Do We Need a Change in Road Winter Maintenance to Accommodate for Automated Vehicles?

A State-of-the-Art Literature Review Considering Automated Vehicle Technology's Usage of Road Infrastructure During Winter

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ABSTRACT

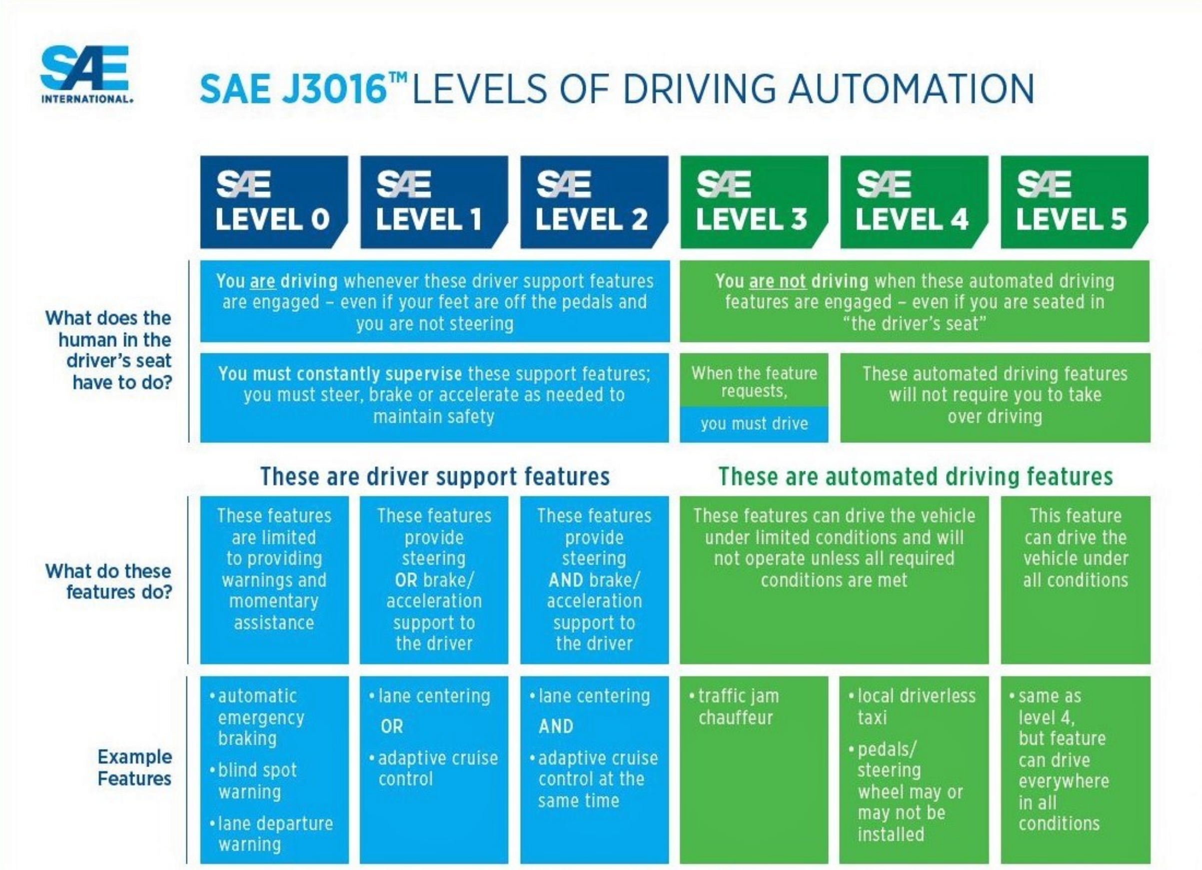
In order for automated vehicles to be allowed to join the modern car fleet, and, in the future, replace the human drivers, they must be able to handle adverse weather, including snowy conditions. This literature review focuses on how automated vehicles utilize the road and how this use is suitable for winter maintenance strategies. Where global navigation satellite system (GNSS) service is unavailable, automated vehicles need bare roads to perform relative navigation based on real-time data about lane markings, obstacles, and road infrastructure. Snow-covered tracks hinder vehicle navigation and lane marking detection, which might generate wheel slippage that in turn causes emergency stop and challenging friction estimates. Although the entry of automated vehicles into the car fleet does not demand change in the strategies of winter maintenance, it does demand higher level of service as of today. Maintaining an entire road network on which autonomous vehicles always can operate is tremendously expensive and likely not feasible. One solution could be to add another maintenance class in a bare road strategy, i.e. an automated vehicle maintenance class with a high level of service and a set of operational criteria allowing automated vehicles to operate. The maintenance class should be used for certain main routes where there is a high frequency of automated vehicles. A model that recommends preferable routes to the destination based on current road conditions within the operational envelope should be provided to the automated vehicle system.

Keywords: Automated Vehicle, Winter Maintenance, Winter Operations, Level of Service, Navigation

1. INTRODUCTION

Recently, automated vehicles and self-driving cars have made a major appearance in the global media. The technology has made huge advances, and research efforts have escalated correspondingly. Investors and competing companies make necessary research and development cheaper, an important factor contributing to innovations and rapid advancements. Litman *(1)* predicts that in the late 2030s or early 2040s, autonomous vehicles will have reached a sufficient level of reliability and affordability to replace most human drivers. Pilot projects with self-driving buses have been set into life in several cities, and Litman *(1)* states that in the 2020s and 2030s self-driving taxi services will be available in many urban areas.

The Society of Automotive Engineers (SAE) has developed an international standard for the levels of automation in vehicles, as seen in **Figure 1**. The scale goes from Level 0, where the human driver has full control and no driving automation, to Level 5, where the vehicle is entirely self-driven *(2)*. Level 2 is defined by a human driver that controls the car, provided with steering and braking support, lane centering and adaptive cruise control *(2)*. Most new cars today are likely to be classified at this level.



SAE INTERNATIONAL

SAE J3016™ LEVELS OF DRIVING AUTOMATION

	SAE LEVEL 0	SAE LEVEL 1	SAE LEVEL 2	SAE LEVEL 3	SAE LEVEL 4	SAE LEVEL 5
What does the human in the driver's seat have to do?	**You are driving** whenever these driver support features are engaged – even if your feet are off the pedals and you are not steering			**You are not driving** when these automated driving features are engaged – even if you are seated in "the driver's seat"		
	You must constantly supervise these support features; you must steer, brake or accelerate as needed to maintain safety			When the feature requests, you must drive	These automated driving features will not require you to take over driving	
	These are driver support features			These are automated driving features		
What do these features do?	These features are limited to providing warnings and momentary assistance	These features provide steering **OR** brake/acceleration support to the driver	These features provide steering **AND** brake/acceleration support to the driver	These features can drive the vehicle under limited conditions and will not operate unless all required conditions are met		This feature can drive the vehicle under all conditions
Example Features	• automatic emergency braking • blind spot warning • lane departure warning	• lane centering OR • adaptive cruise control	• lane centering AND • adaptive cruise control at the same time	• traffic jam chauffeur	• local driverless taxi • pedals/steering wheel may or may not be installed	• same as level 4, but feature can drive everywhere in all conditions

FIGURE 1: *SAE International Standard for the levels of driving automation (2)*

The term "automated vehicle" is used in this article as an umbrella term for autonomous vehicle, self-driving car and vehicle with a high degree of sensor technology and driving assistance. If not mentioned specifically, it may be assumed that the level of autonomy is 4 or 5 with high or full automation *(2)*.

Regions with cold climates experience seasons of snow, ice and subzero temperatures every year. These conditions impair vehicular mobility and can reduce traffic safety, resulting in the need for winter maintenance services. Road owners typically assign a certain level of service (LoS) to each road to ensure acceptable road maintenance quality. In Norway, this is done using a standard that defines maintenance classes with different categories of LoS. Roads are assigned a maintenance class based on their traffic volume and priority level. Each maintenance class defines both the acceptable state of the road, and the speed at which this state should be regained after snowstorms or other disruptive weather events.

A central question many road owners are currently struggling with is: "Do we need to change our winter maintenance services to accommodate automated vehicles?" While this question is too large and complex to be fully answered in an individual study, a literature review of scientific articles has been conducted to find answers, comprised of the following questions:

- How do automated vehicles navigate in winter conditions?
- Do automated vehicles need to know the available friction level?
- What infrastructure elements are critical for automated vehicles, and does their usage affect winter maintenance?

This study is limited to the technological aspects of winter maintenance and not its legal aspects. While questions regarding regulatory challenges are indeed important and highly relevant, they are beyond the scope of this paper.

2. METHOD

The first stage of research included gathering articles that were relevant for the scope of work. Accordingly, the online university library NTNU Oria was used as a portal to scientific databases such as Elsevier, Scopus and Science Direct *(3)*.

The keywords and search criteria used are shown in **Table 1**. The first column displays words which were significant to the title of the articles or abstract. The second column shows words of interest in relation to the first column. The third column shows words worth attention if shown in the title or abstract along with words from the other columns.

TABLE 1: Keywords and search criteria used in the literature review

Major keywords	**Special interest**	**Worth attention**
Autonomous vehicle	Winter maintenance	Driving assistant system
Self-driving car	Adverse weather	Mapping
Snow	Sensor technology	Winter operations
Navigation	Motion control	GPS
Friction	Road conditions	GNSS
Lane marking	Obstacle	LiDAR
Vehicle location	Visual perception	Level of service
Winter	Lane keeping assistance	Hough transform

After the initial search covering a wide range of topics, it was necessary to exclude articles which did not correspond to the purpose of this review. The result was limited to articles published in 2015-2020. Due to the rapid progress in technological advancements, articles published before this time may already be outdated; nonetheless, some articles published before 2015 were included due to theoretical relevancy and discussion of winter maintenance strategies.

The second stage was comprised of a careful reading of the selected articles, which led to rejecting several due to their detailed research of software implementation or advanced sensor technology, areas which lie beyond the scope of this study. Other excluded articles focused on using automated vehicles for winter maintenance and snow-plowing. While this topic is of great interest, focusing on it is not a part of this review. The final stage included reading through reference lists of the selected articles, which enriched the article's overall quality.

3. RESULTS OF THE LITERATURE REVIEW

In the following paragraphs the results of the literature review are presented. A clarification of the way winter maintenance is performed today is given, and an appraisal of the state-of-the-art literature findings on automated vehicle technology related to their maneuverability and navigation. Friction estimation in adverse weather conditions and a summary of the literature's considerations on automated vehicles in winter conditions are also included.

3.1 Winter Maintenance Strategies

3.1.1 General Overview

Regions with cold climates experience seasons of snow, ice and subzero temperatures every year. To prepare for this harsh weather, winter maintenance strategies have been developed. Scandinavian countries have defined guidelines and methods for ensuring acceptable road conditions in the winter season. These strategies are based on roads' traffic volume and priority level *(4)*, types of vehicles (i.e. light or heavy), public transport, pedestrians and cyclists. Additional factors determining the strategy include road geometry, topography, accident level, rush hour issues and environmental conditions *(5)*.

Winter maintenance strategies define methods to reach or retain a road's specific state. Some countries describe level of service (LoS) on different parts of the road network rather than specific strategies. However, when describing a certain LoS, a maintenance strategy is automatically selected *(6)*. The three maintenance strategies are bare road strategy, winter road strategy and closed road strategy. More specifically, the winter maintenance strategies in Norway are split into five maintenance classes, each containing a different LoS for winter operations. The bare road strategy has two strict maintenance classes, while the winter road strategy has three more lenient maintenance classes. After a weather event, these strategies ensure that a road regains its approved road condition within a given time specific to the maintenance class. During a weather event, while there are requirements for efforts that must be executed within a certain period depending on the maintenance class, there are no requirements for the road conditions during the event itself.

3.1.2 Requirements in Winter Maintenance Strategies

The first maintenance strategy is a *bare road strategy*, where the formation of snow and ice layers on the pavement is avoided. Efforts are made to prevent accumulation of snow and ice and minimize the time they are present on the pavement *(6)*. To regain a bare road, pro-active salting should be conducted for anti-icing and anti-compaction purposes, while re-active salting should be used when ice has formed. The Norwegian standard *(5)* specifies two maintenance classes in the bare road strategy. The first class is the strictest, requiring the recovery of a bare road along the entire roadway 2 hours after a weather event. The second class accepts a bare road in the wheel tracks 2.5 to 5 hours after a weather event, while the entire roadway has a response time for restoring approved road conditions between 1 to 5 days. Moreover, in the second class, sanding can be used for friction improvement *(5)*. Finally, while lane markings should be visible in both classes, it is only the strictest class which requires that edge lines be made visible.

The second strategy is a *winter road strategy*, which states that although it is acceptable to have snow and ice present on the surface as a compacted layer, a minimum friction level should be ensured. This strategy is comprised of three maintenance classes. The Norwegian standard *(5)* specifies that the compacted layer should be less than 2 or 3 cm thick depending on the maintenance class. Further, rutting and wheel tracks should be less than 2.5 cm in depth. The service response time for plowing and sanding to restore a road to an approved level depends on the maintenance class. Acceptable levels of snowpack thickness and unevenness need to be achieved within 24 to 48 hours after a weather event. Moreover, in this strategy lane markings are not visible. A winter road strategy is most suited to cold, stable climates where drivers are used to driving on snow and ice *(6)*.

The third strategy is a *closed road strategy*, meaning that a road is closed during the entire winter *(5)*. This strategy is mostly used on mountain passes, and it requires that other route opportunities be made available. Since there is no traffic in this strategy, it will not be discussed further.

3.1.3 Other Requirements

There are requirements for road signs to be readable and visible during snowy conditions. The Norwegian standard specifies that signs which are not visible due to snow, frost, dirt, or visual obstructions must be cleaned and readable within one day *(5)*.

Friction requirements are included in Norwegian maintenance strategies. The first and strictest maintenance class requires a friction coefficient of $\mu>0.4$, equaling normal road conditions. The following three maintenance classes require $\mu>0.25$ in sanding areas, and $\mu>0.3$ on sections that are known to be problematic, such as steep slopes and tight curves. The fifth and more lenient maintenance class requires $\mu>0.20$ in sanding areas and $\mu>0.25$ in problematic areas *(5)*. These requirements apply after a weather event. During a weather event, the friction level might be considerably lower than the values given above.

3.2 Automated Vehicle Navigation

3.2.1 General Overview

Automated vehicles have made a major appearance in the global media recently. Advanced driving assistant systems that include steering control, emergency braking and blind spot detection are now a part of the commercial vehicle fleet, which is defined as Level 2 in the SAE level of autonomy scale *(2)*. Level 3 features, in which the vehicle takes control of all driving aspects in slow-moving traffic, are already available in Audi A8L and Tesla Model X *(7)*. Indeed, Litman *(1)* predicts that in the late 2030s or early 2040s, automated vehicles will have reached a sufficient level of reliability and affordability to replace most human drivers (i.e. Level 4 or 5).

Navigation systems are critical for an automated vehicle's ability to maneuver. Zhao et al. *(8)* divide the navigation process into four sections: Car navigation system, environment perception, path-planning and car control. Cheng *(9)* adds decision making, where the vehicle calculates the optimal route based on the given information, possible paths, and current vehicle state.

3.2.2 The Vehicle Navigation System

The vehicle navigation system utilizes localization and mapping algorithms for calculating the vehicle's global location *(7, 10),* which is the absolute position obtained from global navigation satellite (GNSS) systems (e.g. GPS, GLONASS and Galileo *(8)*). However, the GNSS systems used yield uncertainties in the meter range in vehicle position, and disturbances due to buildings and tunnels, multipath effects and other satellite signals rendered, localization is even less precise *(11)*. More accurate and precise GPS systems with sub-decimeter ranges are available at a high cost. Vehicle developers usually aim to minimize cost and maximize safety. In a cost benefit perspective, localization with a combination of sensors and less expensive GPS are often preferred *(7).*

To account for GNSS inaccuracies, inertial navigation systems (INS) are used: INS operates with odometers and gyroscopes to calculate relative position by the moving distance and direction to the prior position combined with angular and accelerated velocity relative to the curb, intersections and obstacles *(7, 8)*. Furthermore, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications are considered to overcome the limitations of GNSS. V2V and V2I incorporate data gathered from sensors in vehicles and the road infrastructure, interchanging the information, e.g. driving conditions, road parameters and traffic management, to improve accuracy and optimize localization *(7, 11)*.

The automated vehicles also operate with digital maps, in which real-time traffic data, weather forecasts, road signs and other road attributes are integrated in the map *(8)*. These digital maps rely on cloud storage, which provides updated information about road situations like traffic pattern changes, construction sites and weather events that all cause difficult driving conditions *(7, 11)*. Road Weather Information System (RWIS) stations along the roadways provide on-site, real-time meteorological data and road condition forecasts for digital maps.

3.2.3 Environment Perception

Environment perception uses sensors to continuously scan the surroundings with the aim of perceiving lane markings, road signs, and weather conditions in addition to obstacles, e.g. pedestrians as well as other vehicles and elements *(7)*. Obstacles may be static or dynamic, and they represent different driving behavior. The system must classify the diverse performances. Lane detection is critical for automated vehicles, and most lanes are defined by lane markings that can be detected by visual sensors *(12)*. Cold climate regions experience a lack of daylight, weak illumination, and polar nights, so visual sensors must function in non-ideal lights during adverse weather and nighttime. These sensors must discover curved lanes, emerging and split lanes in addition to worn and unclean lane markings. Some sensors require information from inertial sensors, while other sensors track lane markings without any knowledge of vehicle motion *(12)*.

Radars and ultrasonic sonars are used for distance and obstacle detection. Radars use radio waves, while ultrasonic sonars use high-frequency sound waves. Both systems work well in poor weather conditions. Sonars work better at close range, while radars have several ranges. The disadvantages are that the systems cannot capture detailed information and classify objects into categories, and having limited detection outside their range *(7, 12)*.

Cameras with varying fields of view can detect and classify real-time obstacles and lane markings in high resolution. While cameras are low-cost and provide additional information such as texture and colors, they perform poorly in bad weather and are light sensitive *(7, 12)*. Stereo cameras can be used to map the 3D-environment by determining differences between multiple images. Their depth perception is effective for classifying elements; on the other hand, these cameras are sensitive to interruptions caused by bad weather and illumination *(12)*. More expensive and accurate alternatives for 3D-mapping include lasers and LiDAR. LiDAR reconstructs of the surroundings as point clouds, which are then processed into 3D-maps of the environment *(12)*. The system produces a high resolution of element detection and may limit the impact of bad weather *(7)*.

Kageyama et al. *(13)* proposed a method to recognize speed limit signs during nighttime using a high-sensitivity camera. This method determines signs based on contour extraction, shape recognition and color selection, accounting for other objects that emit light during nighttime when daylight is not present. It could distinguish speed limit signs from other road signs, and it had an accuracy reading of 94.3 %. This method needs clean road signs to function properly *(13)*.

Another visual perception is simultaneous localization and mapping (SLAM), where the system has references in an incremental map consisting of sensor data collected during vehicle motion *(8)*. Quack et al. *(11)* led an experiment where SLAM algorithms were based on LiDAR data. In this experiment, the test vehicle had both wheel speed sensors to monitor wheel slip caused by longitudinal and lateral acceleration and an inertial measurement unit to provide translational acceleration data. The results showed that the SLAM-based localization and map produced accuracy levels above 25 cm, which is higher than conventional GNSS positions *(11)*.

Real-time detection of road edges is critical for the vehicle control system to work properly where GNSS systems are inaccurate due to signal interruptions, as without relative position to infrastructure and curbs, obstacles may not be detected. Malmir and Shalchian *(14)* created a lane detection algorithm that copes with cast shadows, occlusion of lane markings, brightness variations and wear. The algorithm consisted of a dual-stage lane detection based on stripe detection and Hough transformation, which is an image-processing technique extracting straight lines by pixel point accumulation in the captured image *(14)*. The algorithm was implemented in a test vehicle and tested in extreme conditions, e.g. fog, nighttime and direct sunlight. The vehicle recognized lane markings with an average accuracy reading of 92.8 % *(14)*. An improved Hough transformation was used by Zheng et al. with a detection accuracy reading of 95.7 % *(15)*.

An algorithm developed by Lee et al. *(16)* has shown that LiDAR can detect lane markings on wet roads. For instance, in combination with camera-based detection and prior path information, LiDAR identifies lane markings when water is on the road. The result from the vehicle with the implemented system had an accuracy reading of 98.16 % on lane marking recognition on good weather days, while on bad weather days with heavy rain, the recognition reading dropped to 78.51 % *(16)*.

Ort et al. *(17)* utilized a localizing ground penetrating radar (LGPR) to obtain precise vehicle localization. They state that automated vehicles can drive without relying on any visual features when using LGPR, even when the surface is covered with snow or rain. The results showed that in clear weather, there was a 0.34 m mean total error with a cross-track error of 0.26 m. In snowy conditions, there was little degradation in localization accuracy, with a mean total error of 0.39 m and a mean cross-track error of 0.29 m. Rain caused higher degradation, with a mean total error of 0.77 m and mean cross-track error of 0.40 m, which could be attributed to water in the ground. However, all these localization values from the LGPR system are significantly higher than the typically 1 m GPS error *(17)*.

3.2.4 Path-Planning

Different path-planning algorithms generate optimal driving routes between the start and finish points, and the calculated trajectory is sent to the vehicle control system for completing the vehicle movement. The algorithms determine the safest and most efficient paths based on information received from environment perception, localization and information from digital maps, and the vehicle decides the best route based on vehicle state, possible paths and risk factors *(7, 8)*.

3.2.5 Vehicle Control

Vehicle control includes the vehicle speed and direction control. The control system monitors the different components, such as anti-lock, anti-skid and anti-collision systems, stability and steering systems, brake and restraint systems *(8)*. Many vehicle control systems use reference systems to identify their self-status and perceive their position information statically and dynamically. The control system must also consider energy consumption and control acceleration when driving towards traffic lights and changes in speed limits *(18)*.

The control system measures 3D-motions and has a micro-electromechanical system consisting of a three-axis gyroscope, electronic compasses, measurement units and motion sensors *(8)*. Lateral control determines the vehicle's yaw movement and front wheel angle, while the longitudinal control, or cruise control, works at maintaining the linear velocity along the path while accelerating. Combining the two controls, the vehicle control system monitors acceleration, braking and steering *(18)*. Finding in-depth information about vehicle control systems is difficult due to classified confidentialities and trade secrets for competing companies.

3.3 Friction Control

In order to assess driving conditions, the vehicle control system needs information about the prevailing friction on the road's surface. Friction force is regarded as one of the primary elements that affects the vehicle; consequently, it is critical for calculating stopping distance and maneuverability, both of which maximize its potential to move safely and avoid obstacles *(19)*.

Friction force is dependent on the materials and characteristics in the tribosystem, i.e. the tire, the pavement, interfacial medium and environment. Introducing sand or snow particles into a tribosystem changes the interaction mechanism. The presence of snow, ice or slush on the surface can significantly reduce the attainable tire-pavement friction. The real-time tire-pavement friction coefficient is not easily attained from sensors due to the interdependency of various variables. To obtain reliable values, the system needs to know the friction value within an accuracy reading of 2 % *(19)*. However, this demand exceeds the capabilities of current estimation algorithms for determining real-time friction levels.

The tire-pavement friction coefficient can be estimated by using other methods. In a survey conducted by Khaleghian et al. *(20)*, high levels of accuracy and repeatability for model-based tire-road friction estimation in relation to experienced-based methods were found. Hong et al. *(21)* proposed a wheel slip control system using an algorithm to estimate friction force based on least square method and Kalman filter, which utilize a series of measurements observed over time to produce more accurate estimations *(21)*. Kim et al. *(22)* combine the abovementioned friction force algorithm with a similar algorithm for estimating real-time road slope values in a deceleration controller unit for autonomous braking systems. The system is validated in field tests, and the performance of the test vehicle is robust *(22)*.

Joa et al. *(23)* developed an algorithm to be used as an independent brake control system for ensuring vehicle stability under various road conditions without any tire-road friction information. The system is based on recovering tire slip angles under the peak values if the current slip angle exceeds the peak, which is done by determining target deceleration and yaw moments. By keeping tire slip angles at a limited range, the lateral stability can be controlled. The algorithm was tested on dry asphalt and wet pebble road. Although this paper does not discuss how well the performance was, it does conclude that the algorithm performs better than the in-built electronic stability system *(23)*.

3.4 Experience with Automated Vehicles in Adverse Weather Conditions

The Minnesota Department of Transportation has tested an autonomous bus during the winter of 2017-2018 *(24)*. Results from the pilot project showed that the autonomous bus performed well during cold, clear weather and bare roads. In light snow conditions with a thin snow layer covering the entire test track, the bus navigated with similar results to the bare road conditions. The bus activated emergency stops due to blowing snow and snow spray-off from the tires. Rainy and foggy conditions had no impact on the vehicle's performance, while driving in severe snow conditions, slush or blowing snow on the track caused it to make emergency stops. The pilot project tested many pavement conditions, and the bus had wheel slippage whenever snow, ice or slush were on the track. During high or varying speeds, the bus slipped more often, leading it to activate of emergency stops and lose its location on the programmed track. Variations in light and temperature did not impact the performance. The bus also executed safe driving operations when interacting with obstacles, other vehicles, pedestrians and bicycles. Although road salt deposits on the LiDAR sensors did not change the bus's behavior, the loose snow which accumulated in its sensor housing might have impacted its performance *(24)*.

Wu et al. *(25)* developed an algorithm for a camera-based lane marking detection system which was tested in several situations, including snowy conditions. Snow had accumulated of both sides on the road, while the pavement surface and lane markings were clean. The average detection rate was 96.33 % for lane markings, but it fell to 48.6 % in the snow situation. Under conditions such as dense fog, ice- or snow-covered pavements, the decrease in contrast between the lane markings and surface leads to false detection and failure in lane marking extraction *(25)*. **Figure 2** illustrates a road condition that is probably unsuitable for automated vehicles.

FIGURE 2: *Road conditions that are probably unsuitable for automated vehicles, where road signs and lane markings are covered with snow. E16 in Valdres, Norway. Photo: Ingvild Ødegård*

4. DISCUSSION

In order for automated vehicles to be allowed to join the modern car fleet, and in the future replace the human drivers, they must be able to handle adverse weather conditions. There are several examples of vehicle technology that produces reasonable results in stable conditions; however, its performance level drops when there is snow on the track. The available literature does not focus on the relationship between winter maintenance and automated vehicles. At the same time, the sensor's usage of lane markings and road signs can be directly implemented in road infrastructure maintenance during the winter to make roads mote suitable for automated vehicles.

In winter conditions, automated vehicles must navigate by the same means as under normal conditions through the four main stages: Vehicle navigation system, environment perception, path-planning and vehicle control system. Winter conditions affect the environment perception, where snow, slush and ice, in addition to lack of daylight, poor illumination and polar nights, all negatively affect the sensors and cameras. Ice- and snow-covered roadways reduce the visibility of lane markings and road signs, and sensors struggle to detect the real-time situation. When compared to normal conditions, the detection rate of lane markings for camera-based systems in snowy conditions is cut in half *(25)*. These circumstances lead to severe problems in relative navigation and cause dangerous situations for both the automated vehicle and its surroundings. LiDAR-based systems fail when snow disturbs the sensors, causing them to execute emergency stops *(24)*. On bad weather days with fog and heavy rain, the LiDAR has difficulties recognizing lane markings *(16)*.

Several studies have shown that lane marking detection at nighttime provides similar detection rate results as during daytime *(14, 25)*. The challenge is when snow is present on the pavement. Due to decreasing contrast between the lane markings and surface, the camera-based system fails to distinguish lane marking from the surroundings, even though the lane marking is clean *(25)*. To produce better quality, Zhao et al. *(8)* suggest implementing a combination of camera-based and LiDAR-based systems, which is a high-cost, complex solution that needs additional implementation technology.

The method proposed by Kageyama et al. recognizing speed limit signs during nighttime needs clean road signs to function properly *(13)*. As mentioned previously, the NRPA Handbook R610 requires road signs to be cleaned and readable after one day *(5)*. During this likely one-day time period with unreadable road signs, automated vehicles cannot interpret the situation properly.

Van Brummelen et al. mention challenges to environment perception that need to be resolved in order to exploit autonomous systems' full potential *(7)*. From a winter maintenance point of view, they include automated vehicle perception in poor weather and lighting, perception in complex urban areas, and autonomous driving without relying on already perceived data. As the literature shows, it is crucial to have information about the real-time data if automated vehicles are to drive in a safe manner. In addition, real-time road slope values are highly important for calculating autonomous braking systems, friction estimation and stopping distances.

The control models described by Alcala et al. *(18)* consider movement in the xy-plane and the wheel's yaw angle. These models do not cover the z-axis or the pitch and wheel roll. The kinematic model is widely used due to its low parameter dependency. This model also assumes no skidding and neglects lateral movements. Rather, it uses the vehicle's current position and linear velocity from an inertial point of view. The dynamic model is more complex, being a function of slip angle, steering angle, longitudinal and lateral rear forces, lateral front force, drag and friction force. Moreover, the position is relative to the vehicle's center of gravity *(18)*. As regards the winter situation, it is essential to take skidding into account, and dynamic vehicle models are preferred to evaluate the level of slipperiness.

The autonomous friction estimation faces challenges on snow-covered surfaces. Snow-covered tracks might generate wheel slippage that causes emergency stops and challenge the friction estimation. The autonomous bus in the Minnesota pilot project experienced wheel slippage whenever snow, ice or slush was on the track. This slippage makes the system lose the exact location, and the vehicle must regain its position by making emergency stops *(24)*. The algorithm developed by Joa et al. *(23)* controls tire slip angle without any tire-road friction information. Releasing the system from being dependent on knowing the friction coefficient is advantageous, since the friction coefficient is a parameter that is difficult to attain due to its dependency on several variables in the tribosystem. Compared to the built-in electronic stability system, positive results and better slip control were received. The algorithm was tested on dry asphalt and wet pebble road. Under both road conditions, the algorithm stabilized the vehicle lateral dynamics by controlling the slip angle *(23)*. Although, it would be of great interest to test the algorithm in snowy conditions, as Malmir and Shalchian say, comparing results of research projects is challenging because each project measures the algorithm's accuracy by its own methods, and a quantitative indicator of accuracy measurement is not always provided *(14)*.

Norwegian winter strategies have requirements for friction coefficients, ranging from $\mu>0.2$ in winter road strategy up to $\mu>0.4$ in bare road strategy *(5)*. The friction coefficient is a result of several parameters in the tribosystem; as a result, it might change rapidly and vary from one road segment to another. The reliability of having a friction coefficient $\mu>0.4$ on bare roads during the winter season at all times after the required time period following a weather event is questionable. During a weather event, the friction might be considerably lower than the values stated above. Therefore, automated vehicles must consider that the available friction coefficient is highly variable along the planned route. Furthermore, V2V-information about friction on the same route cannot be currently implemented directly, since the type of tire, level of wear, speed and other parameters may vary between vehicles. Advanced algorithms should take such parameters into account when defining the friction control. It would be of great interest to test friction algorithms in snowy conditions, or a situation as illustrated in **Figure 3**.

FIGURE 3: *Urban areas having obstacles, snow piles and snow-covered pavement create challenging situations for automated vehicle navigation. Street in Oslo, Norway. Photo: Ingvild Ødegård*

It is critical for automated vehicles to achieve relative navigation, or if the GNSS service is unavailable, make real-time evaluations of the surroundings, for example by detecting road signs, lane markings and road attributes. As the literature shows, automated vehicles need bare roads to perform relative navigation based on real-time data about lane markings, obstacles and road infrastructure wherever GNSS service is unavailable. The advantage of recognizing elements on-site as opposed to retrieving data from digital maps is that the real-time situation is not outdated. With increased technological innovations, sensors and cameras might become more adaptable to snow accumulations along the road edges, in turn possibly reading the road better, even with uncleaned lane markings and road signs. Nonetheless, a certain level of cleanliness on winter roads should be required.

The level of winter maintenance required is extremely high yet needs to be even higher than current levels to take advantage of a fully autonomous transportation system. Maintaining an entire road network on which autonomous vehicles can always operate would be tremendously expensive and likely not feasible. One solution could be to add another maintenance class in a bare road strategy, i.e. an automated vehicle maintenance class with a high level of service (LoS) for winter maintenance. This maintenance class should be used for certain main routes where there is a high frequency of automated vehicles. Further, it would require bare roads and visible lane markings to be ensured immediately after a weather event, since visible lane markings are vital for local navigation. It would also be necessary to explore alternative winter maintenance methods, e.g. sweeping road surfaces (this is common at airports) as well as increasing mechanical snow removal. The friction coefficient should always be tolerable, preferably $\mu > 0.4$. Road signs must include heating elements to melt snow and ice, and road infrastructure should be equipped with V2I-tecnology to inform automated vehicles about the current state of their planned route. Additional RWIS stations on the road network would be necessary to amplify the possibilities for automated vehicles to be able to determine the optimal route.

However, based on the abovementioned discoveries, it is likely that there will be conditions where automated vehicles cannot operate. In case of vehicles that still have a human driver, this may not be a real problem as it can manually take over control. Yet this is a serious problem for fully autonomous vehicles because they will need to assess the overall driving conditions of the entire trip to remain within the vehicles' operational envelope. Since these assessments need to be made ahead of time, they require some sort of forecast. There is therefore a need for a model that recommends preferable routes to the destination based on the current road conditions within the operational envelope. This model could be provided by the road owner to the automated vehicle system. Moreover, RWIS data must be incorporated in the model for sharing meteorological data and road condition forecasts on-site. Algorithms in the model must interpret these forecasts and determine if the trip can be executed or not, ensuring that the selected route falls within the standard throughout the operational envelope. In a longer time perspective, when the car fleet has become fully autonomous, there might be socially profitable to maintain a greater part of the road network and keep it suitable for the modern and fully autonomous car fleet.

Regulatory challenges, risks and responsibilities for the involving parts in providing models for automated vehicles should be investigated.

5. CONCLUSION

Several cited references mention improvement possibilities for vehicle technology. For instance, high-cost sensors and product enhancements combined with advanced algorithms allow automated vehicles to handle complex situations more efficiently *(1, 7, 24)*. The focus in this study was the automated vehicles' utilization of the road infrastructure during winter and an evaluation of possible improvements to be made to winter maintenance strategies. Three questions were raised, and they are answered below:

- In winter conditions, automated vehicles must navigate by the same means as under normal conditions through the four main stages: Vehicle navigation system, environment perception, path-planning and vehicle control system. Winter conditions affect its environment perception, where snow, slush and ice, lack of daylight, poor illumination and polar nights challenge vehicles' sensors and cameras. Further research is necessary to create systems that can handle adverse weather and snowy conditions and simultaneously return real-time output data for localization. It may also be necessary to explore alternative winter maintenance methods, e.g. sweeping road surfaces (this is common at airports) as well as increasing mechanical snow removal.
- Autonomous friction estimation faces challenges on snow covered surfaces. Wheel slippage occurs when the track is covered with snow, which makes the system lose its exact location. Further research is needed to design robust algorithms with fast processing times and return periods that can tackle a wide range of winter road scenarios, with or without information about the friction coefficient. Releasing the system from being dependent on knowing the friction coefficient is preferable.
- In order to achieve relative navigation, the local road infrastructure, edges and lane markings are critical for automated vehicles. As the literature shows, automated vehicles need bare roads to perform relative navigation based on real-time data about lane markings, obstacles and road infrastructure where GNSS service is unavailable. Maintaining an entire road network on which autonomous vehicles can always operate will be tremendously expensive and likely not feasible. One solution could be to add another maintenance class in a bare road strategy, i.e. an automated vehicle maintenance class with a high LoS for winter maintenance, with a set of operational criteria to allow automated vehicle to operate. Automated vehicles should be provided a model that recommends preferable routes to the destination based on the current road conditions within the operational envelope. In a longer time perspective, when the car fleet has become fully

autonomous, there might be socially profitable to maintain a greater part of the road network suitable for the modern and fully autonomous car fleet.

The main findings are that automated vehicles need bare roads to perform relative navigation based on real-time data about lane markings, obstacles and road infrastructure where GNSS service is unavailable. Snow-covered tracks hinder the vehicles' navigation and lane marking detection, and might even generate wheel slippage that causes emergency stops and challenges friction estimation. The level of winter maintenance required is extremely high yet needs to become even higher than current levels to take advantage of a fully autonomous transportation system. In conclusion, automated vehicle technology demand changes in LoS of winter maintenance for allowing automated vehicle to operate in winter conditions. However, this maintenance does not necessarily need to change overnight. Litman *(1)* states that in the 2020s and 2030s, autonomous vehicles will be too expensive for average incomes and unwell not be able to operate in conditions such as heavy rain or snow, unpaved roads; neither in mixed urban traffic nor where GNSS services are unavailable. A realistic timeframe is within the 2040s and 2050s *(1)*.

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