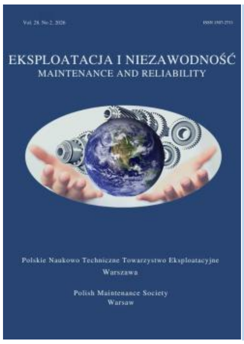

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Maximizing uptime of the aging road tanker fleets in labor shortages and economic uncertainty by implementing preventive maintenance practices

Indexed by: Web of Science Group

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Highlights

- The truck maintenance model and key indicators to determine effective maintenance strategy.
- The algorithm estimating uptime trucks' fleets based on model include unexpected events.
- Tests of basic maintenance for truck availability – planned, preventive and predictive maintenance.

Abstract

Due to the instability of the liquid fuel market, companies planning to distribute them rely primarily on statistics on the occurrence of dangerous situations in the past. As a result, the impact of rare events on the transport process as well as the possible consequences are not taken into account. Therefore, the study attempted to assess both quantifiable risk on the basis of statistical data and non-quantifiable risk, which proved useful in cases of increasing labor shortages and high economic uncertainty, in particular when the average age of road trucks is increasing year on year. The results of the research have shown that the identification of hazards caused by rare events can be effectively assessed through the use of non-quantifiable risk, as well as a PdM (Predictive Maintenance) strategy based on appropriate preventive measures, ensuring a reduction in unplanned fleet downtime by 12-18% and an increase in delivery efficiency by 10-15%.

Keywords
unplanned downtime cut, non-quantifiable risks, proactive maintenance strategies

1. Introduction

The average age of trucks is increasing year by year. According to ACEA reports [1] in the first nine months of 2024, new EU truck registrations saw a 7.5% decline, at the same time, trucks remain the oldest of all vehicle types at 14.1 years in EU. Compared to 2017, the increase is 2.5%.

According to Polish Automotive Industry Association reports for the last 5 years in Poland share in the fleet of the vehicles 20-year and older has increased from 19.6% to 20.1%. At the same time, share in the fleet of the vehicles 11-year and older had over half the fleet, of which share the 20-year and older vehicles has increased from 34,4 % at the end of the 2019 year to 36,7% at the end 2023 year.

The WEF has published the Global Risks Report, which takes a closer look at a number of possible problems between 2026 and 2035, including both trucks production decries (Fig.1) and supply chains disruptions as the most important risks (R=43%) [43].

A number publication detected DHV (Heavy Duty Vehicles) accidents (Fig.2) caused by CF /Chronic or Routine Failures/ or IF /Incidental Failures/ [6]. Unfortunately, researchers seldom pay their attention to the so-called SF (Surprising Failures) and non-quantifiable risks. It is important because firstly improving uptime for the aging trucks increase their operation stability as on LHR (Long-Haul Routes) as on SHR

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(Short-Haul Routes) including built-up areas, and secondly

reduce breakdowns probably and damage for human well-being.

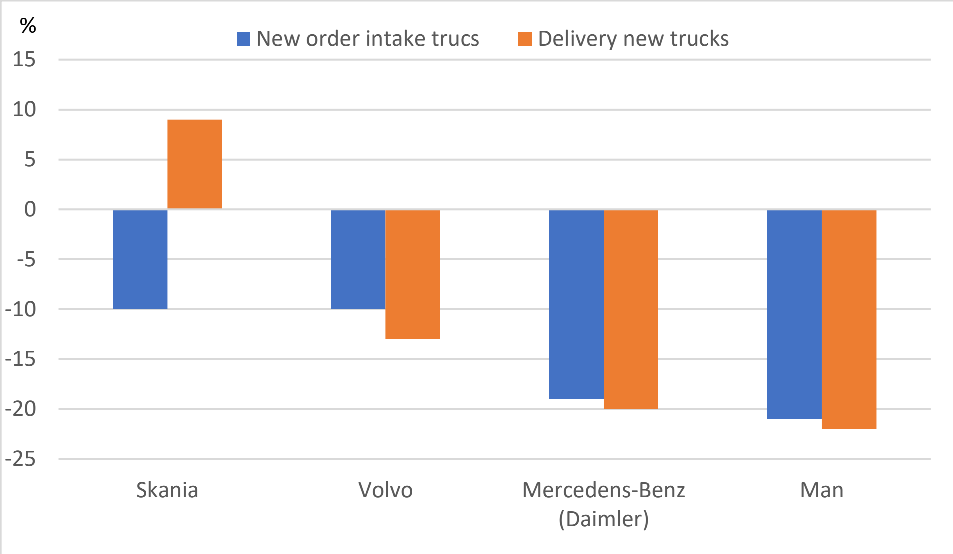
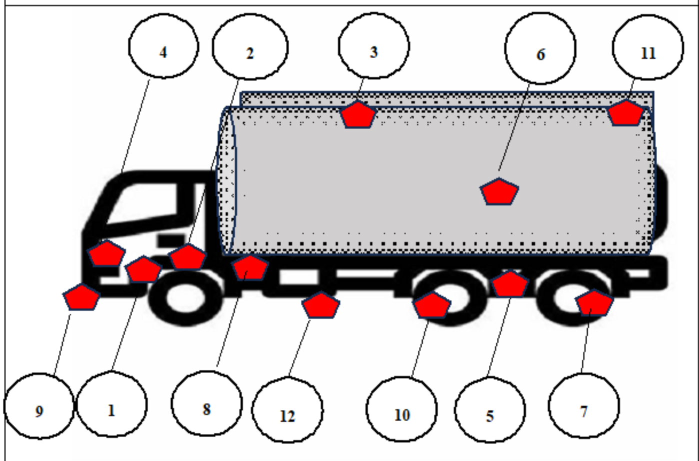


Fig. 1. New order intake trucks in 2024 by brand [33].

Tank truck malfunctions



Input values

Hazard participation vs. HDV age (%)			
Factor	Number years in operation		
	for 7	for 14	for 18
CF	68-74	63-64	59-61
IF	22-24	26-27	27 -28
SI	1-2	5-6	7-9
Total	100		

1. Worn engine parts, cooling system failures; 2. Hydraulic system failures, steering system fails 3. Pump wear, clogged oil lines, or pressure valve failure 4. Wear inside the cylinders 5. Tank leaks and spills 6. Damaged seals, loose fasteners; 7. Worn brake pads or uneven disc surfaces 8. Aging, improper installation or poor contact of electrical components 9. Rusted areas, cracks, dents, or deformation 10. Chassis loosening 11. Valve Failure - blockages, and failure to open or close properly 12. Uneven wear tires

Fig.2. Hazard location and participation.

On a substantive level, this issue has been addressed by the APICS (American Production and Inventory Control) which proposed the use so-called SCOR (Supply Chain Operations Reference) model [28] using of the next stability criterion to assess the deliveries quality:

$$St = F[(RIo, FI, R_S(CF, IF, SF), A)] \rightarrow max \qquad (1)$$

where:

RI_0 - measure of the reliability of newly vehicles /in the analyzed case of road tankers/

FI – measure of the effectiveness of preventive measures /e.g., maintenance strategy/

$R_S(CF, IF, SF)$ - measure of the staff resilience to destabilizing events

A – measure of the personnel adaptability to external and internal changes

According APICS recommendations, a measure of the vehicles vulnerability to destabilizing incidents in the SHR-supply process throughout its life cycle can be presented as follows:

$$\Delta V(t_i) = [RI_0 - \sum Ri(t_i)] \rightarrow min, t_i \in T \qquad (2)$$

where:

$Ri\ (t_i)$ - measure of the DHVs damage over T-years /

frequency of unplanned downtime/

T – operation cycle time.

In the article an attempt was made to fill the knowledge gap for ensuring the stability of SHR-supplies fuels by maximizing their resilience to event adversarial scenarios.

This problem is important because in most publications:

— firstly, supply stability on long-haul and short-haul routes is treated almost the same;

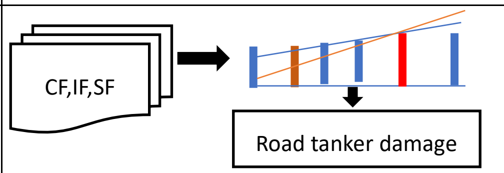
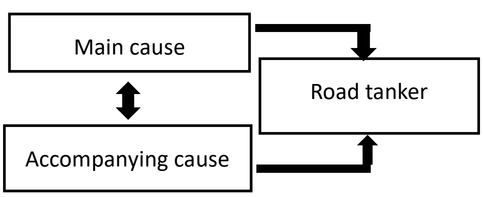
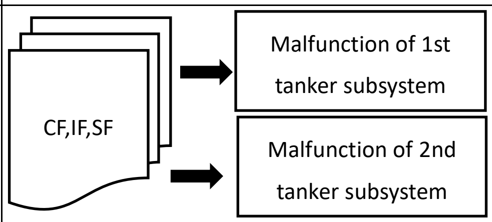
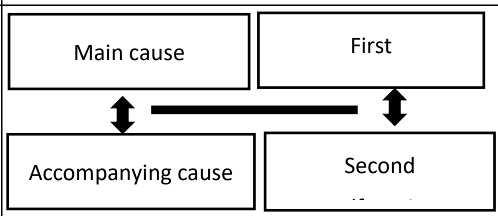
— secondly, a number of scenarios haven't been taken into account for damage trucks studies that were based only on the linear sequence of a CF & IF manifestations as unsafe situation causes (Tabl.1).

Today practice shown that schedule planners strive to eliminate downtime, which can lead to intolerable delays. Therefore, the our research was performed according to the rule:

$$\Delta V(VOD, t_i) = [RI_0 - \sum Ri(t_i)] \rightarrow min, \qquad t_i \in T$$

HR-supplies fuels by maximizing their resilience to event research scenarios.

Table. 1 Types of research scenarios.

Scenario Types	Graphic imaging	Examples
Scenarios 1: A linear sequence of a CF, IF, SF impacts as unsafe situation cause		*Triggering event*: e.g. factory defect of cylinder head *Basic cause*: e.g. block cylinder damage *Consequence:* e.g. engine failure > road tanker damage
Scenarios 2: Convolution of a CF, IF, SF impacts as cause of the unsafe situations		*Main cause* 1: e.g. fuel subsystem failure *Accompanying cause* 2: e.g. ignition subsystem wear *Consequence*: engine start no possible > road tanker damage
Scenarios 3: A combination effects as a result of the CF, IF, SF impacts		*General cause*: e.g. wear of the suspension system *Malfunction of 1st subsystem*: e.g. failure of the shock absorbers *Malfunction of 2nd subsystem:* e.g. steering malfunction *Cumulative effect*: e.g. increase of braking distance by 30%
Scenarios 4: Convolution of a CF, IF, SF impacts and combination effects		*Main cause*: ground wire corrosion *Accompanying cause*: body vibrations *First malfunction*: e.g. difficult engine start *Second malfunction:* e.g. fuses blown *Cumulative effect*: e.g. damage to the electrical system > tanker damage

The following assumptions were made:

— the road tankers availability is a basic condition for the stability of fuel deliveries;

— the reliability of these vehicles depends on both aging and fatigue dynamics;

— numerous hazards increase risk both unplanned downtime vehicles and delivery delay;

— the delays as a result of damage vehicles may be eliminate by successful maintenance.

2. LITERATURE REVIEW

The literature review analyzed a number of models that were developed to study various services aspects on different segments of freight deliveries. Interesting research of these issues (operating costs, operation time, etc.) are presented in [21]. According to [29] from 2022 onward, there is an increase in expenditures on road fleet maintenance, which creates numerous financial problems for T&L industry. An attempt to rationalize the expenses of transportation companies was addressed in [41], which presents models for optimizing costs, supporting decision-making and improving the competence of these companies' employees. A number of publications address DHV damages as a major cause of delayed deliveries and low integration of supply chains [38]. Important publications are proposed the use of VOD rate [19, 24, 35], where has been proven that the cost of delays is generated not while vehicles are moving, but during their stops.

Noteworthy are a number of publications on the problem of reducing the frequency of vehicle breakdowns, the sequence of which is their unscheduled downtime, which increases operating costs, reduces customer satisfaction [3]. In the paper [2], the problem of rationalizing DHV maintenance mode is identified as a more important factor in the T&L industry productivity. The prevalence of DHV diesel engine failures was analyzed in [39]. The variety of issues raised resulted in the development of a new approach to this problem, which was called "deep learning proportional to the threats" [12], and its implementation based on obtaining the right information is dedicated [40]. The advantages of using ML applications in PdM are pointed out by [5]. Most of the emerging models are related to the development of network technologies, providing monitoring of vehicle components, sending information from on-board pressure, temperature and vibration sensors. This favors the collection of BD/*Big Data*/ and the implementation of AI- technologies [17]. A proposal to extend the sensor network from a tractor-trailer to monitor moving and stationary parts of trailers is presented by [39]. Effective systems for processing collected data can provide new knowledge, supporting both the development of an appropriate vehicle maintenance strategy over a selected time horizon [42], as well as planning maintenance schedules [10, 14]. The problem of choosing the optimal servicing strategy for freight transport was analyzed [7]. It was shown that the use of the MCRL (*Monte Carlo Learning*) method provides a 36.44% reduction in DHV downtimes. An strategy for strengthening road transport resilience is presented by [34]. In publication [46] propose method for adapting PdM to industrial needs. However in [11] was developed successful model for "k-out-of-n systems" reliability The issue of using up-to-date information in PdM management based on the failure prediction model is analyzed in [13], and the model of operation of special vehicles with the application of semi-Markov processes is presented by [9] as well as studying [44]. The driver age, exceeding speed limits and proper servicing have been shown to have a significant impact on the accidents frequency involving DHVs.

Another direction of the research analyzed is the question of the effectiveness of maintenance in transport companies. In [27] an integrated approach to analyzing the cause and effect of failures using FMEA has been proposed. The publication [31] presents an original approach to decision support for risk management of DHV failure based on nonlinear goal programming. The use of a simulation model and queuing theory has been suggested to evaluate the efficiency of logistics process execution [22]. The study results of these and other authors, e.g. [16], are valuable for shaping the vehicle servicing policy of transport companies, improving their operations and reducing operating costs. The several study e.g. [18] showed that basic risk factors are "Critical parameters of vehicle state" and "Poor vehicle maintenance". The publication [4] points out that important solutions aimed at reducing the these factors impact through ability to respond to unexpected situations.

A review of the literature shows that there is a content gap regarding the problem of fuel supply safety on built-up areas, where the effects of road tanker accidents can be very severe.

3. Organization of liquid fuels delivery on the short-haul routes

3.1. Basic modes

SHR-fuels supply is carried out up to 350 km and forms basic segment of T&L industry, including about 1.2 million EU enterprises [25]. Today these companies are under pressure:

- intensification of competition sometimes turning into destructive competition;
- an increase causes for vehicle failures, which include design errors, improper maintenance, driving by different drivers who may not be familiar with the vehicle to monitor the truck changes and preventing defects; as statistics show, a 1% increase in vehicle age results in a 0.24% increase in the vehicle failures frequency [37]:
- tiny chance of replacing the defect truck on short notice with a reserve vehicle;
- the growing variety of forms of SHR - deliveries are presented in Table 2.

Conclusion 1: Managers of T&L companies face the problem of improving the logistics of fleet availability based on models that take into account various unsafe events.

Analysis of deliveries practices indicated that such events can be divided into:

Group A. Safety threats are known a priori. These models used include deterministic type of risks A (RAHT, t)[1], which are known (eq. 3) and do not take into account risks of type Ω(RAHT,t) because do not changes in the supply schedule (eq. 4):

$$\mathrm{A(RAHT,t)} = [\propto_1 \mathrm{(RAHT,t)};\ \propto_2 \mathrm{(RAHT,t)};\ldots \propto_n \mathrm{(RAHT,t)}] \geq 0, \tag{3}$$

$$\Omega\mathrm{(RAHT,t)} \equiv 0, \quad \mathrm{t} \in \mathrm{T} \tag{4}$$

where:

$A(RAHT,t)$ - deterministic function of past events occurrence (statistical database)

$\Omega(RAHT,t)$ - random function of occurrence of unsafe events not known in the past

$\propto_i$- weighting factors of routine events known in the past, $\mathrm{i = 1 - n}$

Group B. Safety threats are known in part. These models are based on the assumption that both the expected A(RAHT,t) and the random Ω(RAHT,t) known partly

$$A(RAHT,t) = [\propto_1 (RAHT,t);\ \propto_2 (RAHT,t);\ldots \propto_n (RAHT,t)],\ t \in T \tag{5}$$

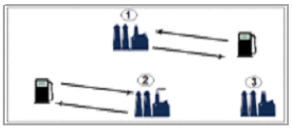
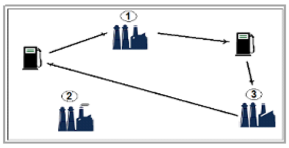
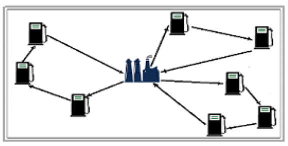
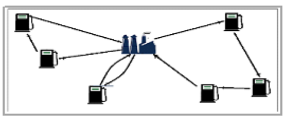
$$\Omega(RAHT,t) = [\omega_1(RAHT,t);\ \omega_2(RAHT,t);\ldots \omega_m(RAHT,t)],\ t \in T \tag{6}$$

where:

ω_j - weighting factor of unsafe events occurring randomly, $j = 1 - m$.

Group C. Safety threats are unknown. These models are based on the assumption that both the random function describing unexpected events $\Omega\mathrm{(RAHT,t)} \neq 0$ as well as a deterministic function $A(RAHT,t) \neq 0$ are not inflicted (no statistics).

Table 2. Basic modes of local and regional SHR-deliveries. Own elaboration based on: [8, 25, 26, 45].

Charts of modes for SHR delivers		Comments
Direct deliveries		*Full-vehicle deliveries by one tanker truck, the tank of which has baffles to suppress liquid streams of liquid fuel. Profitability condition > 90% of vehicle capacity*. VOD Index: 20-30%.*The fuel replenishment problems:* — ensuring road tanker availability; — timely supply in the ordered size
Indirect deliveries		*Split deliveries are carried out by one road tanker. Each customer can be served by more than one vehicle, whose vehicle is divided into compartments by internal bulkheads.* VOD Index: 40 -70%. *Profitability condition: the order of one customer > 10% of the vehicle capacity. The fuel replenishment problems:* — high probabilities of long queues on petrol stations
		*Split deliveries carried out by several road tankers* VOD Index: 70-95%. *Profitability condition - order of one customer > 10% of vehicle capacity,* *The fuel replenishment problems :* — planning effective detour routes; — ensure coordination of on-time deliveries
Mixed deliveries		Mixed scheme realized by direct shipping and multiple-stop shipping/ *Profitability condition - order of one customer > 10% of vehicle capacity*. VOD Index: 80-95%. *The fuel replenishment problems :* - planning effective detour routes; - timely supply in the ordered size

Conclusion 2*:* The practice of both planning deliveries and making appropriate changes to the schedules must be based on knowledge gained from forecasting safety threats that may occur in deliveries routes. According to the index $\langle A_{oI}\ (t)\rangle$ (eq.7) depends on planning maintenance strategy, enforcing the deliveries schedule, managing the spare parts supply.

2.2. Operational availability of road tanker fleets

The stability of SHR fuel supply can be assessed by using i.e. a three-component operational availability $\langle A_o \rangle$ as operational availability rate, measured on a scale covers up 0 to 1, which substantively corresponds to the APICS proposal. Let's analyze eq. 1

First indicator eq.1, namely $\mathrm{RI_0}$ which represents the so-

[1]RAHT - Risk of All Hazards Types

called inherent availability. The right constituent ⟨Aoi(t)⟩ correspond to reliability of newbuilding road tankers /analyzed as eighth class of HDVs /can be full readiness to supply. The value indicator:

$$A_{oi}(t) = \frac{MTBF}{(MTBF+MTTR)} \tag{7}$$

where:

MTBF (Mean Time Between Failures) - average time of road tankers availability;

MTTR (Mean Time To Recovery) - average time of road tankers maintenance.

As vehicles age, the value of this indicator consistently decreases, reaching minimum acceptable levels after 18-20 years of operation cycle [1] [30] [40].

As vehicles age, the value of this indicator consistently decreases, reaching minimum acceptable levels after 18-20 years of operation cycle [40]. Increasingly stringent reliability requirements for freight transport, as well as insufficient investment, led to the closure of 35,000 transport companies in 2023, 10,000 more than in 2022. Such a trend continued in 2024. As a result, the Germany and France fleets, trucks have an average age of 14.2 years [1], with the largest share of vehicles covers up 11 to 20 years of operation time [30].

Second indicator eq.1, namely FI which reflects as "Maintenance Availability". Appropriated constituent AoM(t) and depends on the effectiveness of the spare parts supply, vehicle condition monitoring, diagnostic equipment useful and defect type. It is evaluated by measures (Mean Time Between Maintenance), MMT (Mean Maintenance Time) and MLDT (Mean Logistics Down Time):

$$A_{oM}(t) = \frac{MTBM}{(MTBM+MMT+MLDT)} \tag{8}$$

The T&L companies uses four basic services strategies, among which only predictive strategy being based on the AHA (All Hazards Analysis) principle [19, 32]

Third indicator eq.1, namely R_S which indicate as "Staff availability". Appropriated constituent Aos(t) including drivers and workshops workers. The WEF report shows that labor shortage remains one of the serious risks estimated at 53% [46]. It is rated as:

$$A_{os}(t) = \frac{Total\ employees\ -Total\ job\ vacancy}{Total\ employees} \tag{9}$$

According to significant proportion of the T&I companies instability of chain supplies directly affects the customers satisfaction [6]. Therefore, the main article aim is to research this problem through the study of disposition index $\langle A_o(t)\rangle$ that was calculated as:

$$A_o(t) = A_{oI}(t) \times A_{oS}(t) \times A_{oM}(CF, IF, SF, t) \tag{10}$$

4. Simulation and experimental results

As literature studies indicate, there is a wide set of mathematic al models used in the study of both the reliability of road transport and its maintenance [15, 23]. Their application depends on the objectives set, among which the most common are optimizing the structure of the vehicle fleet, analyzing the impact of the environment on the stability of SHR-deliveries, identifying methods to increase the reliability of vehicles to the manifestation of hazards, identifying ways to mitigate the consequences of breakdowns and accidents, etc. After analyzing the accumulated knowledge, the decision was made to study the dispatchability of road tankers. The research focused on the analysis of the impact of unexpected hazards, supplemented by expanding the number of analyzed RdTT states to four including *absorbing state* reflecting the total loss of road tanker suitability (VOD=0.0)

4.1. Operation model

4.1.1 The basic assumptions

Assumption ***1.*** Road tankers activities consists of n - transitional states of suitability

$s_i \in S\ (i = 0, 1, \dots, n)$, subject to three regularities:

a. The first regularity. The road tanker is roadworthy, which guarantees the execution of the order. Correctness reflects the ideal situation in SHR-delivery practice

b. The second regularity. A tanker truck can lose fitness according to a known distribution of reliability changes. The function of this distribution can be expressed by the following:

$$x_c(t) = [x_1(t); x_2(t); \cdots x_n(t) \tag{11}$$

The regularity allows SHR-delivery planning on the basis of statistical information gathered from past delivery runs [8]. This regularity create number of problems because the moments of loss and overturn of truck operability are vary, secondly, maintenance plan depends on the moments of post-failure reports, and last, the repair time depends on the failure type.

c. The third regularity. A road tanker can lose roadworthiness at different locations and at different times of SHR-delivery. In this case, vehicle fitness is evaluated according to the minimum values of the weakest his construction components, i.e.:

$$x_c(t) = min[x_i(t)], \ \ n = 1, n \qquad (12)$$

This regularity creates a problem with describing the process of restoring the vehicle to road traffic by indicating the possible moments of occurrence and removal of defects.

Assumption *2.* States of the truck availability $\langle s_i \rangle$ are arranged in a three-parts cluster $\langle S \rangle$:

- compliant state- the vehicle is full fitness for SHR deliveries
- pre-emergency state - the vehicle is partial availability and must be serviced
- emergency state - the vehicle is unscheduled downtime

Assumption *3.* The research cluster of vehicle availability states in the terminology of Markov random process can be grouped as follows:

Cluster A. Basic states of road tankers availability:

A1. Achievable states. It occurs if a vehicle from a state of attainability $\langle i \rangle$ can go to another state $\langle j \rangle$ (we denote the transition condition as $i \to j$), that is, there is a path$\langle \ i_0 \to i \to j \rangle$, with possible transitions having probability $P_j > 0, \ j = 1, n$.

A2. Absorbing State. It occurs if the operation process is coming to an end.

Cluster B. Transient states of road tanker availability:

B1. Multidirectional transition states. May occurs when after a certain operation time the vehicle changes running state to the original suitability state.

B2. One-way transition states. It occurs when the vehicle changes running state to another without the possibility returning to its original suitability state.

Assumption *4.* Changes in RdTT availability states can be considered as a semi-Markov process, in which the performance of road tankers during SHR delivery $W_i(s_i, t_n)$ depends on their states $\langle s_i \rangle$ which occur at successive intervals, under condition that at time $\langle t_0 = 0 \rangle$ the vehicle is in a fully operational state $s\langle_0\rangle$:

$$\{W_i(s_i, t_n): t_n \geq 0\} \quad t_n(n \in N) \qquad (13)$$

Assumption *5.* The timing of changes in the states of the road tanker including those causing unplanned downtime as a result of known and unknown events, is described by a vector of known parameters of expected events $B(TR, t)$ or a vector of unknown parameters of random events that threaten the implementation of supply operation $\Omega(TR, t)$, and its values are determined by the distribution of the random vector [$\xi(t_1)$..., $\xi(t_m)$], $m \geq 1$.

4.1.2. Model setup

When making decisions in SHR-supply planning tasks, managers always face complications in assessing RdTT availability, especially under conditions of high probability of various influencing factors [5]. An algorithm was developed based on the:

- database of situations causing vehicle unfitness due to faults
- base of subgroups of unfitness states $H(S_i)$
- database of the conditions of transition of vehicle to the unfitness state:

$$P_{ih}(t) = P\{\xi[\tau(H)] = h|\xi(0) = i\}, i \in S, \quad h \in H, \qquad (14)$$

where:

τ(H) - the moment of first reaching absorbing states

$$\tau(H) = min\{t > 0: \xi(t) \in H\} \qquad (15)$$

In the next step, the problem of replacing the basic Markov chain was solved[$\xi(t)$] using a supporting chain [$\xi^*(t)$], which differs in that a swap of some absorbing states was used $h^* \in H$ for RdTT return to operation has been applied $h^* \in H$:

$$P^*_{ih}(t) = P\{\xi^*(t) = h^*|\xi^*(0) = i\} \approx P\{\tau(H) \leq t, \ \xi[\tau(H)] = h|\xi(0) = i\} \qquad (16)$$

$$P^*_{hh}(t) = 1, h^* \in H,$$

$$P^*_{ih} = 0, \ i, h^* \in H, i \neq h^*$$

Then the probability of states after repairs was calculated according to the formula:

$$P^*_{ih}(t+1) = \sum_{j \in S} P_{ij} P^*_{jh}(t), t \geq 0, \qquad i \in S \setminus H, \ \ h^* \in H, \ \ (17)$$

Equation (16) is a monotonically decreasing function provided that:

$$P_{ih}(t) = \lim_{t \to \infty} P^*_{ih}(t), \ \ i \in S, \quad h^* \in H,$$

The information bases were developed so that they can be applied to each of the following three road tanker availability scheduling levels.

- The first level combines all delivery decisions made within a single order and covering periods measured in hours (2-72). Planned supply schedule taking into account only CF.

- The second level combines decisions on deliveries made during the MTBM period measured in months (up 06 to 12), mileage up to 200,000 km/month. Planned schedule taking into account only CF and IF.
- The third level combines all decisions on both the operation and maintenance of the road tanker measured in years (up to 21). Planned schedule taking into account CF, IF and SF.

A probability matrix was constructed with $P_{ij}(t)$, transitions on a set of states RdTT $\langle Si \rangle$:

1. Vehicle transitions from $\langle s_i \rangle$ to $\langle s_j \rangle$ state take place with probability $P_{ij}(t)$:

$$P_{ij}(t) \geq 0 \qquad \text{for} \qquad \forall S_i, S_j \in S \tag{18}$$

2. The total probabilities:

$$P_{ij}(t) \leq 1 \qquad \text{for} \qquad \forall S_i, S_j \in S \tag{19}$$

3. State $\langle s_i \rangle$ is a suspended (absorbing) if possibility of only transition into itself :

$$P_{ij}(t) = 0, P_{jj}(t) = 1 \tag{20}$$

4. The matrix elements sum reflects the road tanker probability being in one of states:

$$\sum P_{ij}(t) = 1, \text{for } \forall S_i, S_j \in S \tag{21}$$

Thus, having a set of surveyed RdTT states arranged in a modernized Markov chain and a transition matrix indicating probability changes, we can present as:

$$P_{ij}(t) = \{i \mid A_0(t) \rightarrow j | A_0(t+1)\} \tag{22}$$

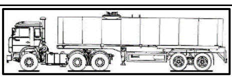
4.1.3. The initial data information

In times of fierce competition, growing need to RdTT disposition index assess [36].

***Task*:** The non-redundant CFTT[2] must be analyzed based on two indicators:

- P[A_0(t)] - probability of road tanker availability to SHR-deliveries;
- R(t) = f (R_k, R_n)- quantifiable /non-quantifiable risk of losing availability;

Table 3. Intensity of failures/ repairs of road tanker in k-th years operation.

	**Input values** /for every year of road tanker operation/						
Interval [1- 7] yrs	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**
$\lambda_k \times 10^{-4}/\, day$	0,94	0,23	0,36	0,054	0,72	0,83	0,08
$\mu_k \times 10^{-1}/day$	2,18	1,82	1,18	1,71	1,67	1,35	1,41
Interval [8-14] yrs	**8th**	**9th**	**10th**	**11th**	**12th**	**13th**	**14th**
$\lambda_k \times 10^{-4}/\, day$	0,25	0,6	0,84	0,96	1,07	1,15	1,24
$\mu_k \times 10^{-1}/day$	0,99	0,91	0,82	1,12	0,86	0,71	0,54
Interval [15-21] yrs	**15th**	**16th**	**17th**	**18th**	**19th**	**20th**	**21th**
$\lambda_k \times 10^{-4}/\, day$	1,41	1,59	1,72	1, 86	2,19	2,31	2,53
$\mu_k \times 10^{-1}/day$	0,35	0,42	0,32	0,26	0,61	0,42	0,34

The following parameters markings were adopted:

λ_k – intensity of road tanker failure at the $k-$th year operation;

μ_k — intensity of road tanker repairs at k-th year operation;

R_k (t)— quantifiable risk of reliability loss;

R_d (t) — non- quantifiable risk of reliability loss;

T_{MTBF} – index value MTBF;

$A_{oI}(t)$ - inherent availability index;

A_0 – total availability index.

The study was conducted for the CFTT, which makes SHR-deliveries on the A6, S3, S6, and Nos. 10, 13 and 31 expressway networks. Most deliveries were made within a radius of 95 to 350 km (41.6%). The road tankers move at a constant speed of 90 km/hr. The intensity both failures ⟨λc⟩ and repairs ⟨μc⟩ rated by all-hazard approach [20] and shown in Table 3. Whereby, changes in road tankers states were divided into 8- categories:

[2]A non-redundant fleet is a fleet that does not have vehicle redundancy. Vehicle redundancy is when a fleet has multiple vehicles that can perform the same task. Non-redundant fleets are less robust than redundant fleets, which have much of their robustness through vehicle redundancy

1. Full road tanker capability to perform SHR - deliveries$-P_1(t)$
2. Scheduled downtime for road tanker $-P_2(t)$
3. Unscheduled downtime for road tanker due to driver shortage$-P_3(t)$
4. Unplanned downtime for road tanker due to CF $-P_4(t)$
5. Unscheduled downtime due to a combination of CF/IF$-P_5(t)$
6. Unplanned downtime for road tanker due to SF$-$ $P_6(t)$
7. Unplanned downtime due to a confluence CF/IF/SF $-$ $P_7(t)$
8. Transfer to an absorbing state (vehicle scrapping) $-P_8(t)$

4.2. Research methodology

An important role in the practice of SHR-supply is played by threatening factors $\zeta_j(t)$, contributing to changes in the availability of RdTT for operations. It was assumed that the dynamics change by leaps and bounds. A corresponding description is provided below.

Let the vector $X = (x_1, x_2, \dots, x_s)$ maps points on the trajectory of RdTT transitions from states $\langle s_i \rangle$ to states $\langle s_j \rangle$, where j – number of states initiated by aging processes. The methodology of the simulation study was based on two assumptions:

Assumption 1: A road tanker availability does not change in any arbitrary period (Δt), if there are no manifestations of threatening factors $\zeta_j(t)$, with a probability of:

$$P[\zeta_j(t)] = [P_0(x_i, t) + P_{ij}(\Delta t)], P_{ij}(\Delta t) = 0; \zeta_j(t) \in J \quad (23)$$

where:

$P[\zeta_j(t)]$ - probability of distribution of random variable of factors $\zeta_j(t)$ impact;

$P_{ij}(\Delta t)$ - probability of adversely events occurrence during the period Δt.

Assumption 2: A road tanker availability varies over the period (Δt), if there will be occurrence of threatening factors $\zeta_j(t)$ with a probability of:

$$P[\zeta_j(t)] = [1 - P_0(x_i, t) + P_{ij}(\Delta t)], P_{ij}(\Delta t) > 0; \zeta_j(t) \in J \quad (24)$$

4.3. Algorithm of transitions

The research algorithm is presented in Fig.3, and the research results are shown in Table 4.

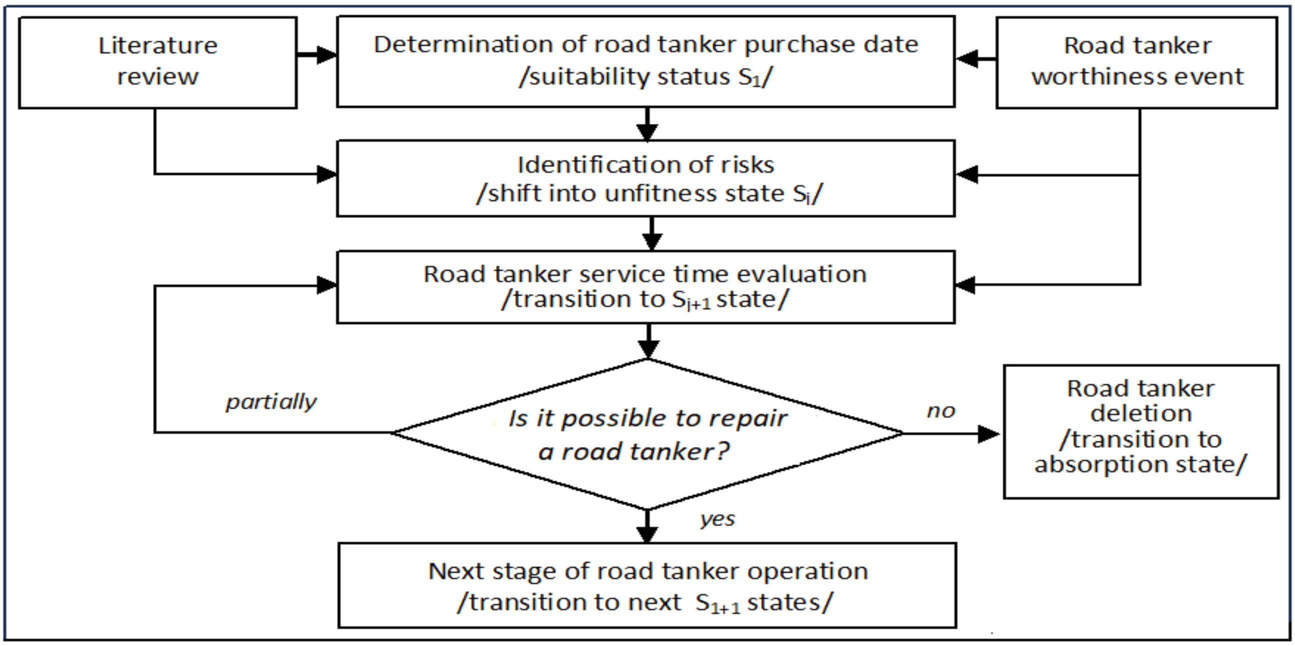


Fig.3. The sequence of research performed.

Comments to the algorithm:

Step 1: The timing was clarified $\langle t_0 \rangle$ start of road tankers operation (state of full fit $\langle s_j \rangle$).

Step 2: It was assumed that at the time $[t_0 + \Delta t]$ road tanker can transition to $\langle s_j \rangle$ state.

Step 3: Period $\langle \Delta t \rangle$ transition RdTT from state $\langle s_i \rangle$ to $\langle s_j \rangle$ is a random variable as known from workshop practices. If the PdM start the precedes the failure of the road tanker, the spare parts supply can be advance planned and is very likely to be delivered on time.

Step 4: It was assumed that the RdTT transition from the state of $\langle s_i \rangle$ to state $\langle s_j \rangle$ takes place according to the probability $P_{ij}(t) > 0$, whereby $\sum P_{ij}(t) = 1$. State $\langle s_j \rangle$ may reflect either a scheduled vehicle shut down for maintenance or the operation continuation in a pre-emergency condition. In the event that, at the time of $\langle t_1 \rangle$ no service will be taken until $\langle t_2 \rangle$, but there is a risk of tanker truck failure in between [t_1 ; $t_2 = t_1 + \Delta t$], consider the both costs of repairing a post-failure RdTT and the lack of spare parts in the warehouse.

Step 5: It was concluded that if from the state$\langle s_j \rangle$ there will be a transition to the absorbing state both the transition process and the road tanker operations are stopped.

5. Simulation studies

According to assumption 2, any vehicle can availability depends on a minimum reliability:

$$A_{0I}(t) = 0, \text{under condition } min\left[A_{0I}^{1}(t), A_{0I}^{2}(t), \dots, A_{0I}^{k}(t)\right] \qquad (25)$$

Table 4. Probability of availability the road tankers fleet and unexpected breakdowns risk.

Growth phases		**Shortage vehicle's lifespanVOD=0,57 /covers up 1 to 7 yrs/**		**Well-kept vehicle's lifespan VOD=0,61 /covers up 8 to 14 yrs/**		**Extended vehicle's lifespan VOD= 0,72 /covers up 14 to 20 yrs/**	
Phase	***T***	$\mathbf{P[A_{0t}(t)]}$	$\mathbf{Rd(t)}$	$\mathbf{P[A_{0t}(t)]}$	$\mathbf{Rd(t)}$	$\mathbf{P[A_{0t}(t)]}$	$\mathbf{Rd(t)}$
Stan 0	0	1,00000	0,0000	0,9473 ± 0.011	0,0092	0,9126± 0.012	0,0285
First phase with Probabilities P1(t) -P3(t)	0,5	0,9964 ± 0.009	0,00259	0,9402± 0.012	0,0096	0,8587± 0.014	0,0374
	1	0,9754 ±.0.009	0,00402	0,9182± 0.012	0,0140	0,8396± 0.014	0,0550
	3	0,9579 ± 0.012	0,00984	0,8926± 0.015	0,0242	0,7915± 0.016	0,0726
	5	0,9346± 0.013	0,01461	0,8176± 0.016	0,0436	0,7200± 0.017	0,0891
	7	0,9107± 0.015	0,01795	0,7898± 0.016	0,0749	0,6769± 0.018	0,1135
Second phase with probabilities P1(t) -P5(t)	9	nd. n/a	nd. n/a	0,7015± 0.019	0,1451	0,6324± 0.019	0,1976
	11	n/a	n/a	0,6712± 0.020	0,1603	0,5811± 0.020	0,2454
	13	n/a	n/a	0,6183± 0.021	0,1825	0,5174± 0.021	0,2714
	14	n/a	n/a	0,5576± 0.021	0,2157	0,4824± 0.023	0,2957
Third phase with probabilit	15	n/a	n/a	n/a	n/a	0,4924± 0.023	0,3162
	17	n/a	n/a	n/a	n/a	0,5001± 0.024	0,3642
	19	n/a	n/a	n/a	n/a	0,5124± 0.025	0,4016
	21	n/a	n/a	n/a	n/a	0,5424± 0.027	0,4658
Recommended service strategies		Planned /scheduled -based/ maintenance strategy		Preventive /time-based / maintenance strategy		Predictive /forecasts-based/ maintenance strategy	
***T* - lifespan (years); $P[A_0(t)]$- likelihood of road tanker availability; $Rd(t)$ – non-quantifiable comparative risk**							

The assessment of breakdown non- quantifiable risk was made under two conditions:

- the risk level is always acceptable if its level is less than the minimum permissible:

$$0 \le Rd(t) \le [A_{oI}^{k}(t) \textstyle\sum_k \lambda_k \Delta t_i^k]_{min} \qquad (28)$$

- the risk level is temporarily acceptable if its level is less than the maximum permissible:

$$[A_{oI}^{k}(t) \textstyle\sum_k \lambda_k \Delta t_i^k]_{min} \le Rd(t) \le [A_{oI}^{k}(t) \textstyle\sum_k \lambda_k \Delta t_i^k]_{max} \qquad (29)$$

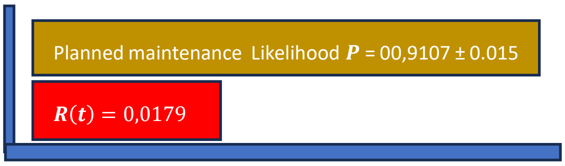
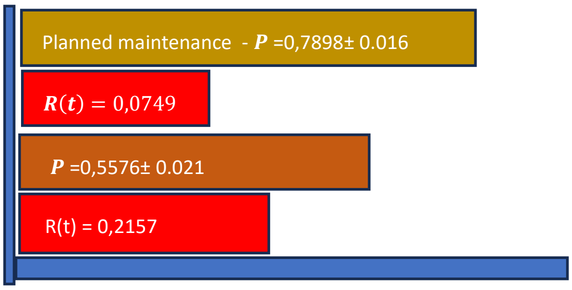
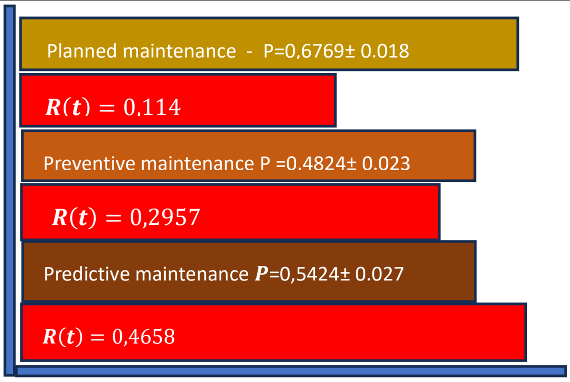
where:

$A_{0I}^{k}(t)$ –road tanker availability in k-th years lifespan.

The diverse maintenance strategies are analysis in table 5. But only preventive strategy ensures consequent saving in resources and maximizing uptime in labor shortages.

Traditionally, mixing planned and preventive strategies has been the preferred option among T&L enterprises [23]. Today, the trends are shifting towards PdM strategy, which is performed through appropriate monitoring of trucks states [5, 27, 40]

Table 5. Comparative analysis of usefulness maintenance strategies.

	Comparative analysis	Comment
Shortage lifespan VOD		The planning maintenance of road tankers fleet according to of OEM recommendations is justified during the first 7 operation years
Well-kept lifespan VOD = 0,61		Over the 8-14 years lifespan, the preventive maintenance of road tankers fleet is an effective tool to minimize unplanned downtime and can be used in supplies modes with as low as high VOD rates
Extended lifespan VOD= 0,72		On the 14-21 years lifespan, the predictive servicing gives the best result in deliveries tasks with a high VOD rate, enables identification of potential problems in the management of spare parts supply, planning supply schedules in advance, avoiding unexpected downtime

6. Discussion

Major turbulence on the liquid fuel market results in uncertainty, and thus lack of full information T&L companies about both the situation on the demand market and the service workshops performing inspections and repairs of road tankers. In these conditions, companies planning the distribution of liquid fuels only on the basis of certain assumptions about possibility of unsafe situations threatening this business-activity, based on previous experience.

The incorrect process of market research on liquid fuels may also introduce additional uncertainty due to errors in analysis and modelling caused by failure to take into account the possible impacts of unknown factors, etc. To address the emerging problems, the researchers used so-called "quantifiable risk". An important specificity of this parameter is its quantitative result based on statistical information about past business-activity.

Above mention disadvantage has arouse interest by process of conducting a qualitative analysis metrics known as non-quantifiable risks. It should include not only the purely descriptive analysis of unsafe situations during fuel distribution, identifying the possible causes of their occurrence, but also i.e. the impact to expected consequences of their manifestations and proposals for identified and minimizing the unknown factors. In our study, an attempt was made to assess quantifiable risk but also non-quantifiable risk, which turned out to be useful in cases where the result of the assessment is planned to be used in relation to the situations not notation in the past on the fuel market.

The reasons why the authors used non-quantifiable risk in research are as follow:

— Quantitative risk assessment are based on probability theory and the results obtained can be aggregated (compared, combined, etc.). However, for the purposes of risk assessment in the field of safety processes performed (vehicle accidents, unavailability of employees), these methods has limitations as they are based on classical (frequency) probability theory;

- Qualitative risk assessments do not require the collection of large amounts of statistical data, which are of little use in conditions of high turbulence of the business and environment, they are easy to use and ensure quick ranking of risk assessments according to different levels of their value;
- Our research has proven that risk business activity under uncertainty conditions can be measured by a relative value based on both the probability of unexpected events occurring and their consequences depending on their severity

7. Conclusions

1. An approach has been proposed to reduce the problem of identifying the unsafety states of road tankers to estimation of the value of the "availability level" parameter based on a two-level model. The first level of the model is based on the AHA - approach (All-Hazards Approach), taking into account both expected and unexpected events, and the second level is based on the identification of an effective maintenance strategy.
2. Under conditions of high volatility in the energy market, VOD is the preferred rate of the state of freight transport operability, having proven its effectiveness both assessments SHR-delivery and the impact of maintenance. Studies have shown that the truck availability level is a function of time for new produced vehicles it has a value of 98-100%, which decreases over time to 55-60%.
3. Studies show that extending the duty tanker cycle increases the risk of reliability loss. When this cycle is extended to 14 years, the availability level decrease to [0.557 ± 0.021], and the failure risk covers up 0.07 to 0.21. In the event of a subsequent extension of operating cycle, the only predictive maintenance is effective strategy. In this case, the probability of availability level covers up 0.49 to 0.54. Since manufacturers are obliged to produce spare parts for 10 years after the end of road trucks production. However, the waiting time for the supply of original spare parts for already out-of-production vehicles can be as long as few months. Therefore, the optimal time to parts order is the 10^{th}-11^{th} year of operational cycle.
4. During the first few years of road tankers operation, the non-quantifiable risk of unplanned downtime is at a negligible level. The extension of vehicle's operating cycle to 12-14 years obliges transportation companies to apply predictive maintenance for reduce road tankers downtime by 12-18% and increase productivity by 10-15%. This type of maintenance has a positive impact on the effective management in SHR-deliveries.

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