Energy level on SGV System

Subjects: Transportation

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Automated industrial vehicles are taking an imposing place by transforming the industrial operations, and contributing to an efficient in-house transportation of goods. They are expected to bring a variety of benefits towards the Industry 4.0 transition. However, Self-Guided Vehicles (SGVs) are battery-powered, unmanned autonomous vehicles. While the operating durability depends on self-path design, planning energy-efficient paths become crucial. Thus, this paper has no concrete contribution but highlights the lack of energy consideration of SGV-system design in literature by presenting a review of energy-constrained global path planning. Then, an experimental investigation explores the long-term effect of battery level on navigation performance of a single vehicle. This experiment was conducted for several hours, a deviation between the global trajectory and the ground-true path executed by the SGV was observed as the battery depleted. The results show that the mean square error (MSE) increases significantly as the battery's state-of-charge decreases below a certain value.

Keywords: energy-awareness ; industry 4.0 ; energy resource management ; trajectory planning ; self-guided vehicle ; SGV-system ; sustainability

1. Introduction

Automated Guided Vehicles (AGVs) have transformed the way we conceive of the transportation of materials. Commercially introduced in the early 1950s, their main task was for intralogistics application [1]. This includes production-to-assembly transfers, warehouse picking and depositing and pharmaceutical supply, among others. Although they are considered to have a high initial investment, they reduce labor costs, improve operational flow and dramatically increase production rates. First AGVs were implemented with primitive devices, and the early guidance system used are tactile sensor-based embedded on or in the floor, such as conductors, optical guides, or magnetic tape, allowing the vehicle to move only in restricted areas [1]. Therefore, the performances of the vehicle, such as speed and safety, are limited.

The recent advances in sensors and control systems have permitted the integration of complex robotic concepts in industrial applications [2]. Laser scanning sensors are used as range finders for long distance measuring with high frequency and a resolution that allows for building a detailed map of the environment. From a safety aspect, the scanners can detect obstacles (i.e., workers, furniture, other mobile platforms, machines, etc.) from several meters, which allows the vehicles to safely navigate with a higher speed. Laser scanners combined with other types of sensors provide a better understanding of the surroundings. , a Self-Guided Vehicle can reach higher guidance level, and is able to freely navigate from places that an AGV cannot; this is referred to as mobile navigation. A navigation is said to be “natural”, which is when it is capable to navigate autonomously and react to situations in a very short time with self-sufficient sensor data, and in any navigable space of a real environment [3].

Today, the problematic goes beyond technology type, the hardware design has gained enough maturity to be industrialized on a large scale. The issue, however, deals with the system efficiency to improve productivity. In this context, *Industry 4.0* was introduced at the Hannover Fair in the beginning of the last decade [4]. Described as the fourth industrial revolution, it gives rise to new types of management to enhance different system levels. Some of the aspects that the Smart Factory paradigm is introducing are: digitization, Human-to-Machine (H2M) interactions and Machine-to-Machine (M2M) communication enhancement, flow optimization, adaptability, flexibility, and sustainability [5]. Sustainability is the least addressed issue in literature and the potential impact is still unknown. Nowadays, the need for energy-efficient vehicles has reached an unprecedented necessity [6][7].

Human-Machine-Infrastructure communication, which is defined as Internet-of-Things (IoT) has been a turning point toward Smart Factory [8][9]. The link between the IoT and energy management has also been extensively studied in [10]. Indoor logistics systems are being enhanced since the advent of industry 4.0. AGV-System is a freight system that is responsible for managing a set of AGVs used for material handling. This system is becoming more intelligent and more flexible thanks to the cutting-edge connectivity, but also the autonomous navigation capabilities of Self-Guided Vehicle (SGVs).

The object of this paper is to bring an overview of the link that exist between the SGVs navigation system performance and the battery source depletion, in the context of smart factory challenges. Figure 1 shows the focus of this paper. Thus, optimal path planning solutions, as part of mobile navigation, are first reviewed. Then, in order to prove the link between the energy level and the navigation sustainability and assess the necessity improving resource management, an experiment was carried out with an SGV. Hundreds of meters have been traveled and pose data were collected in real-time. Finally, the data have been analyzed and compared with the evolution of the battery level.

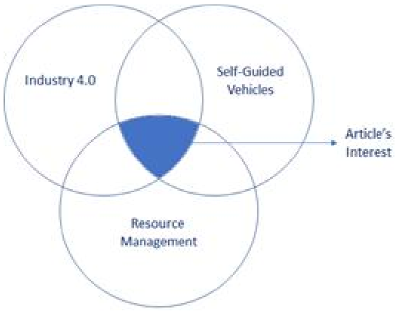


Figure 1. Article's research interest.

2. Context

Material Handling System (MHS) for indoor transportation application has always been an inefficient task in any type of facilities. Around 80% of the total production time is used to move materials from one place to another [11]. Whether it is in industries, hospitals or warehouses, material handling has no added value to the product. The cost varies depending on the load size/weight, route of the environment and the energy source. Therefore, the key objective is to design a cost and energy efficient AGV-system for a specific scenario. Throughput, unit load, flow path design, and the fleet size are the four main factors that are considered by [12] having a direct impact on the operation performance (see Figure 2). Throughput denotes the total time that is needed to handle an entire volume of work. The flow path design defines the track layout for the AGV-System. Unit load is an important aspect that specifies different freight type to carry in size and shape from a use case to another. The fleet size deals with the number of vehicles required to execute the transfers.

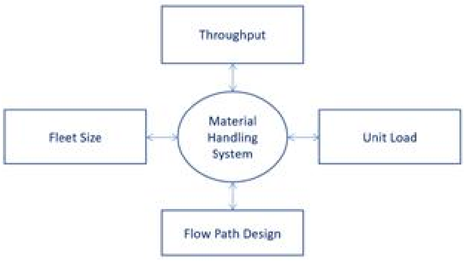


Figure 2. Factors influencing design and operation of Material Handling System [12].

An important factor in the design of the MHS architecture is the flow path design. The latter has an intrinsic effect on the energy consumption of the overall system. In classical AGV-system architecture (with no map handling capability), the physical guidance system is based on a fixed predefined circuit layout, and needs to be modified if the operational flow changes. The planning algorithms are based on a primitive single available path. This type of system does not react to change in the environment. Moreover, this system suffers from a lack of flexibility due to idle time accumulation caused by unpleasant situations, such as deadlocks. The latter has been an issue that has generated attention in literature for past years [13][14].

SGVs have reached a maturity that meets the feasibility of Industry 4.0 paradigm, allowing to be deployed towards decentralized system architecture [15]. It provides a safer working environment, increases automation, time-efficiency, fluidity, and agility. In this paper, we are focusing on the flow path design, defined as the trajectory planning in the SGV navigation system (see Table 1). Full autonomous navigation is a task responsible for moving any mobile platform between any two locations with the known environmental map. The navigation process has the core role of the SGV-system. As shown in Figure 3, navigation consists of four main phases, the perception, localization, path planning, and motion control, through which the SGV must understand orders, plan and execute paths [16]. Perception provides the necessary information about the surrounding environment. The localization assures the real-time position of the vehicle anywhere on the map. Path planning is one of the most important tasks of autonomous mobility. It is often decomposed into local and global planning. The global planner generates a constrained or an unconstrained path between any start and end positions by means of the overall static map. The local planner is an immediate motion planner where the vehicle's cognition is considered. Then a motion execution step generates velocities that tracks the planned trajectory by incorporating the dynamics of the vehicles. Table 1 shows the contrast between the AGV-system and the SGV-system.

Figure 3. Navigation phases of a mobile platform [17].

Most SGVs are powered by a battery system. However, the limited energy density, the long recharging time, and the limited battery lifespan introduce several challenges, which need to be tackled in order to take full advantage of such technology. Unfortunately, the energy-efficiency of SGV-system is not deeply addressed in recent literature [18]. In the context of industry 4.0, the energy consumption of the decentralized SGV-system is higher due to the system modules embedded on every platform. Therefore, the platforms would require recharging more often, causing delays on the operation performances. Therefore, it is necessary to consider the energy constrains while designing the global trajectory so that the total operation time is extended. Nevertheless, the time required to execute a mission could be longer due to the constraints [19]. Therefore, the need of monitoring the level of energy to adapt the trajectory and find a good compromise between time and energy is required. As shown in the state-of-the-art section of this paper, few comprehensive reviews have been published recently, regarding the SGV energy challenges in the context of industry 4.0. By providing some evidences about the influence of the battery state-of-charge (SOC) on the motion performance, this paper aims at highlighting the necessity to consider energy-related constraints during an earlier stage of the global path planning in the context of industry 4.0.

3. Investigating Energy Influence on the Navigation Performances

The firsts to address a resource management solution for energy sustainability issue of moving platforms was the authors in [20][21][22], through which the staying-alive strategy is proposed to send a mobile platform autonomously to a charging station after completing a task. In [23], the authors have considered a topological map with dynamic energy evaluation between different locations. Travel Salesman Problem (TSP) and Tabu-search methods are used for minimum energy route generation considering charging station docking as part of the planning. The issue with this method is that the exact trajectory is unknown. The trajectory is not represented in a grid map with obstacles, so the physical constraints are not fully represented. Another planning type is the coverage planning. It consists in generating a path on which the mobile platform has to cover a maximum point of the free space. Collecting material in several end lines is an example among others. In [24], they proposed a Battery-Constrained Sweep planning algorithm that uses any arbitrary geometry layouts with charging stations to extend the coverage area of the autonomous platform.

Several algorithms have been proposed to minimize the energy consumption path planning problem. Efficient trajectory is influenced by better quality of paths. Path smoothness is also an important aspect of planning energy-efficient trajectory. In [25], the authors proposed an optimal smooth and minimal energy trajectory by minimizing the normal and tangential acceleration variation over an interval of time. The work presented in [26] compares trajectories in terms of energy consumption. Dubins curves are used to link a set of waypoints considering the ground resistance. Compared to A* with Bézier curves smoothing proposed in [27], the algorithm has proven that optimum turning radius limits the energy consumption during rotations. The energy optimal motion profiles are highlighted in [28]. The article shows that bounding the instantaneous velocity of the platform as a function of the turning radius.

An optimal time with restricted energy trajectory is analysed in [19]. A quadratic sequential technique is used with time based objective function. The forces between tires–floor that have a great effect on the optimality with which the trajectory is performed. The authors have also demonstrated that for the same path, the time needed to carry out the trajectory is higher when minimizing energy consumption. So, it is important to weight the energy cost with respect to the mission execution time and the battery SOC.

Considering environmental data for path planning is also studied in literature. A minimum energy planning algorithm is developed for any vehicle type in [29]. Based on a geographic map, an offline optimization of navigation cycle is proposed to reduce the energy consumed by the vehicle. In [30], the effect of the ground friction, which is caused by the contact between the wheels and the floor, is considered when planning. It is shown that a rolling resistance has great effect on the energy consumption of a low-speed indoor vehicle and considering a rolling resistance map may be used to attenuate these losses. The work proposed in [31] proposes an energy-constrained multivehicular navigation. Given an initial battery level, a set of vehicles must meet in any position in the map, in the least amount of time. The planning coordination must generate a path for each vehicle that does not drain off the remaining energy of any mobile platform.

The literature presented so far does not consider the energy resource state when planning the trajectory. The level of the available resources is an issue that is considered in this article. The review of literature shows that there is still a gap for developing an efficient offline trajectory planning algorithm that will yield better resource management.

4. Investigation Method

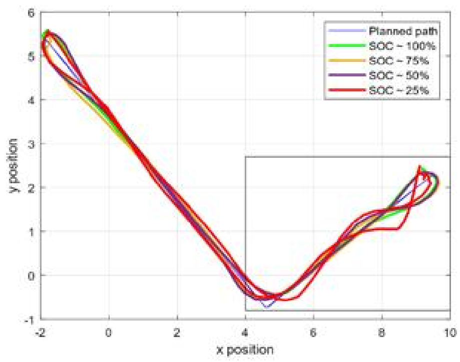
Despite the advances in industrial instrumentation, the navigation is still inefficient and the operation is still not sustainable due to the high energy consumption rate. The initial research on path planning is carried out with the objective to reduce the total travel distance and time. Since the vehicle has a limited amount of energy, it is necessary in the planning approach to seek for adaptation when the resource level drops to a certain threshold. A lower battery level may lead to a nonrobust navigation. In addition, the more efficient the energy consumption, the more lasting and robust navigation will be. Adapting the trajectory through different battery levels is a solution for optimizing the energy at the most convenient moment. Obviously, it is ideal to optimize the amount of available energy that an autonomous platform will use to carry out operations.

The aim of the investigation is to know if the available energy in an electric SGV can influence the operational performance of the vehicle. The operational performance is defined simply as the capability of the platform to follow as close as possible, the global trajectory planned in a known static environment. The operating environment is considered to have no unknown obstacles, which may cause the vehicle to perform collision avoidance or replanning maneuvers (these processes will cause the platform to deviate from the initially planned trajectory).

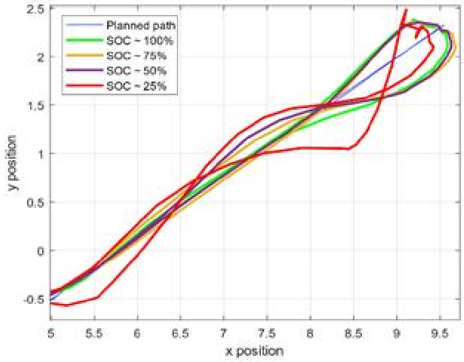
To do so, we performed several experimental tests with a real industrial SVG, designed to be used in the context of industry 4.0. The level of the remaining energy is represented by the battery state-of-charge (SOC) and its value is monitored during the entire experimental procedure. The mean square error (MSE) between the planned global trajectory and the ground-true trajectory is selected as the key performance indicator. Hence, the idea is to assess the relationship between the remaining energy and the capability of the platform to perform a good trajectory execution.

Results & Discussions

The battery is initially fully charged and we assumed that at the beginning of the first lap the . A total of 600 laps that took more than 8 hours have been executed by the industrial SVG. Five trajectories are represented in Figure 4. The thin blue line represents the reference trajectory while the green, yellow, purple, and red represent the trajectories executed at 100, 75, 50, and 25% SOC, respectively.



(**a**)



(**b**)

Figure 4. Executed trajectory for laps at different state-of-charge levels. (**b**) is the zoom of the rectangle in (**a**).

We observed, according to Figure 5 that for a SOC higher than 50%, the MSE does not exceed 0.015 (). Hence, the movement of the platform is close to the reference trajectory (represented on the green surface in Figure 5). When the SOC is between 25% and 50%, the SGV loses precision (orange surface), mainly when performing turns. Below 25% SOC, the MSE becomes significantly high (red surface). For several times, the SGV swerves around the global planner (see red trajectory in Figure 4b); this could be dangerous for the neighboring obstacles. Moreover, we observed that the trajectory is unsmooth at turns; this is due to the current spikes that causes the platform to jerk.

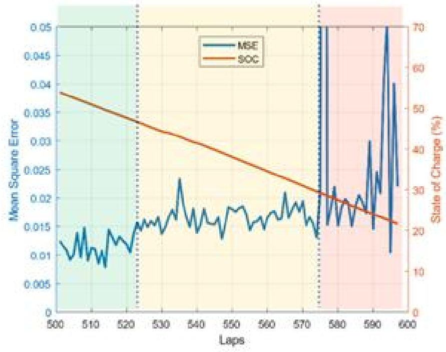


Figure 5. The mean square error (MSE) and state-of-charge (SOC) variation for the last 100 laps.

The surface A, B, and C of Figure 5 represent the evaluation indicator for the navigation performance. In surface A, the MSE indicates that the SGV performances are regular. In portion B of the curve, the gap error has increased, therefore, the planned trajectory has to be constrained in order to not reach the critical navigation represented in C. We have observed that execution time per one lap is slightly increasing when the error increases. We also noted that the high deviations occur when making rotation. These observations result in the fact that the trajectory with high dynamic efforts, mainly rotations, affects the sensing for localization due to current peaks. The observed phenomena shows the importance of monitoring the performance of SGV in real-time in order to adapt the trajectory with respect to the available battery level.

The velocity profiles of the SGV varies for different battery levels. The translational velocity variation for a lap at around 25% SOC is shown in Figure 6; the velocity signals undergoes a chattering effect compared to the velocity at 50%, which is smoother. In addition, the angular velocity profile (see Figure 7) indicates that for a lower battery level, angular speed variation is less smooth, where values reach higher peak values.

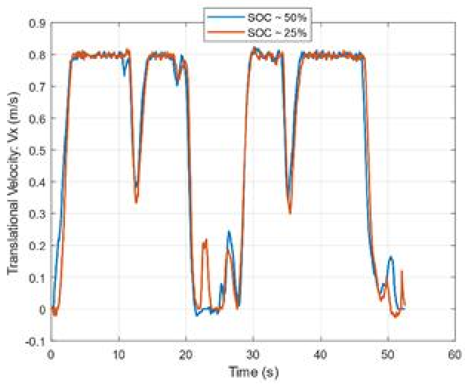


Figure 6. Translational velocity profiles completing a lap at 50% and 25% SOC.

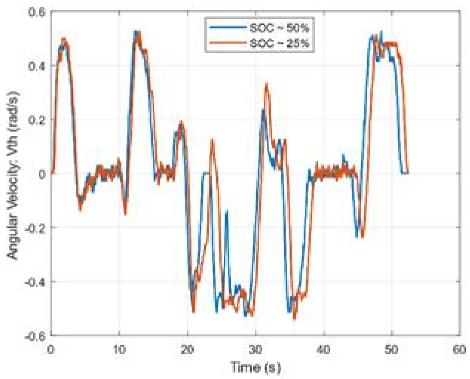


Figure 7. Angular velocity profiles for a single lap at around 50% and 25% SOC.

To illustrate the importance of adapting the vehicle motion, a simulation is carried out on ROS with a vehicle model integrated in a Gazebo environment. The energy model validated in [35] has four main terms represented by Equations (10)–(14). The total energy consumed by the mobile platform is E_{SGV}.

$$E_{SGV} = E_{DC} + E_F + E_K + E_E \tag{1}$$

where E_{DC}, is the energy consumed by the direct current motors defined as:

$$E_{DC} = \int \left((I_a^r)^2 R_a^r + \left(I_a^l\right)^2 R_a^r \right) dt \tag{2}$$

where and are the armature currents, and and are the armature resistance of the left and right DC motors respectively.

The energy dissipated through friction is represented by E_F:

$$E_F = \int \mu m g \left(\left(V_r(t) - L w_r(t)\right) + \left(V_l(t) - L w_l(t)\right) \right) dt \tag{3}$$

where is the coefficient of rolling friction, m is the robot mass, g is the gravity, V_r and w_r are the linear and angular velocities of the right wheel, V_l and w_l are the linear and angular velocities of the left wheel, and L is the axle length of the vehicle.

The kinetic energy E_K is due to motion and is expressed as:

$$E_K = \frac{1}{2} \left(mV^2 + I\omega^2 \right) \tag{4}$$

$$V = \frac{V_r + V_l}{2} \tag{5}$$

where V and (defined in Equation (3)) are the linear and angular velocities of the vehicle, m is the mass, and I is the moment of inertia of the vehicle.

The energy consumed by the embedded circuitry is represented by E_E, is given by the following equation:

$$E_E = \int \left(I_{elec} V_{elec} \right) dt \tag{6}$$

where and are, respectively, the flowing current at the battery and and the supply voltage.

Equations (10)–(15) show that the main terms that affect the total energy are the two velocities. In order to measure the effect of these velocities and battery level on the total energy, we have defined three main case studies with the same scenario, as in Figure 12. Then, the translational and rotational velocities are decreased by 5%, for 25% SOC. Then, based on the energy model, the total energy consumed for a single lap is measured, then compared to the one spent at the initial velocities (see Table 3).

Table 1. Comparative data for a single lap execution at critical SOC.

Case Study	Maximum Velocities		Battery SOC	Total Energy E_{SGV} (Joule)	Execution Time (Second)	Difference in Percentage	
	V_{max} (m/s)	$_{max}$ (rad/s)				Energy	Time
CS1	0.80	0.5	SOC = 50%	8064	51.3	-	-
CS2	0.80	0.5	SOC = 25%	8388	52.5	+4.0%	+2.3%
CS3	0.76	0.47	SOC = 25%	8132	53.6	+0.8%	+4.5%

The execution times shown in Table 3 are comparable to the analysis presented in [31], where the authors have depicted the minimum time required for identical autonomous mobile platforms to travel a certain distance. It has been stated that the vehicle with the lowest initial battery level executes the planned trajectory slower than the other ones, in order to reach its destination. Nevertheless, the reason is not clearly provided. In our experiment, we have quantified the difference between the three cases. In CS 2, it is observed that 4% more energy is spent compared to CS1, in order to complete a single lap. This is due to the time and effort required to self-correct the error between the path execution and the global reference path (represented in Figures 13 and 14). Therefore, more energy is spent due to rotational movement as shown in the two profiles of Figure 16. The rotational movements tend to increase in an environment with several SGVs or other dynamic subjects such as human workers. So, the overall SGV-system is expected to be more energy consuming when operating in such environments.

Furthermore, in CS3, we have been capable to demonstrate that forcing the navigation system to limit its velocities by 5% from the maximum values, would save up to 3% of the total amount of energy needed to complete a lap, when the SOC drops to 25%. Therefore, regarding the limited performance of the battery-powered SGV, it is important to adapt the trajectory, by an up-front consideration of the available resources. In fleet deployment scenarios, the SGV-system efficiency will depend essentially on how the trajectories respective to each SGV are generated. In addition, the lack of resource consideration may generate ineffective trajectories that may compromise the operations before completion.

Performance measure of SGVs have mainly evolved towards safety of working environment. However, performance analysis regarding navigation and sustainability have begun only recently. With this in mind, the prism of the review and the investigation is to open a research breach regarding the sustainability of SGV-systems. We performed a simple navigation experiment with an industrial SGV, and the results show that the platform deviates from the planned path as the battery level depletes. When the battery level drops below 25% SOC, the SGV pose deviates up to 2 meters from the planned position. This might jeopardise the nearby workers or platforms.

As mentioned previously, the conducted experiment did not consider the uncertainties related to localization algorithms that might negatively affect the planning and the execution of trajectories. In addition, considering the battery dynamic model allows an adequate representation of the battery's real discharge rate. Nevertheless, these results contribute to an understanding of the navigation performances regarding the battery level, which are often neglected. Moreover, this would help industrials to evaluate the operational sustainability of their fleet capabilities.

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