TOSHKENT DAVLAT TRANSPORT UNIVERSITETI
Tashkent state transport university

Issue 3, 2023

INTERNATIONAL JOURNAL OF TRANSPORT AND TECHNOLOGICAL MACHINES

ISSN: 3030-363X



THE SCIENCE OF TODAY IS THE TECHNOLOGY OF TOMORROW

TOSHKENT DAVLAT TRANSPORT UNIVERSITETI
Tashkent state transport university

INTERNATIONAL JOURNAL OF TRANSPORT AND TECHNOLOGICAL MACHINES

Published since 2023

Editorial Council:
Mukhitdinov A.A., Ziyayev K.Z., Rustamov K.J, Abdurazzakov U.
Editorial team:
Chief Editor – Rustamova N.R.
Deputy Chief Editor – Rustamov K.J.

Members of the editorial board:
Mukhitdinov A.A., Ziyayev K.Z., Rustamov K.J., Abdurazzoqov U.A., Saman M. Almufti., Habibollah Haron., Gai-ge Wang., Jayson A. Dela Fuente., Ahmad A. AlRabab'ah., Rami Hikmat Fouad AL-Hadeethi., Emad Kamil Hussein., Ayman Abu-Rumman.

TASHKENT STATE TRANSPORT UNIVERSITY

Founder of the scientific and technical journal, “International Journal of Transport and Technological Machines” – Tashkent State Transport University (100167, Republic of Uzbekistan, Tashkent, Temiryulchilar str., house No. 1, office: 379, tel Tel.: +998 97 156 94 21 E-mail: k.j.rustamov82@gmail.com).

In the International Journal of Transport and Technological Machines publishes the most significant results of scientific and applied research carried out in universities of transport and information technology profile, other higher educational institutions, research institutes and centers of the Republic of Uzbekistan and foreign countries.

The journal is published 4 times a year and contains publications in the following main areas:

- Automotive engineering
- Civil Engineering
- Construction Engineering and Management
- Instrumentation technology
- Environmental Engineering
- Environmental Sciences
- Green production
- Industrial Safety
- Mechanical Engineering Technology
- Mining
- Mechatronics

CONTENTS

1 Alimova Z., Madrahimov Sh., Mengliev Sh. IMPROVING THE PERFORMANCE OF OILS OPERATING IN HYDRAULIC SYSTEMS UNDER HOT CLIMATIC CONDITIONS..... 4
2. Navoy D.V., Kapskiy D.V., Khakimov R.M. ALGORITHMIC SUPPORT FOR INCIDENT DETECTION BY STATIONARY TRANSPORT DETECTORS IN THE INTELLIGENT TRANSPORTATION SYSTEM (ITS) OF A METROPOLIS..... 10

UDK 656 (075)

IMPROVING THE PERFORMANCE OF OILS OPERATING IN HYDRAULIC SYSTEMS UNDER HOT CLIMATIC CONDITIONS

Zebo Alimova[1], Sherzod Madrahimov[2], Sherzod Mengliev[3]

[1]Tashkent State Transport University, Uzbekistan
[2]Texas A&M University, Qatar, Doha, Qatar
[3]Tashkent institute of chemical technology, Uzbekistan
Corresponding author: e-mail: zeboalimova7841@mail.ru

Abstract. This article suggests ways to improve the antioxidant properties of hydraulic oils by using additives. Physico-chemical and operational properties of modern hydraulic fluids are significantly improved by the introduction of functional additives into them - antioxidant, anticorrosive, anti-wear. An increase in the antioxidant properties of hydraulic oils is achieved by introducing antioxidant additives.

We conducted a study of samples of MG-32 industrial oils with the addition of zinc dithiophosphate DPZn-11 additives. To do this, the main indicators of MG-32 base oil were determined in accordance with GOST 305-2013 in laboratory conditions. Then preliminary experiments were carried out to determine the effectiveness of the additives. From the results of the analysis, we selected the content of DPZn-11 additives of 1.8%, which shows the optimal value of viscosity and flash point.

The results of laboratory studies of oils with an additive based on zinc dithiophosphate DPZn-11 and recommendations for their use are given.

Key words: hydraulic systems, hydraulic oils, physical and chemical properties, additives, zinc dithiophosphate, research, flash point, alkaline number, flash point.

INTRODUCTION

The operation of hydraulic systems is based on the transfer of energy through a working fluid located in a closed volume. When transferring the force to the actuators, due to the practical incompressibility of the fluid, the force is uniformly and instantly transmitted in all directions.

The design features of hydraulic systems impose strict, sometimes contradictory requirements on oil (for example, increased density and low viscosity, low viscosity and high anti-wear properties, high anti-wear properties and sufficiently high friction properties).

During operation in hydraulic systems, the oil is heated and intensively mixed with air. The main conditions under which oils in hydraulic systems operate are characterized by: a wide fluctuation in ambient air temperature, the transfer of large forces and the impact of high specific loads in pumps, dustiness and humidity of the ambient air.

The anti-wear requirements for the oil are also very high. A wide variety of friction pair materials (steel-steel, steel- cermet) used in hydraulic systems makes it difficult to select oils and additives to them. The presence of some additives in oils reduces the wear of ferrous metals, but causes a lot of wear of non-ferrous metals, and sometimes vice versa.

The use of oil at elevated ambient temperatures (more than +40 °C) there are specific failures caused by deterioration of physical and mechanical properties. Under the influence of high temperatures, oxygen in the air and condensing water, the catalytic action of metals

dramatically changes the chemical composition of oils and their operational properties. This leads to an increase in the viscosity of the oil and to the accumulation of oxidation products in it. Low-molecular and high-molecular acids accumulate in the oil, which will lead to an increase in energy costs for the hydraulic system drive.

2. MATERIALS AND METHODS

This article suggests ways to improve the antioxidant properties of hydraulic oils by using additives. The oxidation of oil, in addition to its general contamination and an increase in the content of acidic products, leads to disruption of the normal operation of the hydraulic system.

The hydraulic systems of machines and mechanisms contain parts made of different metals: different grades of steel, bronze, which can be subjected to corrosion and chemical wear.

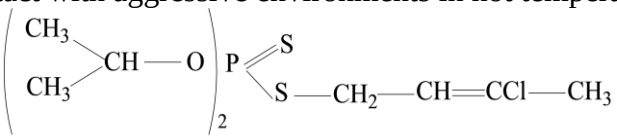
The impact of the external environment on the life of the lubricant is assessed by the dustiness of the air, humidity, and sudden temperature changes characteristic of many areas in which the equipment is operated. The degree of dustiness is estimated by the dust content per unit volume of air. Dust is the cause of intense wear of rubbing parts, and getting into the lubricant is the main component of its contamination. The operation of the hydraulic system in dusty conditions leads to an increase in thermal operating conditions.

Studies of the contamination of lubricating oils operating in hydraulic systems during operation in hot climates (summer air temperature exceeds +50 °C) and high dust content of the air show that hydraulic oils are intensively contaminated with mechanical impurities, water, and products of organic origin, which leads to premature aging of the oil. According to research, 70% of hydraulic system failures occur due to the condition of the oil. Of these, 40% are directly related to the performance of the oil, 60% are related to the purity of the oil.

To achieve this goal, we took samples of MG-32 hydraulic oils and analyzed them according to the main quality indicators.

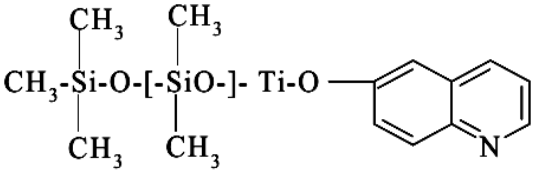
A new class of organic compounds, fluorocarbons, an analogue of hydrocarbons, have many exceptional properties. They are more resistant to oxidation at high temperatures. However, the lubricating properties of these oils are small. In addition, their big disadvantage is poor viscosity-temperature properties. Fluorocarbon-based liquids are capable of interacting with the non-oxidized surface of metals. With prolonged contact, they corrode copper and its alloys, especially in the presence of moisture.

Phosphorus-containing additives have a higher resistance to all types of oxidation compared to other additives. They have incomparably greater chemical and thermal stability and therefore can come into contact with aggressive environments in hot temperature conditions.

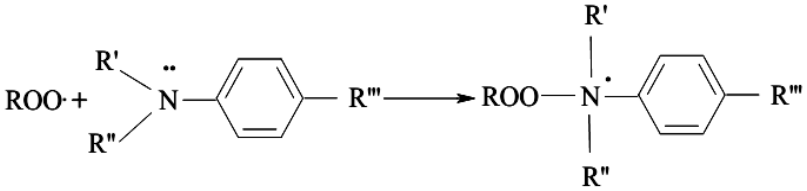


Organic phosphoric acid esters are chemically inert to metals under normal conditions. However, during thermal decomposition or hydrolysis, they form substituted phosphoric acids, which corrode metals, especially copper.

Polyorganosiloxane liquids have unique physicochemical properties: viscosity-temperature, high thermo-oxidative and thermal stability. Polysiloxane liquids practically do not cause corrosion of metals.



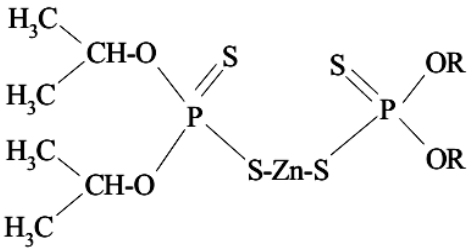
However, insufficient lubricity and high cost limit the widespread use of these liquids. Some nitrogen-containing compounds, mainly aromatic amines, deserve considerable attention as antioxidants.



The most effective anti-oxidizing properties were additives containing metal, sulfur and phosphorus in the molecule at the same time. Testing of several dozen of these compounds as additives to oils has shown that they are very effective not only in fresh oils, but in spent and regenerated ones. Therefore, we chose dialkyldithiophosphate additive.

RESULTS AND THEIR DISCUSSION

We conducted studies of samples of MG-32 industrial oils with the addition of dialkyl dithiophosphate additive DPZn-11.



The mechanism of action of dialkyldithio-phosphate is associated with their thermal decomposition and the formation of a polymer film on the friction surface. The decomposition of dithiophosphate can take place both by radical and by ionic mechanism.

To do this, the main indicators of MG-32 base oil were determined in accordance with GOST 305-2013 in laboratory conditions. Then preliminary experiments were carried out to determine the effectiveness of the additives.

For better solubility, the additive was injected into oil heated to 125°C. To achieve the desired effect, it was necessary to apply it in quantities of 0.5-3%. The following hydraulic oil – MG-32 with different contents (0.2 – 2.5 %) of DPZn-11additives were selected as the object of the study.

The mechanism of action of zinc dithiophosphate is associated with their thermal decomposition and the formation of a polymer film on the friction surface. The force of adhesion between the oil molecules and the material of the lubricated surface exceeds the force of mutual adhesion of the oil molecules, as a result of which a strong layer of lubricant is formed on the metal surface.

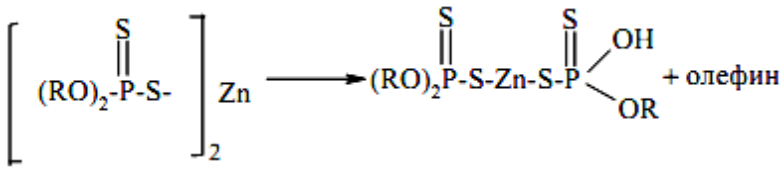
At high temperatures in the zinc-sulfur-air system, reactions between the solid phase and the environment are the main ones. In the process of further decomposition, O-S-S is formed, the interaction of which with the decay products leads to the formation of disulfide.

The effectiveness of this action is characterized by the formation of metal sulfides and disulfides. This model assumes the adsorption of the metal surface and the subsequent dissociation of molecules by S-S bonds with the formation of sufficiently strong compounds with metal.

The decomposition of zinc dithiophosphate molecules by the P-S-Zn bond is also not excluded. In the process of further decomposition, O,S,S-tri-n-alkyltrithiophosphate is formed, the interaction of which with the decay products leads to the formation of disulfide.

The effect of such additives is based on their ability to loosen, wash off deposits from the surface of parts and transfer insoluble substances into suspension and keep these particles in this state without enlargement.

The formation of such complexes facilitates the effect of oxygen at the site of attachment of hydrocarbon radicals to sulfur. The decomposition of dithiophosphate can occur both by radical and by ionic mechanism:



The presence of such a layer eliminates the possibility of dry friction, and since the coefficient of friction between the layers of liquid lubricant is several tens of times lower than the coefficient of dry friction, the energy costs of overcoming friction forces when using such oil are significantly reduced.

The figure shows the changes in the physico-chemical parameters of the tested oil depending on the percentage concentration DPZn-11.

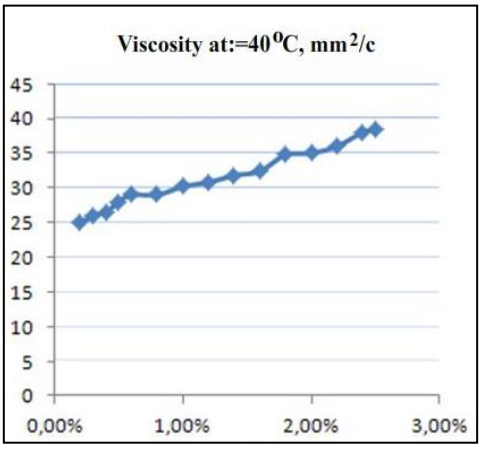


Figure 1

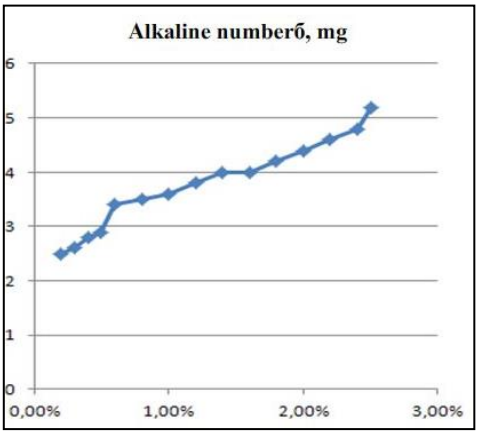


Figure 2

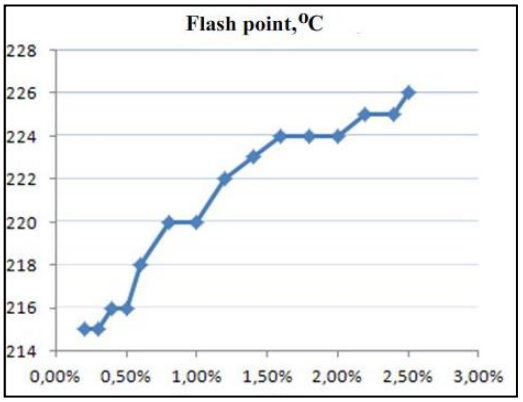


Figure 3

Fig.1,2,3 - Change of physico-chemical parameters of the tested oil depending on the concentration DPZn-11.

From the results of the analysis, we selected the content of DPZn-11additives of 1.8%, which shows the optimal value of viscosity and flash point. With a further increase in the concentration of DPZn-11, the viscosity increases greatly, which can lead to increased friction losses. With increasing viscosity, the thickness and resistance to mechanical influences of the oil layer between the rubbing surfaces increases. In our example, the alkaline number increased from 4.8 to 6; and the flash point rose to 224°C, which indicates the effectiveness of the added additive. This means that when using such an additive, the service life oil will increase.

The results of laboratory studies showed that the addition of DPZn-11to the base oil MG-32 gave an improved result compared to the oils used for agricultural machinery MG-32. Due to the harsh working conditions, oils for hydromechanical transmissions must have appropriate viscosity and anti-wear properties.

CONCLUSION

From the results of the comparison, it can be seen that the operational properties of the obtained hydraulic oil sample far exceed the domestic MG-32 and comply with GOST standards.

This is the effectiveness of the possible application of the new sample obtained by us. In the future, these oils can be admitted to the next stage – to operational tests on special equipment.

References

1. Jerichov V B 2009 Automobile maintenance materials A training manual p 256 St. Petersburg
2. Maharramov A. M, Akhmedova R. A., and Akhmedova N. F. 2009 Petrochemicals and Oil Refining Textbook for Higher Education p. 660
3. Makushev Y. P. 2006 Automobile maintenance materials Omsk, SibADI Publishing House p. 58
4. Stukanov V. A. 2002 Automotive Maintenance Materials Textbook, Laboratory workshop. Moscow p. 208
5. Syrbakov A. P., Korchuganova M. A. 2015 Fuel and lubricants Allowance. - Tomsk: Publishing House of Tomsk Polytechnic University.
6. Alimova, Z., Abdukhalilov, H., Kholmirzayev, B., & Samatayev, T. (2020). Ways to improve the performance of hydraulic oils for agricultural machinery. *Industrial Technology and Engineering*, *3*(36), 17-22.

7. Alimova, Z., Kholikova, N., & Kholova, S. (2020, July). Improvement of properties of oils used in hydraulic systems of road-construction equipment. In *IOP Conference Series: Materials Science and Engineering* (Vol. 883, No. 1, p. 012167). IOP Publishing.
8. Khamidullaevna, A. Z., Parpiena, N. G., & Kabulovna, S. D. (2022). Study of the Work of the Boundary Layers of Lubricants Materials. *Academicia Globe: Inderscience Research*, *3*(12), 119-122.
9. Hamidullayevna, A. Z., Kabulovna, S. D., & Parpiyevna, N. G. (2022). Operability of the boundary layers of lubricants during operation.
10. Khamidullaevna, A. Z., & Parpiyevna, N. G. (2022). Ways to Improve the Operational Properties of Hydraulic Oils for Agricultural Machinery. *Texas Journal of Engineering and Technology*, *8*, 20-22.
11. Alimova, Z. (2020). Ways to improve the properties of lubricants used in vehicles. *VNESHINVESTROM",–2020*.
12. Alimova, Z. X., Ibragimov, K. I., & Turakulov, B. H. (2022). The influence of the operational properties of the working fluid on the reliability of hydromechanical transmissions of cars. *The American Journal of Interdisciplinary Innovations and Research*, *4*(03), 12-16.
13. Khamidullayevna, A. Z., & Parpiyevna, N. G. (2022). Investigation of the operational properties of transmission oils used in vehicles. *The American Journal of Engineering and Technology*, *4*(01), 19-23.
14. Khamidullaevna, A. Z., Karimjon, I., & Bahtiyor, T. (2022). Improving the polishing properties of transmission oils by adding additives. *American Journal of Applied Science and Technology*, *2*(06), 84-86.

Algorithmic support for incident detection by stationary transport detectors in the Intelligent Transportation System (ITS) of a metropolis.

Navoy D.V. [1] **,** ***Kapskiy D.V.*** [1]**,** ***Khakimov R.M.*** [2]**,**
[1]Minsk, State Traffic Police of the Ministry of Internal Affairs of the Republic of Belarus
[2] Tashkent State Transport University (TSTU), Tashkent, Uzbekistan.

Abstract: It is widely recognised that, in addition to the Automated Traffic Management System developed for urban areas, there is a range of techniques and systems for automated traffic management that are specifically designed for suburban or 'access' highways and motorways. This text describes navigation systems and other technologies that involve equipping vehicles with specialized equipment. It also includes various subsystems, such as technical, algorithmic, mathematical, ergonomic, financial, and legal, which are responsible for ensuring the functionality and advancement of automated systems. Intelligent transport systems integrate various components to regulate traffic, including incident detection methods and setups for traffic accidents.

Incident detection algorithms can be categorized as automatic or non-automatic. Automatic algorithms rely on traffic flow condition data acquired from transportation detectors, while non-automatic algorithms rely on eyewitness reports. The article examines the methodologies used to gather data for incident detection algorithms, which are currently dominated by the use of data from stationary traffic detectors. It focuses on the detection of incidents on highways using stationary transport detectors, scrutinizing existing and potential algorithms. These detectors are used in automated traffic management systems and are part of the development of intelligent transportation systems in cities, metropolises, and regions. The goal is to integrate current algorithms into automated traffic management systems, along with modern vehicle technology, including autonomous technology, and connect them to 'smart' transport infrastructure to create a comprehensive and intelligent transport environment.

Keywords: Automated Traffic Management System, Intelligent Transportation System, algorithmic support, incident detection algorithm, stationary transport detectors.

Introduction

Algorithms designed for incident detection can be broadly classified into two primary categories when considering automation: automatic and non-automatic incident detection [61, 62, 63, 65]. Automatic algorithms pertain to those specifically engineered to autonomously identify incidents by utilizing data derived from transport detectors, which reflects the traffic flow's condition. Conversely, non-automatic algorithms or procedures depend on information provided through reports from human eyewitnesses [64, 65].

Based on functional characteristics, incident detection algorithms are divided into algorithms for highways and algorithms for street networks [1, 2, 3].

Based on data acquisition methods, incident detection algorithms are divided into three groups:

- algorithms using data from stationary vehicle detectors (inductive loops, radars, video cameras, etc.).
- algorithms using mobile sensors (Bluetooth, wifi, RFID, GPS, GLONASS sensors, toll system transponders, etc.).
- algorithms that use information from drivers (GSM communications, navigation services, Internet applications, etc.)

This review discusses algorithms that use data from stationary vehicle detectors.

The disadvantages of incident detection algorithms using stationary vehicle detectors include:

1. The need to install and operate vehicle detectors (inductive, video, etc.) leads to interference with traffic flow and sometimes to temporary closure of traffic;
2. The location of installation of vehicle detectors, the frequency of their installation and the number are critical from the point of view of detecting an incident on a particular section of the highway. However, it is extremely labor- and capital-intensive to install stationary detectors along the entire length of the highway.
3. Inductive vehicle detectors, which are mainly used to determine the parameters of traffic flows on highways, are unreliable and often fail, which makes detection of incidents on a particular section of the road ineffective.

The advantages of the algorithms under consideration include their proven reliability and accuracy in identifying incidents over decades, which is their undoubted advantage over algorithms that use mobile sensors or information from drivers [4, 5, 8, 9].

Method

The most commonly used algorithms for detecting incidents on highways are:

1. Comparative pattern recognition algorithms assume that an incident leads to increased traffic density upstream and decreased traffic density downstream. Examples of such algorithms include California TSC #7, #8, #10, APID, and PATREG.
2. By monitoring three basic traffic flow variables: speed, flow and lane occupancy (density), catastrophe theory algorithms are used to detect incidents. The algorithm detects an incident when there is a sharp drop in speed without an immediate corresponding change in occupancy and flow. An example of such an algorithm is the McMaster algorithm.
3. Statistics-based algorithms such as Autoregressive Integrated Moving Average (ARIMA), SND, and Bayesian algorithm are used to compare real-time traffic data with forecasted data, classifying unexpected changes as incidents.

Artificial intelligence algorithms are based on the recognition of visual patterns or classification.

An overview of video processing for traffic applications, covering traffic monitoring and automated vehicle control, is given in [43]. The paper discusses both fixed cameras (road monitoring) and moving cameras (autonomous vehicles) with specific examples of automatic lane detection and object detection. The paper examines eleven different traffic monitoring systems with static cameras. Among the systems reviewed, only Autoscope [26] remains a viable commercial product to date.

A video-based traffic state estimation method used for incident detection is proposed in [42]. The system estimates traffic intensity, speed, and density directly from video images. Incidents are identified based on the segmentation of the three-dimensional traffic state space using threshold values. The system has not yet been evaluated in real-world conditions. However, it represents an interesting model-based approach to incident detection that could be informative.

The authors addressed the challenge of extracting traffic information from uncontrolled, publicly available video streams in their study [46]. This is a significant problem from a broader machine learning perspective, as publicly available video streams can provide a wealth of information about traffic flow. Although primarily a review, the authors identified key challenges in using uncontrolled video for real-time traffic monitoring, including:

- Lack of control and information about orientation (angles of view, distance, etc.), complicating the mapping onto a logical network.

- Consideration of mismatches caused by occlusion and other factors.
- Fluctuating video quality.
- Influence of the environment, including weather and lighting effects.

The authors did not propose specific deployment steps; however, currently, systems utilizing public video are widely adopted due to the advancements in machine learning [11-25].

In the paper [41], a vehicle tracking system based on video is proposed. It relies on a turn-change detection algorithm that requires less calibration than existing systems. Experimental results using videos from the Las Vegas, Nevada area show favorable distinctions from the existing commercial Autoscope setup, based on ground truth measurements. The system has been deployed in a congestion alert system at construction sites and on highways during special events, although a performance evaluation for this application has not been provided.

In the paper denoted as [47], a comprehensive examination of the outcomes stemming from the "Realisation of an AID Enhanced Road traffic" (RAIDER) initiative is provided. This program received funding from a European consortium, comprising entities such as TNO from the Netherlands, AIT from Austria, TRL from the UK, and FEHRL from Belgium. Within this assessment, the AVID (Automatic Video Incident Detection) system is evaluated against three prospective variations of AID (Automatic Incident Detection) systems anticipated to emerge by the year 2030.

The initial system under scrutiny is eCall, wherein vehicles involved in road traffic incidents autonomously relay accident-related information to emergency services—a mandate in Europe since 2018. The second entails the utilization of mobile (floating) devices, wherein vehicles serve as passive sensors, furnishing Floating Car Data (FCD) utilized for AID. The third typifies cooperative systems wherein vehicles actively identify incidents in their vicinity and transmit these detections centrally.

Drawing from an analysis of prevailing technological capacities and anticipated advancements, the authors assert that "video-based vehicle tracking and radar-based scanning represent the sole detection technologies within the purview of this project capable of meeting the specified criteria for accident detection by 2020. These solutions should be perceived as interim measures until they are supplanted by onboard or mobile devices."

In the citation [48], a comparative analysis is conducted among various systems such as AUTOSCOPE, CCATS, TAS, IMPACTS, and TraffiCam, juxtaposing them against video-based vehicle tracking systems like CMS Mobilizer, Eliop EVA, PEEK VideoTrak, Nestor TrafficVision, Autocolor, and Sumitomo IDET. The paper underscores the challenges faced by the latter systems in dealing with vehicle occlusion, highlighting the pivotal significance of camera placement.

Conversely, in reference [58], the authors introduce a real-time video surveillance system employing video analytics, specifically addressing the identification of stationary vehicles. This proposed system aims to resolve deployment-related hurdles, encompassing automatic calibration. The authors compare their system with an unspecified commercial product and advocate for a more comprehensive evaluation of their innovation. Nevertheless, the evaluation of the proposed system was notably limited as the testing scenario featured only one instance of a stationary vehicle, which was successfully detected.

The paper [52] proposes a method for evaluating traffic flow states, including intensity, speed, and density, in each lane. This is achieved by dividing the lanes into tracked cells and tracking objects through them. Incident occurrence conditions are determined using a fuzzy state vector mechanism to classify traffic flow states corresponding to incidents. The results are

compared favourably with the California and McMaster algorithms, which use inductive traffic detectors. However, the authors acknowledge that their algorithm may be affected by external factors such as weather and lighting, as well as the field of view angle, which are common issues with video detectors.

In a similar solution proposed in [49], customizable video analytics are used to evaluate traffic flow intensity and speed. These assessments are then classified as incident or non-incident conditions using a fuzzy logic analyzer. It is recommended to perform manual calibration of parameters based on a specialized analysis of traffic speed data to ensure reliable results. The current system's results are likely to vary significantly depending on the deployment due to the lack of a more reliable calibration method.

In the paper [36], a video-based system is proposed that identifies traffic flow states using object detection and flow analysis model [66, 67]. The authors claim that the system can adaptively switch between learning and online modes based on the stability of the flow model [27-29]. The system was primarily used for evaluating traffic flow states, but the authors assert that it has applications for video incident detection.

Results and Discussion

The effectiveness of a method or algorithm is evaluated based on standard parameters, including the Detection Rate (DR), Mean Time to Detection (MTTD), and False Alarm Rate (FAR) [10].

DR is calculated as the ratio of detected incidents to the total number of incidents, expressed as a percentage. It is important to note that the definition of an incident in the system affects this parameter. Therefore, it is crucial to have a clear definition of what constitutes an incident and what does not.

$$DR = \left(\frac{N_{DI}}{N_{TI}}\right) * 100 \quad (1)$$

where: N_{DI} – the number of detected incidents; N_{TI} – the total number of incidents.

Mean Time to Detection (MTTD) is defined as the time from the occurrence of an incident to the moment it is detected. This parameter does not include the time required to verify the incident (whether the incident indeed occurred).

$$MTTD = \sum_{i=1}^{N}(t_a - t_{inc})/n \quad (2)$$

where: N – the number of detected incidents; t_a – the time when the incident was detected; t_{inc} – the time when the incident occurred.

The False Alarm Rate (FAR) is determined as the percentage of incorrect detection signals relative to the total number of incidents.

$$FAR = \left(\frac{N_{FA}}{N_{TA}}\right) * 100 \quad (3)$$

where: N_{FA} – the number of false alarms; N_{TA} – the total number of alarms.

The performance of automatic incident detection algorithms is influenced by various factors [34], including but not limited to: The factors that affect traffic conditions include operational conditions (such as heavy, moderate, light, at capacity, or significantly below capacity), geometric factors (such as slopes, inclines, and descents), environmental factors (such as dry pavement, wet pavement, snow, ice, and fog), incident duration, incident severity, distance between detectors, incident location relative to the detection station, and traffic flow heterogeneity. Accounting for all the complex factors in a single algorithm is a challenging task, particularly in an arterial environment. None of the existing algorithms have been adapted to consider all these factors, and therefore, their effectiveness cannot be guaranteed for all road conditions. When studying the impact and effectiveness of incident detection algorithms related

to geometry and incident characteristics [6], the results indicate that the choice of the tested California algorithms (Nos. 7, 8, and 10) significantly influences the detection rate (DR) and mean time to detection (MTTD). It is challenging to avoid the negative consequences of external factors [31-40].

In [32], algorithms are categorized into five types: pattern recognition, statistical processing, catastrophe theory, artificial intelligence, and video analytics (refer to Table 1).

Table 1 - Comparison of the effectiveness of algorithms based on data from inductive loops and video detectors [32]

Algorithm Type	*Algorithm*	*Detection Rate (DR)*	*False Alarm Rate (FAR)*	*Mean Time to Detection (MTTD)*
Pattern Recognition	*California No. 7*	*67%*	*0.13%*	*2.91 min.*
	APID	*86%*	*0.05%*	*2.55 min.*
Statistical processing	*SND*	*92%*	*1.3%*	*1.10 min.*
	Bayesian algorithm	*100%*	*0%*	*3.90 min.*
	ARIMA	*100%*	*1.4-2.6%*	*0.39 min.*
	Smoothing models	*92%*	*1.87%*	*0.74 min.*
	DES	*82%*	*0.28%*	*5.05 min.*
	HIOCC	*96%*		
	Filtering models	*95%*	*1.5%*	*0.67 min.*
	Dynamic Models		*less 0.02%*	*Short*
Catastrophe Theory	*McMaster Algorithm*	*100%*	*0.04%*	*1.5 min.*
Artificial Intelligence	*Neural Network Model*	*97%*	*0.21%*	*2.83 min.*
Video Analytics	*INVAID-TRISTAR*	*90%*	*1 every 3 hours*	*0.33 min.*

In the study [30], the effectiveness was evaluated using a sensitivity analysis of the most common traditional automatic incident detection algorithms and the proposed Minnesota algorithm. Three types of algorithms were compared qualitatively and quantitatively: comparative logic (i.e., a series of California algorithms), statistical forecasting (i.e., standard deviation algorithm, double exponential algorithm, ARIMA algorithm, and HIOCC algorithm), and macroscopic traffic analysis (i.e., the McMaster algorithm, dynamic algorithm, and dummy traffic volume algorithm). They found that the investigated algorithms have several limitations related to: 1) unsatisfactory quality of raw data (i.e., data from inductive detectors) and the use of raw data only with limited filtering; and 2) the inability to distinguish incidents from bottleneck clusters or other similar road situations. The best algorithms in comparative logic and time series types were selected based on DR-FAR curves and compared with the Minnesota algorithm using a dataset collected in Minneapolis, Minnesota. The performance comparison figures, DR-FAR curve, and TTD histogram are shown in Figures 1 and 2, respectively. In Figure 2, negative TTD values are due to "0" being the time when the operator determines that an incident has occurred. However, if the operator has determined it, then an algorithm that takes more time is not required.

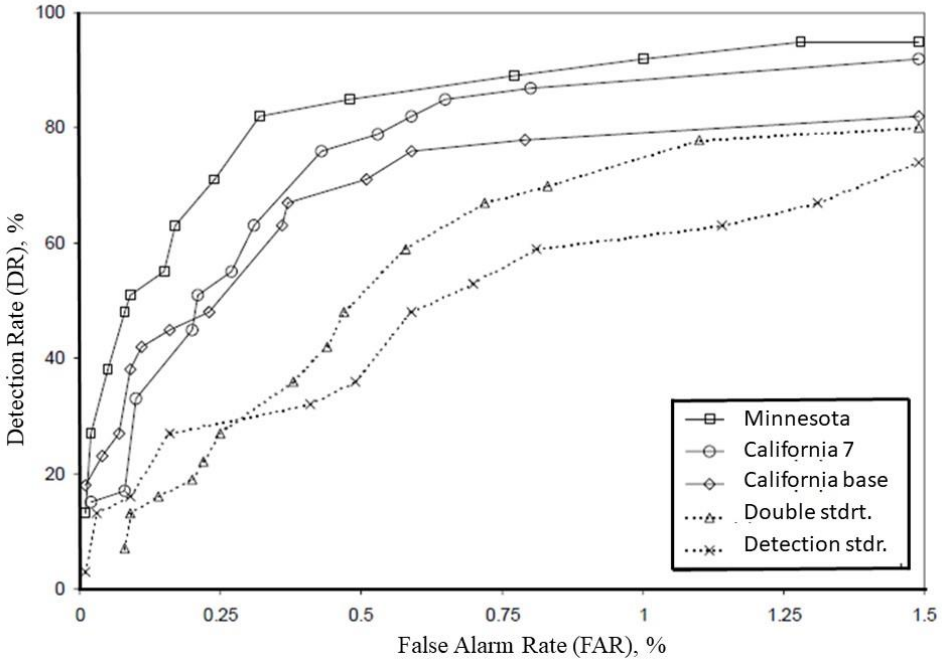


Figure 1. Comparison of algorithms based on DR-FAR parameters [30]

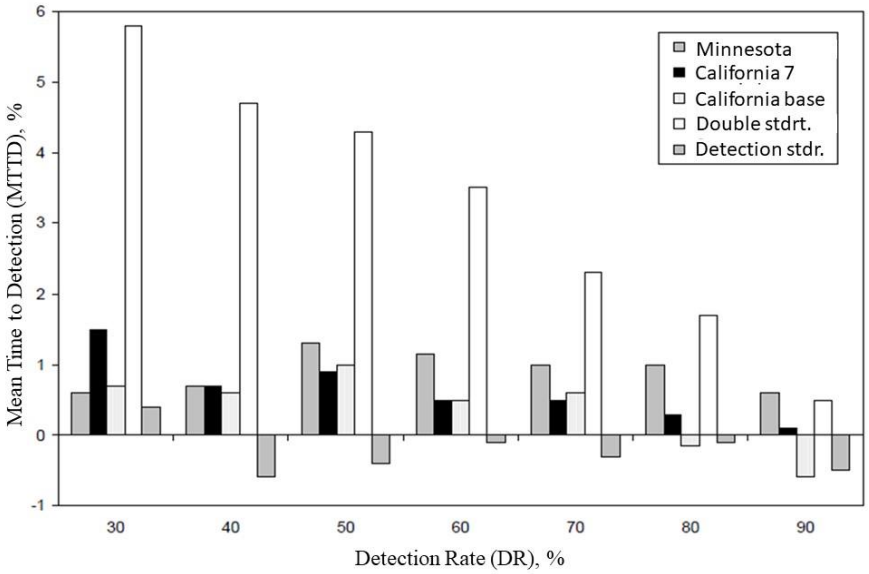


Figure 2. Comparison of algorithms based on MTTD-DR parameters [30]

The author concludes, based on these assessments, that raw inductive loop detector data often proves unsuitable for incident detection if the noise in traffic flow parameters cannot be filtered out before use. In particular, this is a limitation characterizing comparative algorithms, as the distortion caused by the noise makes it difficult for the algorithm to detect "patterns" of incidents in traffic flow data. Similarly, fluctuations created by noise sources can be mistaken for incidents. As a result, the only easily identifiable "patterns" (templates) in traffic flow are those that occur under conditions of severe incidents and satisfy every algorithm test. As for statistical forecasting algorithms, they use filtering according to their design specifications, so their

applicability is severely limited. The main drawback of these algorithms lies in their inability to distinguish incidents from similar traffic flow "patterns" (templates) [75, 76, 77].

In the work [7], the author evaluated a variety of common incident detection algorithms based on theory and practice. The algorithms were assessed in terms of their performance, data requirements, implementation simplicity, calibration simplicity, and operational experience [68, 69]. The algorithms were classified into one of five groups: comparative algorithms, statistical algorithms, time series algorithms, smoothing or filtering algorithms, and modeling algorithms. The results of theoretical assessments and on-site research showed that: 1) most freeway management centers used a modified version of the California algorithm, except for Toronto, where a different algorithm was used; 2) operators generally did not heavily rely on automatic incident detection algorithms; 3) for the most part, operators relied on other mechanisms, such as radio broadcasts or video monitoring (CCTV), to alert them to incidents on the freeways; and 4) among the systems that discontinued using the algorithm, incorrect calibration was the most common reason why algorithms generated a large number of false alarms. Moreover, it was considered that algorithms could not be properly calibrated if an incident did not affect every detection zone [71, 72, 73, 74].

Table 2 – Comparative analysis of algorithms based on data from inductive detectors [7]

Algorithm Type	*Algorithm*	*Detection Rate (DR)*	*False Alarm Rate (FAR)*	*Mean Time to Detection (MTTD)*
comparative	*California basic*	*82%*	*1.73%*	*0.85 min.*
	California No. 7	*67%*	*0.134%*	*2.91 min.*
	California No. 8	*68%*	*0.177%*	*3.04 min.*
	APID	*86%*	*0.05%*	*2.5 min.*
statistical	*SND*	*92%*	*1.3%*	*1.1 min.*
	Bayesian	*100%*	*0%*	*3.9 min.*
time series	*ARIMA*	*100%*	*1.5%*	*0.4 min.*
smoothing or filtering	*DES*	*92%*	*1.87%*	*0.7 min.*
	LPF	*80%*	*0.3%*	*4.0 min.*
flow modeling	*McMaster*	*68%*	*0.0018%*	*2.2 min.*

The work [45] provides a comparison of classical algorithms, a video analysis algorithm and an algorithm using cell phone data. Although the algorithms are recognized as difficult to compare directly due to methodological differences in evaluation, comparative analysis provides a useful benchmark for the resulting performance measures (Table 3). The false alarm forecast in Table 3 is given for the road network in Salt Lake City.

Table 3 – Results of the analysis of algorithms in [45].

Algorithm name	*DR (%)*	*TTD (min)*	*FAR (%)*	*Place of use*	*SLCa forecast of network false alarms per hour*
APID	*86*	*2.50*	*0.05%*	*Toronto, Boston*	*7.74*
DES	*92*	*0.70*	*1.87%*	*Toronto*	*289.48*
ARIMA	*100*	*0.40*	*1.50%*	*Laboratory*	*232.20*
Bayesian	*100*	*3.90*	*0%*	*Laboratory*	*0.00*
California	*82*	*0.85*	*1.73%*	*California, Chicago, Texas*	*267.80*
Low-Pass Filter	*80*	*4.00*	*0.30%*	*Laboratory*	*46.44*
McMaster	*68*	*2.20*	*0.0018%*	*Minnesota*	*0.28*
Neural network	*89*	*0.96*	*0.012%*	*Laboratory*	*1.86*
SND	*92*	*1.10*	*1.30%*	*Not Known*	*201.24*
SSID	*100*	-	*0.20%*	*Laboratory*	*30.96*
California No. 7	*67*	*2.91*	*0.134%*	*California, Chicago, Texas*	*20.74*
California No. 8	*68*	*3.04*	*0.177%*	*California, Chicago, Texas*	*27.40*
Video analysis	*90*	*0.37*	*3.00%*	*France*	*0.03*
Cell phone usage	*100*	-	*5.00%*	*n/a*	*0.005*

In the study [35], a fuzzy logic-based incident detection algorithm was proposed and compared with algorithms such as California TSC#7, APID, PATREG, SND, Bayesian, and the McMaster algorithm. The algorithm's performance was evaluated using data from the research [7]. The results showed the following effectiveness for the fuzzy logic-based algorithm: DR – 100%; FAR – 3.33%; MTTD - 0.68 min.

In the research [44], a comparative analysis of incident detection algorithms based on Artificial Neural Networks (ANN) and Probabilistic Neural Networks (PNN), along with classical algorithms (California, McMaster, etc.), was presented. The summarized results in Table 4 indicated relatively high levels of efficiency, especially for ANN and PNN. This suggests significant value for traffic monitoring systems during deployment [51-60].

Table 4 - Comparative analysis of algorithms conducted in Australia [44]

Algorithm name	*DR, %*	*FAR, %*	*MTTD, min.*
McMaster	*68-88*	*<0.01*	*2.1-3.2*
DELOS [37]	*78*	*0.176*	*1.1*
ANN [53]	*89*	*0*	*2.4*

ANN [53]	*89*	*0*	*2.4*
ANN [40]	*83*	*0.065*	*3.4*
PNN [1]	*98-100*	*0-0.5*	*0.3-2.5*
California 8 Algorithm [38]	*71*	*0.005*	*8.9*
DELOS [38]	*73*	*0.03*	*5.5*
ANN [38]	*97*	*0.176*	*5.2*
PNN [60]	*93*	*0.057*	*2.7*
ANN [60]	*83*	*0.065*	*3.4*

The authors proposed a method of responding to traffic flow using an incident detection algorithm in their publication [50]. The proposed method involves online calibration of threshold values for the California No. 7 and DELOS algorithms, which makes them more robust to changing traffic flow conditions. During testing in Athens, Greece, the proposed algorithm demonstrated a 20% increase in DR efficiency and a 25% reduction in FAR when compared to existing algorithms.

Conclusion

The analysis revealed numerous incident detection algorithms, which are continuously evolving and improving, particularly with the advancement of big data analysis. However, the practical application of these algorithms is restricted due to the high rate of false positives.

Therefore, the employment of fixed vehicle detectors for highways in incident detection algorithms necessitates improvement or the integration of supplementary systems for daily traffic monitoring. This will enable their use as integrated components of intelligent transport systems.

References

1. Abdulhai, B. and Ritchie, S.G. (1999). “Enhancing the universality and transferability of freeway incident detection using a Bayesian-based neural network.” Transportation Research Part C, Vol. 7,No. 5, pp. 261-280
2. Adeli, H. and Samant, A. (2000). “An adaptive conjugate gradient neural network-wavelet model for traffic incident detection.” Computer-Aided Civil and Infrastructure Engineering, Vol. 15, No.4, pp. 251.260
3. Ahmed, M.S. and Cook, A.R. (1977). “Analysis of freeway traffic time-series data using Box- Jenkins techniques.” Transportation Research Record, No. 722, TRB, National Research Council, pp. 1-9.
4. Ahmed, M.S. and Cook, A.R. (1980). “Time series models for freeway incident detection.” Journal of Transportation Engineering, Vol. 106, No. 6, ASCE, pp. 731-745.
5. Ahmed, M.S. and Cook, A.R. (1982). “Application of time-series analysis techniques to freeway incident detection.” Transportation Research Board, No. 841, TRB, National Research Council, pp. 19-21.
6. Al-Deek, H.M., Ishak, S.S. and Khan, A.A. (1996). “Impact of freeway geometric and incident characteristics on incident detection.” Journal of Transportation Engineering, Vol. 122, No. 6, ASCE, pp. 440-446.
7. Balke, K.N. (1993). “An evaluation of existing incident detection algorithms.” Research Report, FHWA/TX-93/1232-20, Texas Transportation Institute, the Texas A&M University System, College Station, TX, November 1993.
8. Black, J. and Sreedevi, I. (2001). “Automatic incident detection algorithms.” ITS DecisionDatabase in PATH,

http://www.path.berkeley.edu/~leap/TTM/Incident_Manage/Detection/aida.html, February 2001.
9. Chang, E.C.-P. and Wang, S.-H. (1994). “Improved freeway incident detection using fuzzy set theory.” Transportation Research Record, No. 1453, TRB, National Research Council, pp.75-82
10. Chen, S., Wang, W., van Zuylen, H., 2009. Construct support vector machine ensemble to detect traffic incident. Expert Systems with Applications 36, 10976-10986.
11. Cheu, R.L. and Ritchie, S.G. (1995). “Automated detection of lane-blocking freeway incidents using artificial neural networks.” Transportation Research Part C, Vol. 3, No. 6, pp. 371-388
12. CLIPS Reference Manual, Version 5.1 of CLIPS, Vol. I. Software Technology Branch, Lyndon B. Johnson Space Center, Sept. 1991.
13. CLIPS User's Guide, Version 5.1 of CLIPS, Vol. II. Software Technology Branch, Lyndon B. Johnson Space Center, Sept. 1991.
14. Collins, J.F., Hopkins, C.M. and Martin, J.A. (1979). “Automatic incident detection—TRRL algorithms HIOCC and PATREG.” TRRL Supplementary Report, No. 526, Crowthorne, Berkshire, U.K.
15. Dia, H. and Rose, G. (1997). “Development and evaluation of neural network freeway incident detection models using field data.” Transportation Research Part C, Vol. 5, No. 5, pp. 313-331
16. Dudek, C.L., Messer, C.J. and Nuckles, N.B. (1974). “Incident detection on urban freeway.” Transportation Research Record, No. 495, TRB, National Research Council, pp. 12-24
17. Fide Tutorial, Aptronix, 1992.
18. Fide Reference Manual. Aptronix, 1992.
19. Jian Lu, Shuyan Chen, Wei Wang, Henk van Zuylen (2011). A hybrid model of partial least squares and neural network for traffic incident detection, School of Transportation, Southeast University, Nanjing 210096, China Civil Engineering and Geosciences, Delft University of Technology, 2600 GA Delft, The Netherlands.
20. Hsiao, C.-H., Lin, C.-T. and Cassidy, M. (1994). “Application of fuzzy logic and neural networks to automatically detect freeway traffic incidents.” Journal of Transportation Engineering, Vol. 120,No. 5, ASCE, pp. 753-772
21. Ishak, S.S. and Al-Deek, H.M. (1998). “Fuzzy ART neural network model for automated detection of freeway incidents.” Transportation Research Record, No. 1634, TRB, National ResearchCouncil, pp. 56-63.
22. Levin, M. and Krause, G.M. (1978). “Incident detection: a Bayesian approach.” Transportation Research Record, No. 682, TRB, National Research Council, pp. 52-58.
23. Lin, C.K. and Chang, G.L. (1998). “Development of a fuzzy-expert system for incident detection and classification.” Mathematical and Computer Modeling, Vol. 27, No. 9-11, pp. 9-25.
24. Masters, P.H., Lam, J.K. and Wong, K. (1991). “Incident detection algorithms of COMPASS— an advanced traffic management system.” Proceedings of Vehicle Navigation and InformationSystems Conference, Part 1, SAE, Warrendale, PA, October 1991, pp. 295-310.
25. Marijke, F. A., & Thomas, P. H. (2004). Evolving transfer functions for artificial neural networks. Neural Computation and Application, 13, 38–46.

26. Michalopoulos, P.G. (1991). "Vehicle detection video through image processing: the Autoscope system." IEEE Transactions on Vehicular Technology, Vol. 40, No. 1, IEEE, pp. 21-29.
27. Michalopoulos, P.G., Jacobson, R.D., Anderson, C.A. and DeBruycker, T.B. (1993)."Automatic incident detection through video image processing. " Traffic Engineering and Control, Vol. 34, No. 2, pp. 66-75.
28. Payne, H.J. and Tignor, S.C. (1978). "Freeway incident-detection algorithms based on decision trees with states." Transportation Research Record, No. 682, TRB, National Research Council,pp. 30-37.
29. Ritchie, S.G. and Cheu, R.L. (1993). "Simulation of freeway incident detection using artificial neural networks." Transportation Research Part C, Vol. 1, No. 3, pp. 203-217.
30. Stephanedes, Y.J., Chassiakos, A.P. and Michalopoulos, P.G. (1992). "Comparative performance evaluation of incident detection algorithms." Transportation Research Record, No. 1360, TRB, National Research Council, pp. 50-57.
31. Stephanedes, Y.J. and Liu, X. (1995). "Artificial neural networks for freeway incident detection." Transportation Research Record, No. 1494, TRB, National Research Council, pp. 91-97.
32. Subramaniam, S. (1991). "Literature review of incident detection algorithms to initiative diversion strategies." Working Paper, University Center of Transportation Research, Virginia Polytechnic Institute and State University, Blacksburg, VA.
33. Tsai, J. and Case, E.R. (1979). "Development of freeway incident detection algorithms by using pattern- recognition techniques." Transportation Research Record, No. 722, TRB, National Research Council, pp. 113-116.
34. Weil, R., Wootton, J. and Garcia-Ortiz, A. (1998). "Traffic incident detection: sensors and algorithms." Mathematical and Computer Modeling, Vol. 27, No. 9-11, pp. 257-291.
35. Bottino, A., Garbo, A., Loiacono, C. and Quer, S. (2016). Street viewer: An autonomous vision based traffic tracking system. Sensors, 16(6). 10.3390/s16060813. http://www.mdpi.com /1424-8220/16/6/813.
36. Chassiakos, A. and Stephanedes, Y. (1993a). Smoothing algorithms for incident detection. Transportation Research Record, no. 1394, pp. 8–16. https://www.researchgate.net/publication/240247850_Smoothing_algorithms_for_incident_ detection.
37. Chung, E. and Rosalion, N. (1999). Effective incident detection and management on freeways. Technical Report ARRB Transport Research Ltd. https://trid.trb.org/view.aspx?id=1164576.
38. CTC & Associates LLC (2012). Automated video incident detection systems: Preliminary investigation. Technical Report Caltrans Division of Research and Innovation. http://www.dot.ca .gov/newtech/researchreports/preliminary_investigations/docs/automated_incident_pi.pdf.
39. Dia, H. and Rose, G. (1997). Development and evaluation of neural network freeway incident detection models using field data. Transportation Research, 5C(5), 313–331. http://www .sciencedirect.com/science/article/pii/S0968090X97000168.
40. Chintalacheruvu, N. and Muthukumar, V. (2012). Video based vehicle detection and its application in intelligent transportation systems. Journal of Transportation Technologies, 2. 10.4236/jtts .2012.24033. https://pdfs.semanticscholar.org/32f9/b191f946c301b20f24f6d2a9425383a8707f .pdf.

41. Fishbain, B., Ideses, I., Mahalel, D. and Yaroslavsky, L. (2009). Real-time vision-based traffic flow measurements and incident detection. In Real-Time Image and Video Processing 2009, number 7244 in Proc. SPIE, pages 72440I. 10.1117/12.812976. https://www.spiedigitallibrary .org/conference-proceedings-of-spie/7244/1/Real-time-vision-based-traffic-flow -measurements-and-incident-detection/10.1117/12.812976.full?SSO=1.
42. Kastrinaki, V., Zervakis, M. and Kalaitzakis, K. (2003a). A survey of video processing techniques for traffic applications. Image and Vision Computing, 21(4), 359 - 381. https://doi.org/10 .1016/S0262-8856(03)00004-0. http://www.sciencedirect.com/science/article/pii /S0262885603000040.
43. Luk, J., Han, C. and Chin, D. (2010). Automatic freeway incident detection: Review of practices and guidance. In 24th ARRB conference: building on 50 years of road and transport research: proceedings. http://railknowledgebank.com/Presto/content/GetDoc.axd?ctID=MjE1ZTI4YzctZjc1YS00MzQ4LTkyY2UtMDJmNTgxYjg2ZDA5&rID=NTY=&pID=MTQ3Ng==&attchmnt=VHJ1ZQ==&uSesDM=False&rIdx=NzgyNA==&rCFU=.
44. Martin, P. T., Perrin, J. and Hansen, B. (2001). Incident detection algorithm evaluation. Technical Report Utah Deportment of Transportation. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.569.5951&rep=rep1&type=pdf.
45. Loureiro, P. F. Q., Rossetti, R. J. F. and Braga, R. A. M. (2009). Video processing techniques for traffic information acquisition using uncontrolled video streams. In ITSC '09. 12th International IEEE Conference on Intelligent Transportation Systems. 10.1109/ITSC.2009.5309595.
46. Netten, B., Weekley, J., Miles, A., Nitsche, P. and Baan, J. et al. (2013b). RAIDER – realising advanced incident detection on european roads: Generic specifications for incident detection systems. Technical Report ERA-NET ROAD.http://www.cedr.eu/download/other_public_files/research_programme/eranet_road/call_2011/mobility/raider/02_raiderd4_1_genericspecificationsforincidentdetectionsystems_v5.pdf
47. Li, Q., fu Shao, C. and Zhao, Y. (2014). A robust system for real-time pedestrian detection and tracking. J. Cent. South Univ., 21, 1643–1653. 10.1007/s11771-014-2106-1.
48. Mehboob, F., Abbas, M. and Jiang, R. (2016). Traffic event detection from road surveillance videos based on fuzzy logic. In 2016 SAI Computing Conference (SAI), pages 188-194. 10.1109 /SAI.2016.7555981.
49. Nathanail, E., Kouros, P. and Kopelias, P. (2017). Traffic volume responsive incident detection. Transportation Research Procedia, 25(Supplement C), 1755 -1768. World Conference on Transport Research -WCTR 2016 Shanghai. 10-15 July 2016. https://doi.org/10.1016/j.trpro .2017.05.136. http://www.sciencedirect.com/science/article/pii/S2352146517304271.
50. Porikli, F. and A. Yilmaz, Object detection and tracking, in Video Analytics for Business Intelligence. 2012, Springer.
51. Ren, J. (2016). Detecting and positioning of traffic incidents via video-based analysis of traffic states in a road segment. IET Intelligent Transport Systems, 10, 428-437(9). http://ieeexplore .ieee.org/document/7510542/.
52. Ritchie, S. and Cheu, R. (1993). Simulation of freeway incident detection using artificial neural networks. Transportation Research, 1C (3), 203–217. http://www.sciencedirect.com/science /article/pii/S0968090X13800010.

53. Shukla, A. and M. Saini, “Moving Object Tracking of Vehicle Detection”: A Concise Review. International Journal of Signal Processing, Image Processing and Pattern Recognition, 2015.
54. Shahade, A.K. and G.Y. Patil, Efficient Background Subtraction and Shadow Removal Technique for Multiple Human object Tracking. International Journal, 2013.
55. Vasu, L., Effective Step to Real-time Implementation of Accident Detection System Using Image Processing. 2010.
56. Vinay, D. and N.L. Kumar, Object Tracking Using Background Subtraction Algorithm. International Journal of Engineering Research and General Science, 2015.
57. Wan, Y., Huang, Y. and Buckles, B. (2014). Camera calibration and vehicle tracking: Highway traffic video analytics. Transportation Research Part C: Emerging Technologies, 44, 202 213. https://doi.org/10.1016/j.trc.2014.02.018. http://www.sciencedirect.com/science/article /pii/S0968090X14000606.
58. Zhang, W., Q.J. Wu, and H. bing Yin, moving vehicles detection based on adaptive motion histogram. Digital Signal Processing, 2010.
59. Zhang, K. and Taylor, M. (2006). Towards universal freeway incident detection algorithms. Transportation Research, 14C(2), 68–80. http://www.sciencedirect.com/science/article/pii /S0968090X06000337.
60. Monografiya / Yu.A. Vrubel, D.V. Kapskiy, D.V. Rojanskiy, D.V. Navoy, Ye.N. Kot. – Minsk: BNTU, 2011. – 230 s.
61. Kapskiy, D.V. Konsepsiya razvitiya avtomatizirovannыx sistem upravleniya dorojnым dvijeniyem v Respublike Belarus / Kapskiy D.V., Ye.N. Kot // Nauchno-texnicheskiy jurnal «Vestnik BNTU». – 2005. – № 5 – S. 63–66.
62. Vrubel, Yu.A. Opredeleniye poter v dorojnom dvijenii / Yu.A. Vrubel, D.V. Kapskiy, Ye.N. Kot. – Minsk: BNTU. – 240 s.
63. Vrubel, Yu.A. Upravleniye dorojnым dvijeniyem: uchebno-meto-dicheskoye posobiye / Yu.A. Vrubel. – Minsk: BNTU 2007.
64. Kapskiy, D.V. Avtomatizirovannыye sistemы upravleniya dorojnым dvijeniyem / .V. Kapskiy, Vrubel Yu.A., Navoy D.V., Rojanskiy D.V., Kot Ye.N. / Dopuщyeno Ministerstvom obrazovaniya Respubliki Belarus v kachestve uchebnogo posobiya dlya studentov uchrejdeniy vыsshego obrazovaniya po spesialnosti «Organizatsiya dorojnogo dvijeniya» - Minsk : Novoye znaniye ; M.: INFRA-M, 2015. 368 s.
65. Usmanov, U., Ruzimov, S., Tonoli, A., & Mukhitdinov, A. (2023). Modeling, Simulation and Control Strategy Optimization of Fuel Cell Hybrid Electric Vehicle. Vehicles, 5(2), 464–481. https://doi.org/10.3390/vehicles5020026
66. Topalidi, V., Yusupov, U., & Allaberganov, S. (2022). Improving the efficiency of transport logistics support. 030072. https://doi.org/10.1063/5.0089587
67. Barkhanadzhyan, A. L., Khakimov, R. M., Ibragimov, B. D., Sobirova, D. K., Abdukarimova, G. U., & Ayrapetov, D. A. (2020). Problem of using waste of paint and varnishing materials and their disposal. Bulletin of the Tomsk Polytechnic University, Geo Assets Engineering, 331(9), 179–185. ttps://doi.org/10.18799/24131830/2020/9/2821
68. Hakimov R., Ayrapetov D. Anti-Corrosion Coatings For The Protection Of Metal Parts Of Transport Equipment (2023) AIP Conference Proceedings
69. Shermukhamedov, A., Azizov, A., Ergashev, N., Shermukhamedov, Y., & Abdukhamidovich, A. K. (2022). Substantiation of the Parameters of the Wheel Propeller Tread Lugs. In AIP Conference Proceedings (Vol. 2432). American Institute of Physics Inc. https://doi.org/10.1063/5.0091148

70. Togaev, A., & Shermukhamedov, A. (2021). Mathematical model for calculating the reliability of the characteristics of the designed trailer frame. In E3S Web of Conferences (Vol. 264). EDP Sciences. https://doi.org/10.1051/e3sconf/202126404054 Shermukhamedov A. A., Togaev A.A. Calculating the stress-strain state of frame structures of autotractor trailers at various external influences // European Applied Sciences. – Stuttgart (Germany), 2016. – №1. – pp. 70-76.
71. Shermukhamedov, A., Ergashev, N., & Azizov, A. (2021). Substantiating parameters brake system of the tractor trailer. In E3S Web of Conferences (Vol. 264). EDP Sciences. https://doi.org/10.1051/e3sconf/202126404019
72. Shermukhamedov, A. A., Juraev, M. N., & Kenjayev, S. N. (2023). Efficient Distribution of Motor Vehicles of Different Loading Capacities on Routes. In AIP Conference Proceedings (Vol. 2612). American Institute of Physics Inc. https://doi.org/10.1063/5.0134786
73. Shermukhamedov, A. A., & Astanov, B. J. (2023). Mathematical Model of Dynamic Characteristics of a Hydraulic Drive with Distributed Parameters Taking into Account the Influence of the Temperature Factor. In AIP Conference Proceedings (Vol. 2612). American Institute of Physics Inc. https://doi.org/10.1063/5.0121022
74. Shermukhamedov, A., Annakulova, G., Astanov, B., & Akhmedov, S. A. (2021). Mathematical modeling of a hydraulic hitched system of gantry tractor with high clearance used in horticulture and viticulture. In IOP Conference Series: Materials Science and Engineering (Vol. 1030). IOP Publishing Ltd. https://doi.org/10.1088/1757-899X/1030/1/012152
75. Nurmetov, K., Riskulov, A., & Ikromov, A. (2022). *Physicochemical aspects of polymer composites technology with activated modifiers*. 20011. https://doi.org/10.1063/5.0106358
76. Avdeichik, S. V, Gol'dade, V. A., Struk, V. A., Antonov, A. S., & Ikromov, A. G. (2022). Implementation of the Nanostate Phenomenon in Materials Science of Functional Nanocomposites Based on Industrial Polymers. *Surface Engineering and Applied Electrochemistry*, *58*(3), 211–220. https://doi.org/10.3103/S1068375522030061
77. Ubaydullaev, G., Riskaliev, D., Ergashev, N., Rashidov, A., & Shadiev, S. (2021). Determination of installation bases of parts during their mechanical processing. In E3S Web of Conferences (Vol. 264). EDP Sciences. https://doi.org/10.1051/e3sconf/202126405046