │   └── 1
        └── 4
            └── 1
[3, 6, 5, 2, 1]
```

Figure 18 Possible AGV paths : Scenario 4

7 Conclusion

AGVs have been under constant development since their invention, moving from guided wire navigation to autonomous navigation, from mechanical bumpers to contactless sensors as well as improved control strategies. Such development has ensured improvements with regard to routing strategies as well and hence opened up various domains of application, apart from warehouses and port logistics. There is very limited research applicable to significantly harsh environments like, the light metal and forging industry. These industries have unique operating challenges such as extremely dynamic environments, uneven and old flooring, as well as high operating temperatures and magnetic fields. As the operating environment that is under consideration is highly dynamic, it is crucial that the AGV is intelligent enough to react to such dynamics in the environment.

A crucial aspect of dynamics in the form of human interference to such AGVs has not been studied so far. Intelligent AGVs are expected to work in conjunction with various human operators and this would result in situations wherein the human would interfere in AGV operations. In the current standard, one can observe that the factory floor has been segregated into areas where the AGV can travel with some traffic rules and few other confined areas for humans. A segregation of this manner would mean reduced flexibility for the AGV and this has known to cause bottlenecks in operation which could last hours before being resolved. Therefore, it is important to have a workspace where the AGV is allowed to move freely in the presence of human operators, as this results in increased flexibility and productivity as the probability of bottlenecks are significantly reduced.

Therefore, the main objective of this scientific study is: *With the introduction of intelligent AGVs, stochastic behaviour needs to be addressed, that is, how would these AGVs react to disturbances created by such random human behaviour and process interference?* For the purpose of this research, the question framed is: *For instance, if a certain pathway is blocked in the potroom of an aluminium smelter due to such stochastic behaviour, how would the AGV find the optimal path?* Initially, it is important to realize an intelligent AGV, and the literature review combined with market research helped the study by formulating a planning approach for an intelligent AGV for the operating environment under concern, which is a light metal and forging industry. The research devises an algorithm which is further implemented using Python, and this model analyses the dynamic behaviour of an AGV by studying various scenarios. The algorithm incorporates the stochastic behaviour of blocked passageways by introducing a probability distribution for the same. This ensures that a certain path is blocked at random. The model that is built is equipped to react to the disturbance by automatically finding the next optimal path and traversing it. Therefore, the algorithm formulated and the subsequent model is capable of dynamically re-routing itself around stochastic disturbances in the potroom layout that has been considered.

The model has been analysed for 4 different scenarios and for each of these cases, the sequence of tasks to be carried out is optimized, followed by the path to be taken. The results for every scenario has been tabulated and illustrated, which shows the way in which an AGV would react to stochastic human disturbances during operations in the form of blocked passageways. Hence, this research has contributed as a proof of concept by modelling a simple situation wherein an intelligent AGV can dynamically re-route itself to serve tasks in the presence of stochastic human disturbances.

8 Future recommendations

This research has contributed as a proof of concept by modelling a simple situation wherein an intelligent AGV can dynamically re-route itself to serve tasks in the presence of stochastic human disturbances. Further, this research focusses only on one AGV, whereas in real world scenarios there is usually a fleet of AGVs, and this would demand coordination between them for successful operation. Further, the layout of the potroom considered is also simplified for research purpose as it is symmetric in nature. Therefore, it would be recommended to investigate a more realistic potroom design, although this research attempts to investigate a simplified case.

The model created can be easily extended to a more detailed representation of the potroom logistics by using advanced metaheuristics. The detailed model in the future can also incorporate process interferences, which has not been considered in this research. Further, this approach can also be utilized in industries with similar challenges, for instance, cement industry, power generation industry, aerospace and construction to name a few. The algorithm and the model can also be utilized for various other indoor applications where human-robot interaction is crucial.

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Appendix A:

Research paper

Dynamic AGV routing depending on sensor-based collision avoidance: A case for the light metal and forging industry

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Abstract- AGVs have seen an upward trend in development over the last 60 years. The technology has developed from mechanical bumpers and guided wire navigation to contactless sensors and free navigation technique in the current age. Further, the control on AGVs has moved from central control system to local intelligence which opens up various possibilities with respect to operations as well as applications. The growing trend of AGVs has been due to the sudden growth in digital technology and the ever-increasing demand to reduce human intervention in operations. This has ensured that the AGVs enter new domains of applications like the light metal and forging industry. This research will develop an algorithm and a subsequent model in the form of a Python code which is used to evaluate the dynamic routing of an AGV in the presence of stochastic behavior. The potroom of an aluminum smelter is chosen as the case. It acts as a proof of concept for the problem at hand as it restricts the work to a simplified situation of a single AGV operation in a scaled down and symmetric potroom.

Keywords- AGV, Light metal and forging industry, Aluminum smelter, Potroom, Dynamic routing, Mapping & localization, Navigation, Collision avoidance

I. Introduction

An Automated Guided Vehicle (AGV) is a mobile robot used for various purposes in manufacturing, warehouses and inventory management. They are mainly material handling equipment which drastically reduce operational times and the need for humans by introducing automation. The major reasons for indulging in autonomous equipment are, increased productivity, reliability and safety since human involvement is either eliminated or largely reduced. As per [39], the 60 years of AGV history can be divided into 4 separate eras, and these are distinguished by the technology available and the emotional attitude towards these systems, as seen in *figure 1*.

The initial era of AGVs began in America in the year 1953 with the idea of replacing drivers on a tractor used for transporting goods. In terms of technology it was limited to a simple track-guided system with sensors such as mechanical bumpers and emergency switches. Subsequently, inductive guidance were used for navigation purposes as well as coloured strips on the floor for navigation purposes. The second era witnessed the introduction of electronics at a large scale. Microprocessors and PLCs were used for the purpose of positioning and guidance of AGVs and this improved precision, further, active inductive track guidance became the norm. Third era observed AGVs with electronic guidance and contact-free sensors. Conductive cable guidance was replaced by free range technologies such as magnetic and laser navigation. These developments ensured faster AGVs in terms of driving, manoeuvring and material handling. It also meant new areas of application, such as, bulk-storage warehouses, lean production factories, hospitals and so on [51]. The fourth era of AGVs will not effectively replace the previous one, but build on the developments of the previous era. Few of the functional demands of the future AGVs include, truly autonomous driving, obstacle avoidance, ability to recognize disturbances, adaptability in terms of material handling, traffic and battery usage [38].

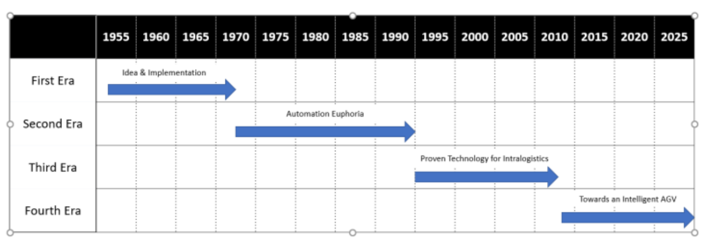


Fig. 1. History of AGV Development

It is evident from the literature study conducted that, most of the research in the field of AGVs and most importantly, intelligent AGVs confined its applications to warehouses and port logistics. There is very limited research applicable to significantly harsh environments like, the light metal and forging industry. These industries have unique operating challenges such as extremely unstructured and dynamic environments, uneven and old flooring, as well as high operating temperatures and magnetic fields. As the operating environment that is under consideration is highly dynamic, it is crucial that the AGV is intelligent enough to react to such dynamism in the environment. The fourth era of AGVs are capable of dealing with dynamic surroundings. There has been some research conducted in how intelligent AGVs would react to dynamic changes with regard to the process involved, that is, customer demands, manufacturing schedules and so on. However, a crucial aspect of dynamism in the form of human interference to such AGVs has not been studied so far.

In the current situation, one can observe that the factory floor has been segregated into areas where the AGV can travel with some traffic rules and few other confined areas for humans. A segregation of this manner would mean reduced flexibility for the AGV and this has known to cause bottlenecks in operation which could last hours before being resolved. Therefore, it is important to have a workspace where the AGV is allowed to move freely in the presence of human operators, as this results in increased flexibility and productivity as the probability of bottlenecks are drastically reduced. An intelligent AGV can readily deal with the first situation as they are equipped to react dynamically to such obstacles during operation. However, if an entire passageway has been blocked, it would result in disruptions with regard to the tasks to be completed as well. There has been no research conducted with regard to the impact of human stochastic behavior in terms of blocked passageways on a certain AGV operation. Hence, based on the conditions mentioned, the problem statement to be answered in the research is as stated below:

"With the introduction of intelligent AGVs, stochastic behaviour needs to be addressed, that is, how would these AGVs react to disturbances created by such random human behaviour and process interference?"

The introduction of natural navigation solved the problem of fixed AGV routing. Further, the introduction of obstacle avoidance technology allowed an AGV to be able to move around an obstacle and not just come to a stop and wait for the obstacle to be moved. Drastic advancements in the field of AGV technology has paved the way for research into dynamic AGV routing due to stochastic behavior in the specific case of a light metal and forging industry and hence, this work contributes to the scientific domain by filling these research gaps. This research will develop an algorithm and a subsequent model in the form of a Python code which is used to evaluate the routing of an AGV in the presence of stochastic behavior. It acts as a proof of concept for the problem at hand as it restricts the work to a simplified situation of a single AGV operation. However, the basis of this work can be further extended to solve a more detailed real world operation with a fleet of AGVs, and this can be done by the use of advanced heuristics. Although this research uses the case of a light metal and forging industry, the same can be quite easily be applied to industries with similar challenges such as, cement industry, power generation industry, aerospace, construction and so on.

The research starts with an literature review of AGV technologies with regard to mapping & localization, navigation and obstacle avoidance. It also addresses dynamic routing of AGVs. Then, a brief understanding of the research area, specifically the case of light metal and forging industry in the form of an aluminium smelter has been addressed. Further, various technological requirements in order to achieve an intelligent AGV has been analysed. Then, an algorithm has been developed, followed by a Python code which helps analyse the dynamic routing of AGVs in the presence of stochastic behaviour. Finally, some experiments are conducted on the model by studying certain scenarios which further helps the research understand the problem at hand and the subsequent results are tabulated.

II. LITERATURE REVIEW

Some of the important aspects considered in the literature review carried out include, the technological aspects of an AGV as well as scientific study about dynamic routing. The technological aspects of an AGV relevant to the research are mapping & localization, navigation and obstacle avoidance.

A. Mapping & Localization

Both mapping and localization are interdependent and they should be able to deal with sensor noise and uncertainty. The current standard for the above working environment consists of an AGV with a 2D scanning solution which following reflective tags installed in the factory. This also means the factory needs to be mapped, which is a tedious process with the technology being employed and various traffic rules need to be defined, which does not always end up giving the most effective and efficient solution. In addition to this, working with reflective tags would mean high installation and maintenance costs.

As per [12], there are two distinct type of map representations, namely, feature-based maps and featureless metric maps. Feature based maps are those which lists the various features and related information of the area being mapped, whereas, featureless metric maps represent just the geometry of the environment. Fairfield (2009) defines localization as the using sensor measurements in order to estimate the robot's pose, that is, position and orientation, relative to a map. Further, [8] suggests the use of use of Simultaneous Localization and Mapping (SLAM) technique. It is defined by [8] as, simultaneous estimation of the state of the robot equipped with on-board sensors, and the construction of map of the environment which the sensors are perceiving. SLAM is known to provide local localization and in order to have a global localization the GPS module is utilized [20]. If dead-reckoning is used for localization purposes, the robot can drift over time, however, using a map would mean that robot can re-set its localization by referring to the landmarks in the map generated. Hence, SLAM is quite helpful when a prior map is not present and it needs to be built.

The emergence of SLAM is due to the increased functionality of AGVs in indoor applications. Indoor applications rule out the possibility of using GPS to cater for the localization errors. Further, SLAM presents a valuable alternative for user built maps and proves that AGV operation is possible without ad-hoc localization infrastructure [8]. SLAM can be applied for both 2D and 3D motion and it includes the following, landmark extraction, data association, state estimation, state update and landmark update [30]. [30] also stresses on the importance of considering the hardware on the AGV for implementing SLAM.

One of the important parameters to consider is the odometry performance of the robot. This measures how well the robot can estimate its own position with the help of wheel rotation. The range measurement device can be laser scanners, sonar or vision. Laser scanners is the most widely used range measurement as they are precise, efficient and due to the fact that it requires very little computation. Sonar has comparatively bad measurements and their advantages lie in underwater operation. Vision has been traditionally intensive when it comes to computations and they are quite error prone as it depends completely on light. However, in recent years there have been developments in this field and with advances in algorithms, computation power is becoming less of a concern.

The literature also points to use of 2D scanners in order to project a 3D map of the operating environment. There has been numerous work based on this idea. [13] delivers a real-time and low-cost 3D perception and reconstruction system suitable for autonomous navigation and large-scale environment reconstruction. This particular 3D mapping system is based on a 2D planar laser scanner which rotates due to the help of a motor and is suitable for continuous mapping. The 3D scanner developed using these methods is tested successfully in an indoor and office-like environment [13]. Further, research on a 2D laser range finder which has been mounted on a spinning platform to generate a 3D point cloud and it spins about the center scan line of the sensor has been conducted by [6]. These experiments have been conducted on a flat, paved surface as well as an off-road terrain and they have been relatively successful.

[37] presents a study which digitizes indoor environments at a relatively fast pace reliably without any intervention and solves the SLAM problem. The 3D laser range finder acquires 3D scans at given poses and an ICP algorithm is used to register the 3D scans and localize the robot. However, in this research, robot self-localization has not been addressed. Although the research by, [13], [6] and [37] have provided exceptional results, the application areas are mostly confined to indoor environment and areas where there are no harsh operating conditions, such as, high temperatures and static magnetic fields.

B. Navigation

Some of the early technology involved the AGVs following a guided rail system, furthermore, guided wire or painted line solutions on the floor of the working environment were developed. As technology developed, AGVs started using reflective tapes in the environment in conjunction with a rotating laser for the purpose of navigation. In addition to reflective tapes in the environment, few other methods of navigation that were explored in the earlier days by [3] include, odometry or dead-reckoning. An important limitation of dead-reckoning method is its susceptibility to errors due to various reasons, which include, wheel slippage, tire wear and floor quality. Such an error can accumulate over time and it needs to be corrected by using an absolute positioning system. With such a method there is a huge reliance on floor conditions and hence it is not the best approach for navigation [3].

As per [3], various beacon-based systems have also been developed for navigation purposes. The general idea behind such a method is to have laser, optical or ultra-sound scanners on top of the AGV which is capable of scanning the environment and looking for beacons around the operating environment. The beacons will reflect a signal and by determining the angle of reflection from at least 3 fixed beacons, the pose of the AGV can be determined and hence its heading. This system is very reliable and suitable for a factory environment with flat and smooth floors, wherein the required speed of operation is low and most significantly, the environment is not subjected to constant changes for long periods of time as only this would justify the high installation and maintenance costs of such a system. There are several issues with such a system, namely, limited range of scanning systems, accuracy is majorly dependent on the accuracy with which beacons are installed in the operating environments, beacons can be obstructed due to various reasons and beacons are affected by external conditions, such as, dust and light.

There has been extensive research of autonomous vehicles in the domain concerning underground mining and construction by [31] and [3] respectively and this is quite interesting for our research as the operating environment is slightly similar in the fact that it is unpredictable, dynamic and harsh. However, both these studies do not help us solve the problems of the environment under concern. The challenges in this industry include, mapping, navigation and obstacle avoidance. The work by [22], [31], [3] and [33] mainly focusses on navigation of autonomous vehicles. [22] proposes the use of Dijkstra's algorithm for navigation planning when there are better alternate and reliable solutions. [31] proposed an absolute and reactive navigation technique for autonomous vehicles and these are known to have multiple limitations from the tests that have been conducted. The choice of sensors for the purpose of autonomous functioning are also significant. [35] presents the use of ultrasonic sensors, however, these sensors have limitations with regard to reflection and resolution. Similarly, [36] have proposed the use of RADAR, which have multiple limitations in the considered environment for research. Work carried out by [7], [20], [26] and [28] suggest the use of vision based sensors for autonomous operations. These sensors are known to have limited field of view, they require certain lighting conditions and they could possibly be blinded by the high temperature environments in various industries.

Majority of the above research that has been conducted is validated by tests in either indoor office-like environments or outdoor. Both these cases do not reflect the high temperature and altered magnetic field, in addition to dust, unpaved floor and a dynamic environment, which are relevant for the following industries, light metal and forging, cement industry, oil and gas industry, industries dealing with power generation and chemical industries. There has been limited research about autonomous vehicles in the area of research that is our concern, specifically by [10], [29] and [27]. [10] presents the implementation of an autonomous navigation system onto a 30 ton Load-Haul-Dump (LHD) truck with a 2D laser scanner as the primary sensor. [29] presents a study which proves that vision can be used as a primary sensor to locate and load aluminum. This study addresses the challenge of using vision based sensors in an outdoor environment, by using artificial visual fiducials and by creating a novel landmark. [27] presents a waypoint navigation framework for unmanned ground vehicles. In this research, the authors redesign a 6DOF LiDAR SLAM algorithm to achieve 3D localization on the base map, including real-time vehicle navigation. Low-frequency, high precision SLAM updates is fused with high-frequency, odometric local state estimates from the vehicle. The navigation costmap is a 2D grid which has been computed from a 3D base map. This system has been shown that it works reliably in a dynamic environment [27].

C. Obstacle avoidance

An intelligent AGV should be capable of thinking like a human and therefore, adjust to dynamic changes in the operating environment accordingly [38], therefore, another significant factor that needs to be considered is obstacle avoidance. [22] provides solution for AGV navigation in an unguided (normal) and guided environment with obstacle avoidance strategies. The approach used in this research is two-fold, that is, an artificial potential function can be used to navigate the AGV in an unguided environment. Attractive and repulsive forces approach is useful in avoiding obstacles in an unguided environment. However, the limitations to this approach is the fact that obstacles are assumed to be spherical in nature and the fact that the algorithm fails in the presence of a saddle point. Furthermore, there has been extensive work done in the use of depth cameras and ultrasonic sensors for obstacle detection by [22] and [35].

Further, there has been research about obstacle avoidance using vision sensors by [7], [4], [28], [14], [25] and [5]. These scientific studies present the use of vision based sensors for the purpose of obstacle avoidance. Additionally, the closest scientific work that would be relevant to this particular research is the use of 2D/3D laser scanners for the purpose of obstacle management. There are also cases where laser scanners are used in conjunction with other type of sensors for better results. [20], [15] and [32]. [20] presents a fusion system for stereo-vision and laser-rangefinder for outdoor obstacle detection. Due to various limitations of the laser range finder and stereo vision approach, they are combined to obtain better results. [15] aims to identify the objects that are difficult to detect with the existing 2D sensors and hence propose better models for them. Further, to investigate if there are 3D perception systems, like cameras which can be used for this purpose. This study aims to go beyond the previous literature which considers just humans, box or cylindrical type of objects as obstacles in the industrial working environment. A few examples of other important obstacles to consider include, a protruding bar, suspended objects, a ladder and so on. The working environment can usually be classified as, partially observable, stochastic, sequential, dynamic, continuous and multi-agent. The results also show that for all vision sensors, illumination conditions and placement of camera plays a significant role in obstacle detection. The TOF camera and Kinect device are known to get in trouble during daylight or when specular reflections take place [15, 16, 17, 18, 19].

[32], discusses how prior knowledge of the environment can help improve the quality of sensor fusion, hence increasing the performance of an obstacle detection system. The work shows that in regions where sensor behavior changes within the map, it is possible to automatically select an adequate sensor configuration which improves detection capabilities. The experiments also show that this results in better performance when compared to single sensor configuration [32]. The research specific to 2D/3D laser scanners is by [24]. It presents a method of detection and tracking of moving objects using a laser range finder. It has three modules, scan segmentation, object classification and object tracking. Finally, [36] presents the utilization of RADAR technology for obstacle avoidance in automobiles. The proposed vehicle collision avoidance system is an improvement on the current cruise control system seen in automobiles. This system uses radar technology to detect vehicles in its path and hence slow down or stop accordingly. The proposed system is also capable of detecting obstacles like walls, trees, people and so on and hence its applications can be extended [36].

D. Dynamic routing

Research about dynamic AGV routing has been mostly relevant to indoor, well-structured warehouses and to port logistics. Most of the scientific study borrows techniques from autonomous driving vehicles which operate on road, however, the safety claim on these vehicles are totally the driver’s responsibility. This cannot be the case for an industrial environment as certain safety standards need to be met for the functioning of AGVs capable of dynamically re-routing themselves around obstacles, both static and dynamic. Research as per, [11], [1], [34], [41] and [40] present their work on dynamic or free ranging AGVs around operating environments.

[11] presents an algorithm for dynamic free ranging of AGVs. It is based on the microscopic pedestrian behavioural model. The current standard in the research does not offer efficiency and optimal paths. Therefore, the proposed algorithm ensures free ranging trajectory for AGVs while avoiding static obstacles and collisions with other operating AGVs. [1] focusses on a routing problem in a supply chain network. The disruptions considered in this case include, production irregularities and vehicles being disrupted randomly. The problem has been formulated as a mixed-integer linear program, followed by a two-stage heuristic based on simulated annealing [1]. In this above case, the disruptions modelled can be classified as process interferences, however, the disruptions due to human interference also needs to be studied and this has not yet been done in the scientific domain.

Similar to the previous work, [41], focuses on capacitated location-routing problem in which depots are stochastically disturbed. This work provides a scenario based mixed-integer programming model in order to optimize the situation and further, a metaheuristic algorithm has been developed. Heuristic results showed that the model was successful enough by balancing the operating and failure costs of such disturbances [41]. [34] proposes an algorithm for dynamic routing of AGVs in automatic warehouses. The routing algorithm in this research is based on the expected dynamic behaviour of the traffic in the warehouse. It has been formulated for a single AGV and it can further be expanded to a fleet of AGVs. The research mainly aims at optimizing the dynamic behaviour of AGV traffic [34]. This research goes a step further by trying to analyse the dynamic disturbances due to traffic, but still fails to address the impact of human events. The importance of human-robot interaction in a work space is provided by [2]. As mentioned, it focusses on the importance of collaboration between humans and robots in various applications, namely, space, healthcare, rescue operations and so on. The article stresses on the point that the robots should not just concentrate on the safety aspects while working in an environment with humans involved, but it is also extremely crucial that the focus is also on collaboration between the two. This is important in order to achieve efficiency in operations including safety [2].

III. SYSTEM DESCRIPTION

It is important to understand the difference between a standard AGV and an intelligent AGV as it has a direct impact on the manner in which operations are performed. The fundamental attribute of an intelligent AGV is its ability to make decisions on its own, with reference to navigation, obstacle management and task management. On the other hand, a standard AGV basically obeys simple orders from a higher level of control structure and they tend to be constrained in terms of navigation and obstacle management since they do not have the ability to adapt to changes or disruptions in the operating environment. An intelligent AGV is known to be a lot more sophisticated and equipped with sensors and powerful on-board computers which assist the AGV in decision making and adaptability.

For a fully autonomous system, the vehicle should be aware of the following: where am I, where am I going and how do I get there. The first question is answered through localization, second question is answered through path planning and the third is answered through navigation. An intelligent AGV should be equipped with software that can generate maps of the environment either on-site or through pre-loaded drawings. It uses the sophisticated set of sensors and scanners to then localize itself and then plan a path efficiently. Once the path has been defined, it should be intelligent enough to navigate itself to the destination from the point of origin and perform assigned tasks. While navigating through the operating environment, the AGV should be equipped enough to not just stop when an obstacle occurs, but also be able to dynamically navigate around it, in order to ensure high productivity and reliability.

Finally, another vital aspect of an intelligent AGV is obstacle management. An intelligent AGV should be capable of adapting to disruptions in the operating environment by dynamically re-routing itself around obstacle. A basic illustration of a situation wherein an intelligent AGV is faced with an obstacle can be as seen in *figure 2*. The origin and destination points are defined by the yellow and blue circles respectively. Before the operation begins, the AGV will generate a path between the two and this is depicted by the black line. The AGV starts its operation and the black circle indicates its current position. At this moment, the sensors on the AGV will detect the obstacle in front of it and will react to it by re-routing itself around the obstacle instead of coming to an emergency stop and waiting for the obstacle to be cleared. The dotted red line indicates the new path taken by the AGV to reach its destination.

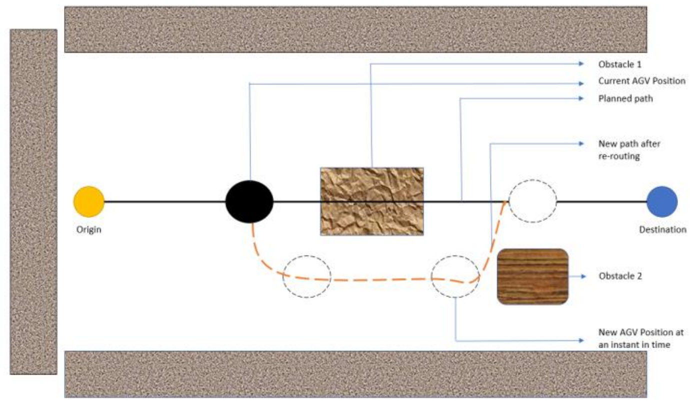


Fig. 2. Illustration of obstacle management

Further, as per literature and subsequent analysis, various attributes of an AGV over the years is as tabulated in *table I*. Based on the *table I* and market research, GLAMA Maschinenbau GmbH decided to use the incubed IT smart shuttles. This was done in order for the shuttle to act as a proof of concept, not just for GLAMA Maschinenbau GmbH, but also for its various clients. The shuttle was tested for a period of time, albeit in indoor office-like operating conditions, with the intention of modifying it further based on the requirements of the smelter and then testing it in that particular environment.

Table I Technological roadmap for AGV

Mapping and Localization	**Navigation**	**Obstacle Avoidance**
Global Positioning System (GPS)	Artificial potential function & Dijkstra's algorithm	Attractive & Repulsive force approach
Global Navigation Satellite System (GNSS)	Reactive navigation	Ultrasonic sensors
Odometry	Simultaneous Localization & Mapping (SLAM)	RADAR
Inertial Navigation System (INS)		Vision sensors
Beacons		2D laser scanners
Simultaneous Localization & Mapping (SLAM)		3D laser scanners

Smart shuttles produced by incubedIT are known for their intelligent and autonomous navigation, as seen in *figure 3*. A decision was made at GLAMA Maschinenbau GmbH to use the shuttle to perform some simple tests. The shuttle was tested for a few days in the office space and it responded quite well, hence proving the concept of autonomous navigation of such a shuttle, including automatic re-routing around obstacles.

The shuttle is equipped with numerous sensors which assist in the process of navigation and localization and these include, wheel odometry sensors, inertial measurement unit, 2D laser scanners mounted on the front, rear and on the sides of the shuttle, as well as a few optional sensors. The laser scanners which are mounted on the shuttle provides dynamic safety fields. When an obstacle is detected in that particular field, an emergency stop will be activated. These safety fields should be defined based on the shuttle's linear speed. The shuttle developed by incubed IT features a differential drive with 2 DC motors, hence it is capable of turning on the spot. The shuttle has a maximum forward velocity of 2m/s and a maximum reverse velocity of 0.3m/s. The shuttle software is capable of autonomous and intelligent behaviour. It is capable of controlling the shuttle hardware functionality, localization, path planning, dynamic navigation which includes, obstacle avoidance and path re-routing and finally, the process of executing orders autonomously [21].

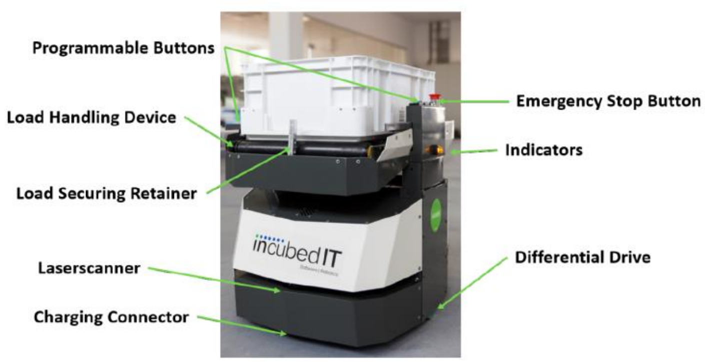


Fig. 3. incubed IT smart shuttle

IV. CASE DESCRIPTION

The research focusses on the light metal and forging industry, specifically, an aluminum smelter. The production of primary aluminum is done by two independent energy-intensive processes in order to transform the ore, bauxite, to aluminum by electrolytic reduction. First process is referred to as the Bayer process where thermochemical digestion is used to convert bauxite to alumina. This is followed by the Hall-Heroult process, which uses electrolytic reduction to produce molten aluminum [23]. A smelter has three important blocks, namely, the carbon area, potline and the castroom, as shown in the *figure 4*. The manufacturing of carbon anodes are done in the carbon area, production of liquid aluminum takes place in the potline and in the castroom the liquid metal is poured into molds.

Further, the research specifically focusses on the potline. The area housing the cell lines are referred to as a potline or potroom. In large smelters, these potrooms are more than 1km in length, 50m wide and about 20m high. The potroom is usually equipped with close to 100 electrolytic cells, each of them being 10 to 15m in height. The design of potrooms in various smelters around the world is quite similar, as seen in *figure 5* [23]. The movement of materials inside the smelter complex is done inside covered passageway or on external roads. The internal passageways are mainly asphalt pavement. The potroom floor is concrete and these surfaces have wear, cracks and some chipping. External roads are asphalt pavement. Materials are also being transported inside potrooms where there is a presence of magnetic field, and this can be up to 400 Gauss in some areas. The magnetic field is stronger in the axis along the potroom and close to the pot. The passageway has limited lighting and they are relatively dusty. A Wi-Fi network is available inside the potroom. The facility is also equipped with dedicated pedestrian walkways and they are separated by concrete walls. In the potroom area, the mobile equipment circulate amongst plant operating personnel and pedestrian-vehicle interface is a crucial factor to be considered in AGV operations.

Fig. 4. Aluminium smelter layout

Fig. 5. Modern aluminium potroom [23]

V. MODEL DESCRIPTION

The following section is built upon the previous sections of the research, more specifically based on the characteristics of an intelligent AGV and the operating conditions to be studied. The importance of an intelligent AGV has been addressed and obstacle avoidance plays a major role. This is because it enables the AGV to be able to dynamically react to disturbances in the operating environment and not come to an abrupt stop. Hence, under the assumption of an intelligent AGV, the remainder of the research is conducted. The initial part of the section describes a mathematical approach to solving dynamic routing problems and an example formulation has been presented. The final part of the section focusses on the approach to be followed in this study, that is, a graphical approach. Therefore, the final section presents the case at hand in the form of a graph with nodes and edges. It includes the representations and the fact that the problem has been simplified for the purpose of this research. It also addresses the various assumptions considered and the problem is hence solved accordingly.

A. Mathematical Formulation

The article [9] presents a mathematical formulation for vehicle routing with time windows and temporal dependencies. To begin with, a mixed integer programming formulation is presented, followed by a time indexed formulation. The objective with a traditional vehicle routing problem with time windows is to find the most optimal set of routes, optimal being the cheapest, for a set C of n customers. The fleet of vehicles are denoted as V, and they are located in a central depot, which has a start depot location, 0, and an end depot location, n+1. All of these above variables form a set, N. The capacity of each vehicle is given by q and each customer i has a demand, d_i. The time window for service is given by $[\alpha_i, \beta_i]$, where, α_i represents the earliest service time and β_i represents the latest possible time of service. Similarly, $[\alpha_0, \beta_0]$, represents the scheduling horizon, where, α_0, represents start time of vehicles from the depot and, β_0, represents the latest return time of the vehicle to the end depot. τ_{ij} gives the total travel time between two points i and j, and this includes the service time. Cost of travel between these two points is given by c_{ij}. An assumption is made such that, q, d_i, α_i, β_i and c_{ij} are nonnegative integers. Further, it is also assumed that τ_{ij} is a positive integer. These variables, in addition to a few others are further summarized in the following table for easier representation.

Table II Variables used in the formulation

Variable	Description
C	Set of n customers
V	Set of vehicles
q	Capacity of each vehicle
$\mathbf{d_i}$	Customer demand
$\boldsymbol{\alpha_i}$	Earliest service time
$\boldsymbol{\beta_i}$	Latest possible service time
$\boldsymbol{\alpha_0}$	Start time of vehicles from the depot
$\boldsymbol{\beta_0}$	Latest return time of vehicles to the end depot
$\boldsymbol{\tau_{ij}}$	Total travel time between i and j
$\mathbf{c_{ij}}$	Cost of travel between i and j
$\mathbf{x_{ijk}}$	Decision variable for routing
$\mathbf{s_{ik}}$	Decision variable for servicing

The mathematical formulation is as follows, wherein, x_{ijk} is a binary variable and if it is equal to 1, it means that vehicle k drives directly from customer i to customer j. Further, s_{ik} is a continuous variable, and is defined as the start time for service at customer i, if serviced by vehicle k. The model also fixes, s0k = α_0 and $s_{n+1,k} = \beta_0$.

$$\min \sum_{i\in N} \sum_{j\in N} \sum_{k\in N} c_{ij} x_{ijk} \tag{1}$$

$$\sum_{j\in N: j\neq i} \sum_{k\in V} x_{ijk} = 1 \qquad \forall i \in C \tag{2}$$

$$\sum_{i\in C} d_i \sum_{j\in N} x_{ijk} \leq q \qquad \forall k \in V \tag{3}$$

$$\sum_{j\in N} x_{0jk} = 1 \qquad \forall k \in V \tag{4}$$

$$\sum_{i\in N} x_{ihk} - \sum_{j\in N} x_{hjk} = 0 \qquad \forall h \in C, \forall k \in V \tag{5}$$

$$\sum_{i\in N} x_{i,n+1,k} = 1 \qquad \forall k \in V \tag{6}$$

$$s_{ik} + \tau_{ij} - M(1 - x_{ijk}) \leq s_{jk} \qquad \forall i, j \in N, \forall k \in V \tag{7}$$

$$\alpha_i \sum_{j\in N} x_{ijk} \leq s_{ik} \leq \beta_i \sum_{j\in N} x_{ijk} \qquad \forall i \in C, \forall k \in V \tag{8}$$

$$x_{ijk} \in \{0,1\} \qquad \forall i, j \in N, \forall k \in V \tag{9}$$

The objective here is minimize the total costs of travel over the edges and this is represented by the objective function (1). The objective function is further subject to the constraints (2) – (9). (2) ensures that all the customers are visited by exactly one vehicle and (3) indicates the capacity constraints. (4), (5) and (6) ensure that the routes are not segmented, that is, a vehicle which arrives at a customer also leaves the customer eventually. (7) ensures that there is enough time for travel between the visits when it has to serve two customers between points i and j. Constraint (8) is present to ensure that the time windows are obeyed, additionally it also ensures that $s_{ik} = 0$ when the vehicle k does not visit customer i. (9) represents the integral constraints for the model.

Further, temporal dependencies can be expressed by generalized precedence constraints. A new parameter δ_{ij} is introduced at this stage and it denotes the minimum difference in time from customer i to j. The set Δ defines the customer pairs (i,j) for which temporal dependency exists. The generalized precedence constraints are formulated as,

$$\sum_{k\in V} s_{ik} + \delta_{ij} \leq \sum_{k\in V} s_{jk} \qquad \forall (i, j) \in \Delta \tag{10}$$

B. Case Model

The following AGV model aims at replicating the situation in the potroom at an aluminium smelter. There are various methods known to solve this kind of a situation. The potroom can be represented as a graph with nodes and edges. The nodes in the graph indicate the start and end points, including the areas where the AGV is expected to stop. The edges represent the free space and where the AGV is expected to travel in order to reach its destination. *Figure 6* presents a brief graphical network representation of the potroom logistics in an aluminium smelter. It represents a potroom with 10 cells, indicated by rectangular blocks. Black coloured oval nodes represent the AGVs available for operation, which are 3 in this case. Additionally, an automated overhead crane has been represented by a blue coloured oval node as it is involved in material handling operations in the potroom as well. Various nodes in the graph are represented by yellow circled nodes and these are connected to one another to form a layout through blue coloured edges.

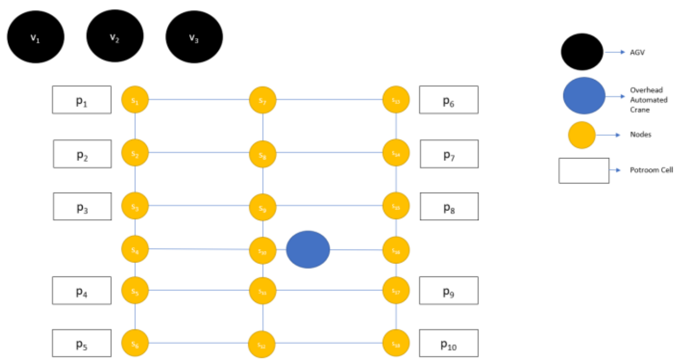


Fig. 6. Graphical representation of potroom logistics

The following assumptions are necessary to be made about the AGV and the graphical representation:

- The designated graph is known to be finite, connected and it represents free space.
- The graph is undirected, that is, a path exists from vertex a to b and vice versa.
- The starting and end positions of the AGV are represented in the graph and are well known.
- AGV can only stop at predefined loading or unloading stations.
- AGV should be able to reach their destination through various paths.
- Operation schedule is known.
- Sensor information is assumed to be available to the AGV.

Furthermore, in this research, for analysis purpose, the graphical representation used will be reduced to a more concise version as shown in *figure 7*. It is a simple and scaled down graphical representation of the potroom in an Aluminium smelter with the help of nodes and edges. This is due to the fact that the research aims to provide a proof of concept, which can be built upon further to extend it to a more detailed model with metaheuristics. Therefore, in this research, only one AGV is considered, and the black oval represents the AGV available for operation. The number of pot cells have been reduced to 5 and they are referred to as p_1, p_2, p_3, p_4 and p_5. Another important consideration made is the fact that the initial point as well as the delivery point of the AGV are the same, denoted by node s_1. The nodes s_2 to s_6 represent the pot cells and denote the nodes to be served by the AGV. Since, the aim of the research is to investigate the influence of stochastic human behavior in the manner of blocked passageways, *figure 8* depicts one such situation, where the edge 2-3 is blocked.

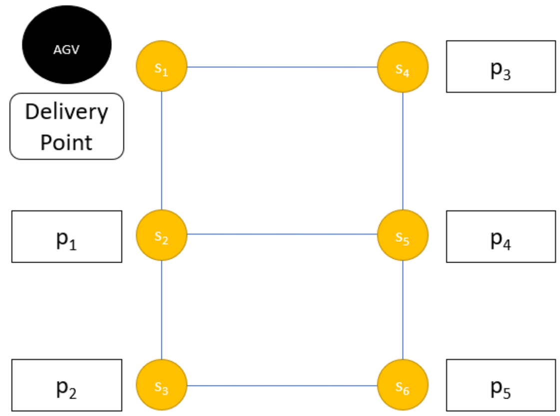


Fig. 7. Graphical representation of normal potroom logistics

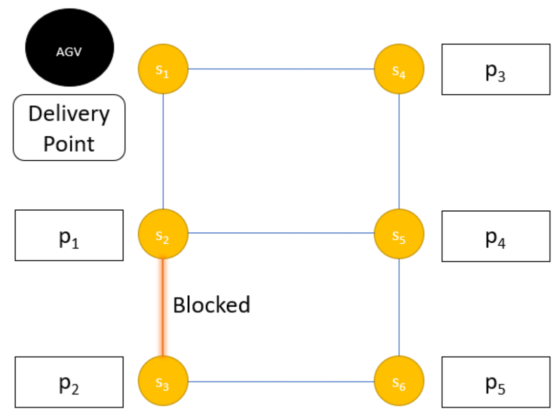


Fig. 8. Graphical representation of potroom logistics with stochastic disturbance

VI. SOLUTION APPROACH

The algorithm used to derive the most optimal path in terms of minimum time taken to complete all the tasks has been described, as well as the most optimal path when one of the edges has been randomly blocked. The following assumptions have been made about the model,

- At the start of the operation there is no occurrence of an event.
- Distance values between the nodes are fed into the AGV, which is then translated into an array of task costs.
- The same applies when an edge has been blocked, since it is fair to make an assumption that the entire factory is connected, and information can be shared.

With regard to the model built, the AGV is located at its initial position s_1, which also happens to correspond to the delivery point. In this model, the AGV will serve each and every cell in the potroom, further delivering it at the assigned node. The model aims to achieve the most optimal path for such a case by minimizing the time taken to serve all the pots. In addition to this, an event-based disturbance is added to the model, wherein, the model considers one of the paths to be inaccessible based on a probability distribution. This is an indication of one of the paths being blocked due to stochastic human disturbances at the potroom. For this additional case, the model aims to achieve the most optimal path.

The basic algorithm can be seen in *figure 9*. It begins with creating the layout of operation through a graphical representation. This is then followed by an optimization process of the sequence of tasks to be performed and the routing decision. Finally, in order to understand the behaviour of the model in the presence of stochastic human behaviour, an event in the form of one of the paths being blocked is generated, and the process repeats with the aim being optimization.

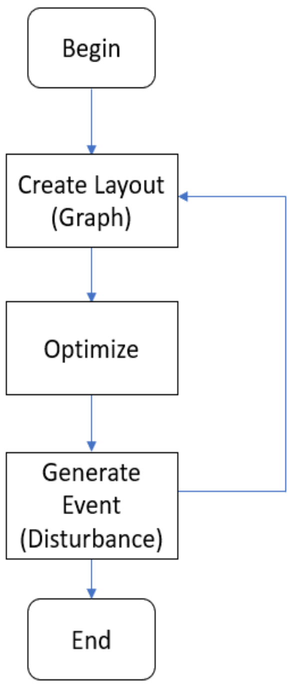


Fig. 9. Basic algorithm

Furthermore, a detailed description of the algorithm can be seen in *figure 10*. The first step in the process is generation of the network of operation in the manner of a graph with nodes and edges. Subsequently, costs with regard to assignment of tasks and routing needs to be initialized. The model then optimizes the sequence of tasks to be performed. This is followed by the model generating all the possible paths from the initial point of the AGV to the pot cell which needs to be served. With the help of this information, the model can optimize the route that needs to be chosen. At this instance of time, the AGV is aware of the order in which the tasks need to be served as well as the most optimal path to be chosen for each task. The model also incorporates the human stochastic behavior at the workspace by blocking one of the edges from operation. This can be seen as a representation of a part of the AGV passageway being blocked in reality due to human interference. Therefore, the algorithm introduces a probability function which will result in the removal of an edge. Once this occurs, the graphical representation and the cost initialization functions will be modified accordingly. Furthermore, the same process of optimization of task sequence and routing decision will be carried out until all the tasks are served.

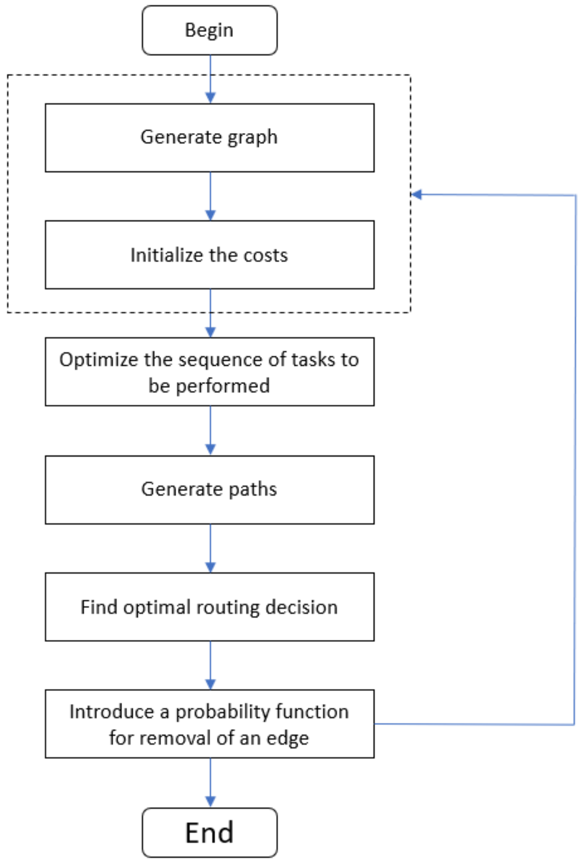


Fig. 10. Detailed representation of the algorithm

As per the devised algorithm, a code has been written in Python for the model described and some of the important parts of the code are described here. To begin with, various libraries used in the code include, NumPy, node, RenderTree, search, defaultdict, random, time and operator. Libraries are basically a collection of functions and methods which allows one to perform actions without writing that part of the code. This is followed by initializing the various associations of the nodes in the model and further, initializing the costs of travel between two nodes.

The function AGV_Output determines the sequence of tasks to be performed as per the cost initialization matrix by optimization. This functions returns the sequence of tasks as output. Subsequently, the next function create_nodes generates all possible paths as per the sequence of tasks to be performed. The function cost_calculator calls the function cost_from_route in order to calculate the costs for the required paths between two nodes. Further, cost_calculator will optimize the path to be taken by considering the calculated costs per path. The output from cost_calculator will be the minimum path and the associated cost. The function cost_task_updater is used to update the initialized costs to a larger number when that particular has been completed. This function helps the model keep track of the tasks that have been completed during operations. The output from this function is progress_array and this is an array of completed tasks and it is checked throughout the code. In order to represent the stochastic human behavior in terms of blocked passageways randomness is introduced in the code. If a certain edge is removed at random, the code checks the progress_array for already completed tasks and accordingly re-initializes the costs. The entire process is then repeated until all the tasks are complete.

VII. RESULTS

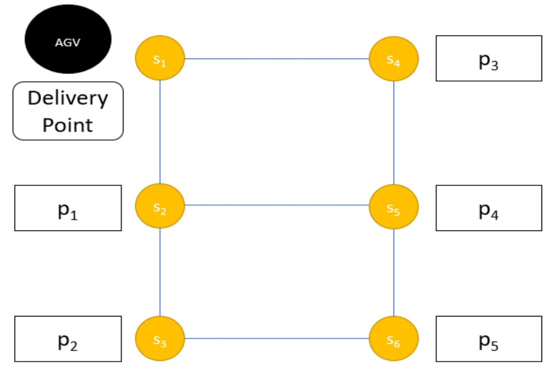
This section of the paper provides the results of the research in quantitative form and as illustrations. The Python code as per the algorithm devised helps in the analysis of a situation when there is stochastic human behavior in the form of blocked passageways. Due to time constraints and since the idea was to provide a proof of concept which could be further extended to a more detailed model, the AGV model generated is of the most simplified form. The human stochastic behavior has been represented in the form of a probability distribution through the code. Since the model is simplified, there are only 3 scenarios of blocked edges for which the AGV routing is dynamically changed and these are reported accordingly. For the purpose of demonstration, the results have been tabulated by manually blocking a edge. However, the model constantly checks for disturbance based on the probability distribution and routes the AGV accordingly. There are 4 distinct scenarios for which the results have been tabulated and illustrated further,

- Scenario 1: When all the paths are available for operation
- Scenario 2: When edge 1-2 is blocked
- Scenario 3: When edge 1-4 is blocked
- Scenario 4: When edge 2-3 is blocked

A. *Scenario 1*

The following situation is when the operations in the potroom have not begun yet or have just begun, as seen in *figure 11*. In such a situation, all the paths are usually available for operation. Based on this assumption, the sequence of tasks are assigned and further, the AGV route is optimized to ensure it takes the least amount of time to serve all the tasks. To begin with, the input costs needs to be initialized based on the distance between nodes. Since the layout is assumed to be symmetric, the costs can be tabulated as shown in *table III*. Based on the cost initialization, sequence of tasks to be served can be optimized. For this particular case, the sequence of tasks are : 2-4-3-5-6.

Based on the sequence of tasks to be served, the AGV path for each task from the initial position of the AGV will be explored, followed by optimization in order to ensure least time. For tasks 2, 4, 3 and 5 there are 3 different possible routes from the initial position of AGV, which is node 1 to the node of the tasks. Additionally, for the final task 6, there are 4 possible paths between the initial node and node 6. The total costs of serving all the tasks is 90 units. These results are tabulated in *table IV* and subsequently, illustrations for the same are provided in *figure 12*.



Fig, 11. Representation of potroom layout: Scenario 1

Table III Initial cost matrix

	1	2	3	4	5	6
1	1000	5	1000	5	1000	1000
2	5	1000	5	1000	5	1000
3	1000	5	1000	1000	1000	5
4	5	1000	1000	1000	5	1000
5	1000	5	1000	5	1000	5
6	1000	1000	5	1000	5	1000

Table IV Output: Scenario 1

Tasks	**Possible Paths**	**Most Optimal Path**	**Associated Cost**
2	1-2 1-4-5-6-3-2 1-4-5-2	1-2	10
4	1-4 1-2-5-4 1-2-3-6-5-4	1-4	10
3	1-2-3 1-4-5-2-3 1-2-5-6-3	1-2-3	20
5	1-2-5 1-4-5 1-2-3-6-5	1-2-5	20
6	1-2-3-6 1-4-5-2-3-6 1-2-5-6 1-4-5-6	1-2-3-6	30

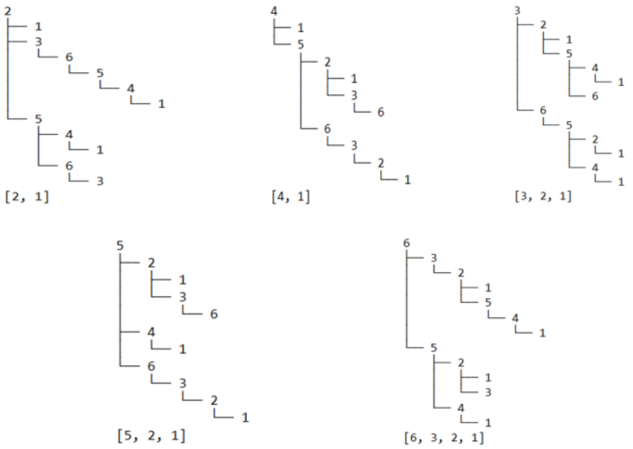


Fig. 12. Possible AGV paths: Scenario 1

B. Scenario 2

The following situation is when the operations in the potroom have begun and the probability distribution included in the code removes an edge at random as seen in *figure 13*. This can be seen as a real world representation of the path 1-2 being blocked due to random human disturbance. In such a situation, all the paths except 1-2 are available for operation. Based on this assumption, the sequence of tasks are assigned and further, the AGV route is optimized to ensure it takes the least amount of time to serve all the tasks.

To begin with, the input costs needs to be re-initialized based on the distance between nodes and the edge removed. Since the layout is assumed to be symmetric, the costs can be tabulated as shown in *table V*. The costs 1-2 and 2-1 are the ones that are re-initialized due to the edge 1-2 being blocked. Based on the cost initialization, sequence of tasks to be served can be optimized. For this particular case, the sequence of tasks are : 4-3-5-2-6.

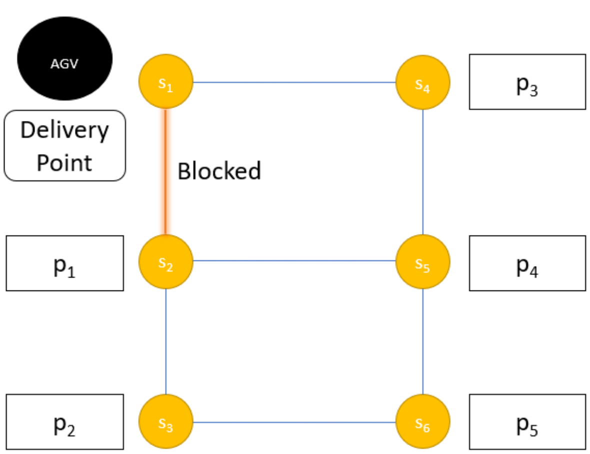


Fig. 13. Representation of potroom layout: Scenario 2

Table V Reinitialized cost matrix

	1	2	3	4	5	6
1	1000	1000	1000	5	1000	1000
2	1000	1000	5	1000	5	1000
3	1000	5	1000	1000	1000	5
4	5	1000	1000	1000	5	1000
5	1000	5	1000	5	1000	5
6	1000	1000	5	1000	5	1000

Table VI Output: Scenario 2

Tasks	**Possible Paths**	**Most Optimal Path**	**Associated Cost**
4	1-4	1-4	10
3	1-4-5-2-3 1-4-5-6-3	1-4-5-2-3	40
5	1-4-5	1-4-5	20
2	1-4-5-6-3-2 1-4-5-2	1-4-5-2	30
6	1-4-5-2-3-6 1-4-5-6	1-4-5-6	30

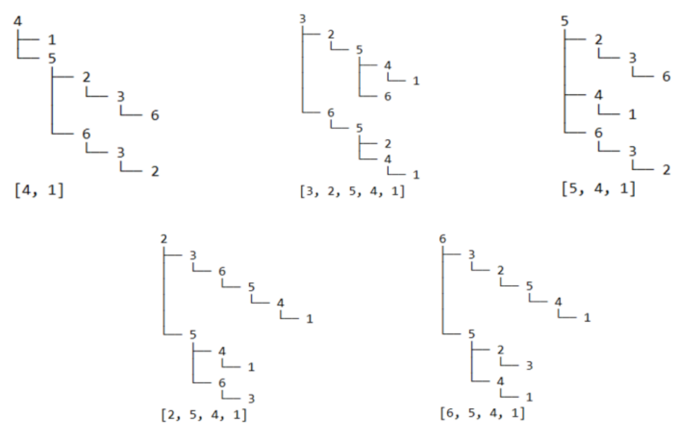


Fig. 14. Possible AGV paths: Scenario 2

Based on the sequence of tasks to be served, the AGV path for each task from the initial position of the AGV will be explored, followed by optimization in order to ensure least time. When paths are being explored, one can notice that the code ensures that edge 1-2 is not in the options available. Due to this reason, the number of possible paths available will be relatively lesser when compared to case 1. For task 4 and 5 there is only one possible path that the AGV can follow. For the remaining 3 tasks there are 2 possible paths each from the initial point to the node where the task needs to be served. The total costs of serving all the tasks is relatively greater than case 1 at 130 units. These results are tabulated in *table VI* and subsequently, illustrations for the same are provided in *figure 14*.

C. Scenario 3

The following situation is when the operations in the potroom have begun and the probability distribution included in the code removes an edge at random as seen in *figure 15*. This can be seen as a real world representation of the path 1-4 being blocked due to random human disturbance. In such a situation, all the paths except 1-4 are available for operation. Based on this assumption, the sequence of tasks are assigned and further, the AGV route is optimized to ensure it takes the least amount of time to serve all the tasks. To begin with, the input costs needs to be re-initialized based on the distance between nodes and the edge removed. Since the layout is assumed to be symmetric, the costs can be tabulated as shown in *table VII*. The costs 1-4 and 4-1 are the ones that are re-initialized due to the edge 1-4 being blocked. Based on the cost initialization, sequence of tasks to be served can be optimized. For this particular case, the sequence of tasks are : 2-3-5-4-6.

Based on the sequence of tasks to be served, the AGV path for each task from the initial position of the AGV will be explored, followed by optimization in order to ensure least time. When paths are being explored, one can notice that the code ensures that edge 1-2 is not in the options available. Due to this reason, the number of possible paths available will be relatively lesser when compared to case 1. For task 4 and 5 there is only one possible path that the AGV can follow. For the remaining 3 tasks there are 2 possible paths each from the initial point to the node where the task needs to be served.

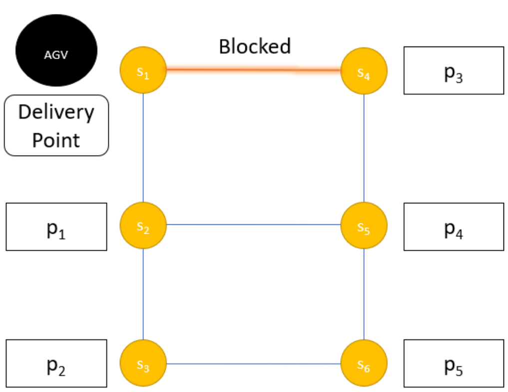


Fig. 15. Representation of potroom layout: Scenario 3

Table VII Reinitialized cost matrix

	1	2	3	4	5	6
1	1000	5	1000	1000	1000	1000
2	5	1000	5	1000	5	1000
3	1000	5	1000	1000	1000	5
4	1000	1000	1000	1000	5	1000
5	1000	5	1000	5	1000	5
6	1000	1000	5	1000	5	1000

Table VIII Output: Scenario 3

Tasks	**Possible Paths**	**Most Optimal Path**	**Associated Cost**
2	1-2	1-2	10
3	1-2-3 1-2-5-6-3	1-2-3	20
5	1-2-5 1-2-3-6-5	1-2-5	20
4	1-2-5-4 1-2-3-6-5-4	1-2-5-4	30
6	1-2-3-6 1-2-5-6	1-2-3-6	30

The total costs of serving all the tasks is relatively greater than case 1 at 110 units. These results are tabulated above in *table VIII* and subsequently, illustrations for the same are provided in *figure 16*.

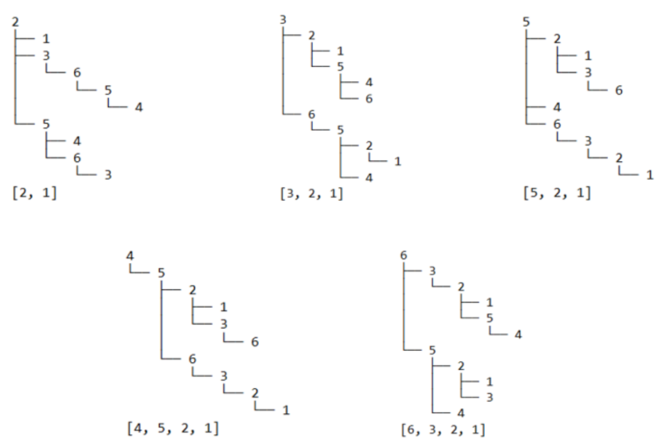


Fig. 16. Possible AGV paths: Scenario 3

D. Scenario 4

The following situation is when the operations in the potroom have begun and the probability distribution included in the code removes an edge at random as seen in *figure 17*. This can be seen as a real world representation of the path 2-3 being blocked due to random human disturbance. In such a situation, all the paths except 2-3 are available for operation. Based on this assumption, the sequence of tasks are assigned and further, the AGV route is optimized to ensure it takes the least amount of time to serve all the tasks.

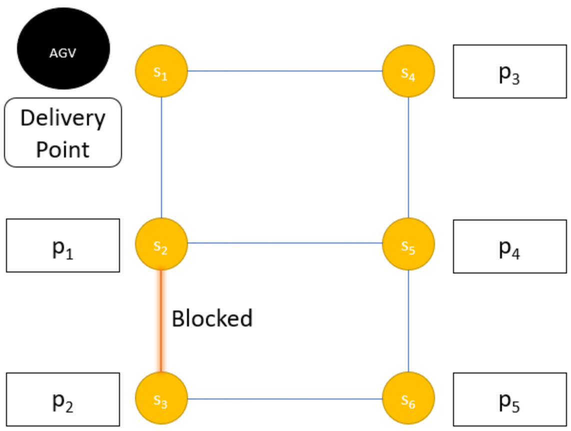


Fig. 17. Representation of potroom layout: Scenario 4

To begin with, the input costs needs to be re-initialized based on the distance between nodes and the edge removed. Since the layout is assumed to be symmetric, the costs can be tabulated as shown in *table IX*. The costs 2-3 and 3-2 are the ones that are re-initialized due to the edge 2-3 being blocked. Based on the cost initialization, sequence of tasks to be served can be optimized. For this particular case, the sequence of tasks are : 2-4-5-6-3.

Table IX Reinitialized cost matrix

	1	2	3	4	5	6
1	1000	5	1000	5	1000	1000
2	5	1000	1000	1000	5	1000
3	1000	1000	1000	1000	1000	5
4	5	1000	1000	1000	5	1000
5	1000	5	1000	5	1000	5
6	1000	1000	5	1000	5	1000

Based on the sequence of tasks to be served, the AGV path for each task from the initial position of the AGV will be explored, followed by optimization in order to ensure least time. When paths are being explored, one can notice that the code ensures that edge 2-3 is not in the options available. Due to this reason, the number of possible paths available will be relatively lesser when compared to case 1. For all the five tasks there are only two possible routes from the initial position of AGV, which is node 1 to the node of the tasks. The total costs of serving all the tasks is relatively greater than case 1 at 110 units. These results are tabulated in *table X* and subsequently, illustrations for the same are provided in *figure 18*.

Table X Output: Scenario 4

Tasks	Possible Paths	Most Optimal Path	Associated Cost
2	1-2 1-4-5-2	1-2	10
4	1-4 1-2-5-4	1-4	10
5	1-2-5 1-4-5	1-2-5	20
6	1-2-5-6 1-4-5-6	1-2-5-6	30
3	1-2-5-6-3 1-4-5-6-3	1-2-5-6-3	40

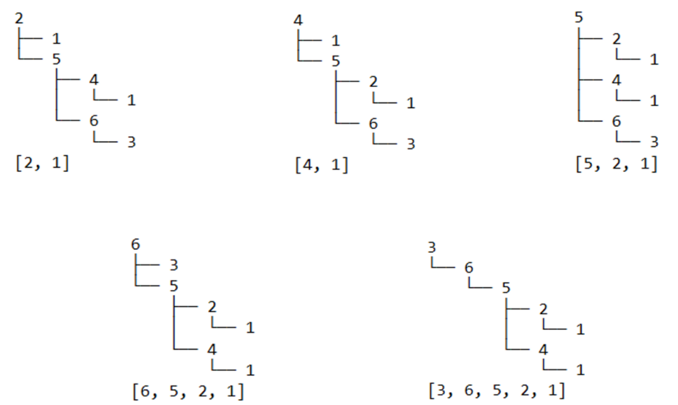


Fig. 18. Possible AGV paths: Scenario 4

VIII. CONCLUSION

The main research question to be answered in this scientific study was, *"With the introduction of intelligent AGVs, stochastic behaviour needs to be addressed, that is, how would these AGVs react to disturbances created by such random human behaviour and process interference?."* Due to time constraints and due to the fact that the purpose of this research was to provide a proof of concept for the case, the research question was further simplified and can be better represented as, *"For instance, if a certain pathway is blocked in the potroom of an aluminium smelter due to such stochastic behaviour, how would the AGV find the most optimal path?."* To begin with, it is important to realize an intelligent AGV, and the literature review combined with market research helped the study by formulating a technological roadmap for an intelligent AGV for the operating environment under concern, which is a light metal and forging industry. This was carried out by focussing on certain important aspects of an AGV, namely, mapping & localization, navigation and obstacle avoidance.

Once it became clear that an intelligent AGV can be realized in the near future, the next step in the research was to address the main research question. The most important aspect with regard to this was dynamic re-routing, and an AGV which is intelligent is capable of moving around an obstacle. However, from literature it was evident that the area concerning stochastic disturbances in operations except for process interferences in some cases were not addressed. This study concentrates on the potroom in an aluminium smelter. It successfully devises an algorithm which is further translated into a model using the Python code, and this model analyses the dynamic behaviour of an AGV by studying various scenarios. The algorithm incorporates the stochastic behaviour of blocked passageways by introducing a probability distribution for the same. This ensures that a certain path is blocked at random. The model that is built is equipped to react to the disturbance by automatically finding the next most optimal path and traversing it. Therefore, the algorithm formulated and the subsequent model is capable of dynamically re-routing itself around stochastic disturbances in the potroom layout that has been considered.

The model has been analysed for 4 different scenarios with the first one being the scenario wherein every path is available for travel. The remaining 3 scenarios include a certain path being blocked at random, in our case, this being, 1-2, 1-4 and 2-3. For each of these cases, the sequence of tasks to be carried out is optimized, followed by the path to be taken. The results for every scenario has been tabulated and illustrated, which shows the way in which an AGV would react to stochastic human disturbances during operations in the form of blocked passageways. Hence, this research has successfully contributed as a proof of concept by modelling a simple situation wherein an intelligent AGV can dynamically re-route itself to serve tasks in the presence of stochastic human disturbances.

IX FUTURE RECOMMENDATIONS

This research has successfully contributed as a proof of concept by modelling a simple situation wherein an intelligent AGV can dynamically re-route itself to serve tasks in the presence of stochastic human disturbances. Due to time constraints, this research focusses only on one AGV, whereas in real world scenarios there is usually a fleet of AGVs, and this would demand coordination between them for successful operation. Further, the layout of the potroom considered is also simplified for research purpose as it is symmetric in nature. Therefore, it would be recommended to investigate a more realistic potroom design, although this research attempts to investigate a simplified case.

The model created can be easily extended to a more detailed representation of the potroom logistics by using advanced metaheuristics. The detailed model in the future can also incorporate process interferences, which has not been considered in this research. Further, this approach can also be utilized in industries with similar challenges, for instance, cement industry, power generation industry, aerospace and construction to name a few. The algorithm and the model can also be utilized for various other indoor applications where human-robot interaction is crucial.

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Appendix B:

Python code of the AGV model

The following section presents the code which has been formulated for the purpose of generating an AGV model, which has the ability to re-route itself around obstacles which have been created due to stochastic human behavior.

```
import numpy as np
from anytree import Node, RenderTree, search
import re
from collections import defaultdict
import random
import time
import operator


node_dict = defaultdict(int)
node_dict[1] = [2,4]
node_dict[2] = [1,3,5]
node_dict[3] = [2,6]
node_dict[4] = [1,5]
node_dict[5] = [2,4,6]
node_dict[6] = [3,5]

cost_tasks = np.array([5, 10, 5, 10, 15])

cost_tasks_edge_rem_1_2 = np.array([15, 10, 5, 10, 15])
cost_tasks_edge_rem_1_4 = np.array([5, 10, 15, 10, 15])
cost_tasks_edge_rem_2_3 = np.array([5, 20, 5, 10, 15])

cost_route = np.array([[1000, 5, 1000, 5, 1000, 1000], [5, 1000, 5, 1000,
5, 1000], [1000, 5, 1000, 1000, 1000, 5],[5, 1000, 1000, 1000, 5, 1000],
[1000, 5, 1000, 5, 1000, 5], [1000, 1000, 5, 1000, 5, 1000]])


def AGV_Output(cost_tasks_internal):

    cost_dict={2:cost_tasks_internal[0],3:cost_tasks_internal[1],4:cost_
    tasks_internal[2],5:cost_tasks_internal[3],6:cost_tasks_internal[4]}

    route_vals = sorted(cost_dict.items(), key=operator.itemgetter(1))

    route = [s for s,v in route_vals ]

    min_time = 0

    return route, min_time
```

```
def create_nodes(node_dict, min_node):

      nodes_list = [node for node in node_dict.keys() if min_node.name in
      node_dict.get(node)]

      for node_check in nodes_list:
            if (min_node.depth==0):
            ancestors_list = []
            else: ancestors_list = str(min_node.ancestors[-1])
            ancestors_list   =   [int(s)   for   s   in   re.findall(r'\d+',
            ancestors_list)]  if((node_check  !=  1)  &  (node_check  not  in
            ancestors_list)):
            new_min_node = Node(node_check, parent = min_node)
            create_nodes(node_dict, new_min_node)
            if (node_check == 1):
            new_min_node = Node(node_check, parent = min_node)

      return main_node


def cost_from_route(route):
      cost = 0

      for i, j in zip(route[:-1], route[1:]) :
            cost += cost_route[i-1][j-1]

      return cost


def cost_calculator(routes):
      min_cost = 1000
      min_route = []

      for route in routes:
            node_list = [int(s) for s in re.findall(r'\d+', str(route))]

            if cost_from_route(node_list) < min_cost:
            min_cost = cost_from_route(node_list)
            min_route = node_list

      return min_route, min_cost*2
```

```
def    cost_tasks_updater(AGV_tasks,    elapsed_time,    cost_per_task,
cost_tasks_orig:

      dict_cost0 = cost_tasks_orig[AGV_tasks[0]-2]
      dict_cost1 = cost_tasks_orig[AGV_tasks[1]-2]
      dict_cost2 = cost_tasks_orig[AGV_tasks[2]-2]
      dict_cost3 = cost_tasks_orig[AGV_tasks[3]-2]
      dict_cost4 = cost_tasks_orig[AGV_tasks[4]-2]

      dict_cost  =  {AGV_tasks[4]:(dict_cost0  +  dict_cost1  +  dict_cost2  +
      dict_cost3  +  dict_cost4),  AGV_tasks[3]:(dict_cost0  +  dict_cost1  +
      dict_cost2  +  dict_cost3),  AGV_tasks[2]:(dict_cost0  +  dict_cost1  +
      dict_cost2),    AGV_tasks[1]:    (dict_cost0    +    dict_cost1),
      AGV_tasks[0]:dict_cost0}

      progress_array = cost_tasks_orig.copy()
      for task, value in dict_cost.items():

            if elapsed_time > value:
                  progress_array[task-2] = 1000

      return cost_tasks_orig, progress_array


print_var = 0
AGV_tasks, _ = AGV_Output(cost_tasks)

print('original sequence of tasks ', AGV_tasks)
cost_tasks = np.array([5, 10, 5, 10, 15])
cost_per_task = defaultdict(int)
total_cost = 0
for task in AGV_tasks:
      main_node = Node(task)

      create_nodes(node_dict, main_node)
      for pre, fill, node in RenderTree(main_node):
            print("%s%s" % (pre, node.name))

      operate = search.findall(main_node, filter_=lambda node: node.name in
      [1])
      min_route_print ,task_cost = cost_calculator(operate)
      total_cost    +=    task_cost    cost_per_task[task]    =    task_cost
      print(min_route_print)
```

```
valid = 0
start_time = time.time()

progress_array = [5,10, 5, 10, 15]
while(1):
# Replicating Sensor
      if len(set(progress_array)) == 1:
            end_time = time.time()
            print(end_time-start_time)
            print('Done!')
            break

      random.seed(4)
      removal_prob = random.uniform(0,1)

      if ((removal_prob > 0.2) & (valid == 0)):
            random.seed(4)
            edge_removed = [random.randint(1,6), random.randint(1,6)]
            if edge_removed[1] in node_dict.get(edge_removed[0]):
                  print('edge removed',edge_removed)
                  node_dict[edge_removed[0]].remove(edge_removed[1])
                  node_dict[edge_removed[1]].remove(edge_removed[0])
                  cost_route[edge_removed[1]-1][edge_removed[0]-1] = 1000
                  cost_route[edge_removed[0]-1][edge_removed[1]-1] = 1000
                  if (((edge_removed == [1,2]) | (edge_removed == [2,1])) &
                  (cost_tasks[0] != 1000)):
                        cost_tasks = cost_tasks_edge_rem_1_2
                  elif (((edge_removed == [1,4]) | (edge_removed == [4,1]))
                  & (cost_tasks[2] != 1000)):
                        cost_tasks = cost_tasks_edge_rem_1_4
                  elif (((edge_removed == [2,3]) | (edge_removed == [3,2]))
                  & (cost_tasks[1] != 1000)):
                        cost_tasks = cost_tasks_edge_rem_2_3
                  valid = 1

      if valid:
            AGV_tasks, _ = AGV_Output(cost_tasks)
            if not print_var:
                  print('changed sequence of tasks ', AGV_tasks)
            cost_per_task = defaultdict(int)
            total_cost = 0
            for task in AGV_tasks:
                  main_node = Node(task)

                  create_nodes(node_dict, main_node)
                  if not print_var:
                        for pre, fill, node in RenderTree(main_node):
                              print("%s%s" % (pre, node.name))
```

```
            operate = search.findall(main_node, filter_=lambda node:
            node.name in [1])
            min_route_print, task_cost = cost_calculator(operate)
            total_cost += task_cost

            cost_per_task[task] = total_cost
            if not print_var:
                  print(min_route_print)

      print_var = 1

current_time = time.time()
elapsed_time = current_time-start_time
time.sleep(5)

cost_tasks,    progress_array    =    cost_tasks_updater(AGV_tasks,
elapsed_time, cost_per_task, cost_tasks)
```