Neural Net for Preventive Diagnostics System of Technical State of Vehicles in an Intelligent Transport System

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Abstract: - One of the main challenges facing European experts is organizing a dynamically functioning and efficient transportation sector. Efforts in this regard have been focused mainly on projects aimed at developing intelligent automotive transportation systems (IATS), which integrate information and communication technologies (ICT) into transport infrastructures and vehicles (Car-to-Car, Network on Wheels, FleetNet, COM2REACT, CARTALK2000, SAFE TUNNEL, CVIS, GST, WILLWARN, etc.). This work is multifaceted and contingent upon specific objectives. One of the most significant problems in developing and implementing new transport systems is striking the right economic balance between upgrading existing infrastructure and introducing innovative technologies, as embodied by the concept of the so-called Intelligent Automotive Cooperative Transport System (IACTS), which considers interactions both between vehicles themselves and between vehicles and communication infrastructure. In this case, urban transport management encompasses real-time monitoring of road conditions, along with implementing controls or influencing traffic flows based on gathered data to alleviate congestion, enhance safety, efficiency, eco-friendliness, etc. For these purposes, neural networks, characterized by rapid information processing and decision-making capabilities, are widely employed. Specifically, they can be utilized for predictive analyses of vehicle malfunctions, forming the foundation for relevant services. The goal of this study is to design a neural network for a preventive diagnostic system targeting the technical status of vehicles within an IACTS framework, thereby mitigating the impacts of vehicular breakdowns during road operations.

Key-Words: - intelligent transportation system, central server, communication technologies, sensor data, diagnostic system, artificial intelligence, detecting a failure, forecasting, reliability analysis.

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1 Introduction

As a component of an IACTS, a vehicle must be equipped with communication capabilities for exchanging information with other vehicles and with the road infrastructure. This requires special equipment integrated into the onboard network for collecting local data that can be shared wirelessly between vehicles via the Internet. The same information can be instantly transmitted to the central communication hub (system).

The personal component can be embodied in mobile consumer devices such as smartphones and navigation systems, capable of running various IACTS applications. These devices are typically intended to assist individuals in their activities and utilize suitable hardware. Additionally, they can support IACTS applications that rely on interaction with other road users or infrastructure, such as providing information for visually impaired persons. The broad scope of the application extends to server-based solutions as well.

From an architectural perspective, personal embedded devices or those connected via technologies like Bluetooth should be regarded as part of the vehicle's equipment. Such devices can provide supplementary information either generated internally within the system (like navigation data or vehicle technical status) or sourced externally via communication means. Additionally, the car can directly employ communication channels through the connected personal devices, simultaneously utilizing its own internal hardware capabilities to display information to the driver.

Principles for standardizing road information have not yet been fully developed. Most of the work has focused on standardizing communication between infrastructure and users (i.e., from the vehicle control center, I2V). An important step in this direction was the decisions based on "vehicle-to-vehicle" (V2V), "vehicle-to-infrastructure" (V2I), and "vehicle-to-everything" (V2X) interconnections, aiming not only at improving the efficiency of the transport system itself but also enhancing safety for all road users. This approach could be implemented in a communication system that provides high-quality and reliable alerts to drivers about both their own vehicle's condition and that of other vehicles involved in traffic. Clearly, a solution could be achieved by developing a service platform that includes a driver assistance system (intelligent monitoring of the technical state of the vehicle being used) in real time, [1], [2]. Despite being highly relevant, this issue remains complex and unresolved.

Some researchers working in this field have focused on developing and utilizing motion sensors and traffic monitoring systems in large cities (including smart lighting for optimizing traffic, dedicated traffic information channels, near-real-time traffic maps accessible through Google and NAVTEQ, and new generations of GPS navigators, etc.).

However, the main challenge with this approach is that all these components and methodologies are not integrated, and therefore cannot provide comprehensive real-time information. A centralized database for intelligent traffic management on a large scale proves too slow to deliver results in real-time. Additionally, GPS navigators (such as TomTom and Garmin) primarily feature one-way communication channels. Vehicles equipped with V2I, V2V, and V2X technologies are rare, and they cannot sufficiently populate the central communication station's database.

The widespread availability of sensor data with high spatial and temporal resolution is expected to increase significantly due to rapidly falling prices [2], driven in part by their mass adoption. One method to address this challenge involves the extensive use of open data standards and standardized web services to structure and manage heterogeneous data.

In this context, the primary issue lies in processing vast amounts of data from vehicle sensors in real time and integrating them into the control center software. The nomenclature of the hardware employed in IACTS is entirely determined by its concept and fundamental objectives. In this regard, the application of semantic-logical approaches, which inherently form the basis for developing artificial intelligence systems, can serve as a catalyst.

2 Problem Formulation

A key requirement for real-time motion control systems to generate meaningful contextual information from analyzed incoming data is its high quality.

In this context, "quality" is defined by three criteria:

1. Accuracy;
2. Completeness;
3. Timeliness.

Traditionally, the parameter of "timeliness" has not received much attention, as analysis primarily focuses on processing static data with low temporal deviations. With the emergence of various real-time data sources (such as cameras, GPS sensors, mobile phones, traffic light controllers, etc.) and the development of new paradigms for real-time sensor applications (situational awareness), the timeliness of databases is rapidly gaining significance. Therefore, a mechanism must be developed to integrate sensor measurements and other real-time data, combining different data sources obtained through standard interfaces.

The choice of hardware for the Intelligent Automated Traffic System (IATS) is entirely driven by its design and core objectives. Semantic-logical approaches, which form the foundation for developing AI-based systems, can act as a catalyst.

Road traffic density continues to rise. It’s reasonable to expect that traffic volumes may soon reach levels where even minor obstacles (like small accidents or repairs) could lead to significant congestion. Such situations result in wasted time and resources, reduce traffic flow efficiency, and exacerbate environmental issues. In big cities, traffic jams significantly increase exhaust gas concentrations, making this problem particularly urgent. Hence, implementing new technologies to optimize traffic management is becoming increasingly critical.

One way to enhance the performance of heterogeneous distributed networks, which constitute the mathematical model of IACTS, is to implement real-time traffic flow management based on up-to-date data regarding vehicles' technical conditions. This allows for dynamic reconfiguration of the transportation network during emergencies (activating backup routes or rerouting), [3], [4], [5]. Regardless, addressing this challenge requires the establishment of a preventive diagnostic system for vehicles, linked to the development of methods for predicting stages and causes of faults in critical components. This approach is also integral to the concept of the "smart" car. The evolution of artificial intelligence in vehicles relies on the construction of suitable neural networks, characterized by their network structures.

To enhance the efficiency of heterogeneous distributed networks, which form the mathematical model of IACTS, real-time traffic flow management can be implemented based on current data about vehicles' technical states. This enables dynamic reconfiguration of the transport network during emergencies, such as activating backup routes or rerouting, [2], [6]. Solving this problem necessitates the development of a preventive vehicle diagnostics system, aimed at identifying stages and causes of faults in critical components. This approach aligns with the concept of the "smart" car. Vehicle artificial intelligence relies on the creation of appropriate neural networks, characterized by their network structures.

The primary advantage of such networks is the high speed of information processing and decision-making. That's why neural networks are utilized to process data in real time and predict failures. The main technical limitation of using neural networks is the reliance on statistical data, whose study and acquisition require considerable effort and resources.

Improving vehicle operational safety is a high-priority task not just for today but also for the near future. While the level of vehicle safety is improving daily, issues related to accounting for external conditions (including the human factor) and the status of transport control systems (subsystems, components) that influence the occurrence of hazardous situations remain largely unaddressed. It is challenging to overstate the importance of vehicle safety settings achievable solely through the use of modern electronic diagnostic and control tools.

Recently, significant efforts have been directed towards broadening the application scope of experimental research methods. Typically, an experimental model is developed based on operational data, allowing for the inclusion of nearly all significant factors and providing a more comprehensive representation of the essential interconnections among the vehicle's subsystems that impact the final outcome.

Understanding the mechanisms underlying the vehicle's states is primarily tied to clarifying and determining which properties, to what extent, and in what manner affect this system. Initially, it is crucial to define its structure and properties using models of varying complexity. This method of specifying an abstract system proves effective when studying the system's properties becomes challenging due to the intricate nature of the data. It can be represented through information models. By compiling such models, an information database for the vehicle's neural network can be established.

Systematization of methods (mathematical, experimental, economic, etc.), based on the analysis of the reliability of engineering products, which are typically complex technical systems, could provide certain assistance in these activities. The main areas of such research can be identified as follows:

- Study of failures in elements of a complex technical system and the reasons behind their occurrence;
- Establishment of connections between elements within a complex technical system;
- Development of methods for analyzing complex technical systems at both global and local levels;
- Examination of conflicting (e.g., from a manufacturability standpoint) recommendations and achieving compromises when refining the general model.

Generally, the mathematical approach is applied in two ways: for formulating and solving the general problem of reliability analysis in complex systems, and for addressing specific local issues (e.g., analyzing the stress state of a component). It can be argued that the mathematical formulation of the problem of studying complex system reliability inherently includes information about potential outcomes and the selection of an optimal strategy. Simultaneously, it should be acknowledged that the role of mathematical theories in achieving results might not be overstated. The strength of these approaches lies in the development of a search strategy that can yield successful outcomes.

The decision-making process can be formulated as the following sequence of steps:

- Selection of decision criteria and verification of their consistency;
- Development of information models representing the entire neural network of a complex system (element selection, connection assignment);
- Selection (or development) of effective methods for analyzing the resulting model.

Initially, statistical methods were used to predict vehicle failures and calculate the optimal operating mode, but they failed to deliver highly accurate analysis results, [7], [8]. Numerous studies on reliability issues assume that operating time follows an exponential distribution. Under this assumption, the expected pattern of future item failures remains unchanged as long as the product is in service. This invariant property (prior usage does not affect subsequent operability) strictly defines the boundaries of the distribution's applicability. Consequently, for elements subject to irreversible physical and chemical aging processes during operation, this invariant property does not hold. Interestingly, some works suggest that a complex system composed of multiple elements with non-exponential failure-free operation time distributions can be approximated as a system with exponentially distributed operating time, [2].

Substantial advancements have been made by employing adaptive neural networks in vehicle reliability studies. Typically, the failure distribution function and root causes are a priori unknown, reducing the accuracy of predictions and necessitating the processing of vast amounts of statistical data (Big Data). From this perspective, an intelligent preventive diagnostics system should incorporate a machine learning algorithm based on continuous monitoring of critical parameter values, which are signals received from sensors installed in the vehicle as intelligent agents (IA), [9], [10].

3 Problem Solution

A modern car, comprising complex composite systems, represents a fusion of precision mechanics, electronics, and computer programs. Furthermore, to monitor the technical condition parameters of critical components, multiple sensors (IA) are typically used, with their information arriving in the form of complementary time-series data.

The goal of a vehicle's preventive diagnostics system is to monitor the technical state of individual vehicles and subsequently optimize the overall functioning of the transport system, which involves:

- Monitoring the technical condition parameters of a vehicle;
- Detecting a failure (malfunction) in a vehicle (component, assembly, equipment, etc.) at early stages, identifying the causes of the failure and its potential consequences;
- Developing a minimal set of measures to maintain the transport system's functionality at an acceptable level (e.g., issuing a preemptive signal to the driver to reroute or switch lanes).

The block diagram for the sequential solution development of a vehicle's preventive diagnostics system is depicted in Figure 1.

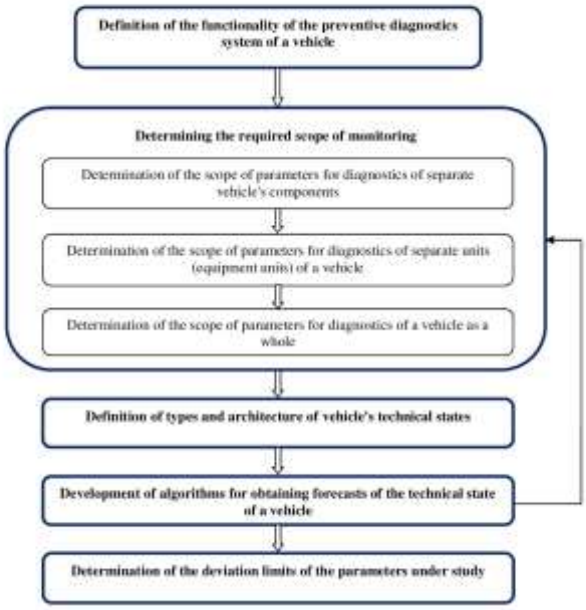

Fig. 1: Block diagram for the sequential solution development of a vehicle's preventive diagnostics system

The most important diagnostic functions in terms of the significance of the results obtained are:

- Identification of specific defects (failures) in elements and units, i.e. detection of a failure (malfunction) with the determination of the location and, if possible, the causes of the failure, which in turn allows not only correcting the current situation but also recording the failure for gathering statistics;
- Monitoring the technical state of the vehicle allows prompt reception of summarized (or, if required, detailed) information on its condition and transmitting it to the central server (CS) for arranging coordinated actions by repair services that are adapted to the actual technical state of the vehicle;
- Forecasting the technical state of equipment elements (units) and the progression of detected defects, enabling preventive measures to avoid potential failure of vehicle elements (units);
- Forecasting the overall technical condition of the vehicle will enable the identification of trends and the significance of deviations in component parameters from their design specifications, allowing for proactive planning of maintenance activities.

The forecasting system utilizes mathematical modeling, incorporating multiple control parameters and detailed information on the vehicle's technical state, such as bearing vibration. This approach involves developing a comprehensive database on the vehicle, employing advanced mathematical tools, and dedicating considerable time to fine-tuning the system to match the vehicle's actual characteristics across its entire spectrum of operating conditions.

It is essential to acknowledge that mechanical faults do not arise suddenly during vehicle operation. Hence, preventive diagnostics should emphasize continuous monitoring of the operational readiness of vehicle components and early detection of impending failures. Methods for assessing the technical condition of vehicles using specialized algorithms involve a combination of the following fundamental events and indicators:

- Directly measured diagnostic parameters exceeding established limit values;
- Presence of an adverse trend in either directly measured or computed diagnostic parameters;
- Simultaneous presence of an adverse trend in multiple diagnostic parameters, even though each individually remains within acceptable limits;
- Spontaneous shutdowns occurring without the driver's command;
- Data from the integrated diagnostic system;
- Vehicle technical data, including records of inspections, certifications, and maintenance procedures.

Although each case of emergency or pre-emergency situations in complex technical systems requires individual consideration, the more accurate the anomaly identification process is, the earlier in time an impending failure can be determined. Thus, the preventive intelligent diagnostics system will have more time for network reconfiguration (such as activating backup resources or rerouting).

The rate at which an emergency situation unfolds in monitored zones should dictate both the frequency of polling and the prioritization of equipment usage. As the rate of change in the observed parameter increases, so too should the priority assigned to servicing network devices. Simultaneously, it's imperative to adjust the polling frequency in direct proportion to the evolving dynamics of the monitored parameter.

Applying identification methods to the analysis of time-series data from diverse sensors (IAs) produces markedly distinct error curves (ROCs). This variance stems from the fact that different emergencies may emerge, each detected and evaluated uniquely by different sensors. Consequently, constructing composite models that leverage sensor data from multiple monitoring servers is anticipated to boost performance and bolster the diagnostic system's overall stability. These models can be combined by aggregating event occurrence probabilities using formulas for joint probability calculations.

While addressing emergencies or near-emergency scenarios in intricate technical systems demands tailored approaches, enhanced accuracy in anomaly identification enables earlier detection of impending failures. This affords the preventive intelligent diagnostics system additional time to execute network reconfigurations, such as engaging backup resources or initiating rerouting protocols.

Each network device will be assigned a unique probability density function for a specific metric, which will be updated as new data (from new operating modes or loads) emerges. In conjunction with retraining the algorithm for identifying emergency situations in complex technical systems, this approach embodies the principle of model adaptability. The proposed monitoring methodology emphasizes the necessity to develop a method for proactively identifying the technical condition of components in a complex system, based on the analysis of their time-series metrics.

Consequently, the primary objective of this study is to optimize the monitoring procedure for vehicle components' functional states by enhancing the predictive capability to detect transitions from normal to pre-failure or failed states. This aims to mitigate or prevent emergency situations and enhance reliability by minimizing uncertainties in technical condition assessments.

With this target setting, the subject of study can be the network monitoring subsystem, with its key component being the monitoring server, and the subjects of monitoring can be regarded as network devices (vehicles) operating within an intelligent transport cooperative system, characterized by operational, non-operational, and pre-failure technical states.

The scientific task then is to develop a method for preventive identification of the status of network vehicles to enhance the efficiency of the monitoring procedure, ensuring reliable and accurate results through predictive analytics.

The number of types of vehicle technical states is chosen considering the following factors:

- Having a small number of vehicle technical states, prescribed as just two types (normal and abnormal), may hinder optimizing responses to technical malfunctions;
- Conversely, having a large number of vehicle technical states can lead to blurred boundaries

between them, complicating the decision-making algorithm.

The decision-making process can be reduced to the following sequence of actions, [10], [11]:

1. **Selection and Verification of Decision Criteria**: Ensuring the consistency of decision-making criteria;
2. **Development of a Structural Model**: Creating a structural or network model of a complex system, which includes selecting elements and assigning connections between them;
3. **Selection or Development of Analysis Methods**: Choosing or developing effective methods for analyzing the resulting model.

The software and hardware complex of the diagnostic system, as part of the central control system, should have the capacity to perform the following functions:

- **Data Collection**: Automatically gathering data from monitored objects, with an option for manual input.
- **Database Maintenance**: Maintaining a comprehensive database of monitored objects, including records of failures, maintenance activities, and repairs.
- **Operational Log Management**: Keeping detailed logs of defects and events.
- **Condition Assessment**: Evaluating the state of vehicles based on the technical conditions of their components.
- **Message Generation**: Producing operational notifications and alerts.
- **Technical State Prediction**: Forecasting future technical states of vehicles and estimating their remaining service life.
- **Real-time Diagnostics Utilization**: Using real-time diagnostic information to train the neural network, taking into account the responsibilities of individual drivers, and providing relevant notifications to both the responsible driver and others within their designated area.

Thus, the most effective classification of the technical conditions of a vehicle and its components is as follows:

- **Good:** Corresponding to the established standards of operation for the vehicle and its components.
- **Acceptable:** There are deviations from the established standards of operation for the vehicle, but they remain within permissible value limits.
- **Dangerous:** Subject to enhanced control and preventive measures, identified by the CS through analysis with a neural network of potential causes and consequences of breakdowns. In such cases, the obtained data are utilized by the neural network for self-training.
- **Emergency:** Indicates actual failure of the vehicle.

This classification enables consideration of the criticality of a particular vehicle failure by introducing correction factors, which initially can be determined based on expert assessments. The correction factors are applied according to the failure classification as follows:

- extreme criticality k_1;
- high criticality k_2;
- moderate criticality k_3;
- low criticality k_4,

In this context,

$$0 \le k_l\, p_{ij}(t) \le 1. \tag{1}$$

Here k_l, $i=\overline{1,N}$ represent the correction coefficients, $p_{ij}(t)$ i, $j=\overline{1,N}$ denote the expert-estimated probabilities of subsystem i failing due to the failure of subsystem j at the exploitation time t.

Since both the failure probabilities of vehicle systems and the correction factors are initially chosen based on expert assessments, it's recommended to determine them by minimizing the function:

$$\sum_{i,j=1}^{N} k_{ij} \cdot p_{i,j}(t) - P(t) \to \min, \tag{2}$$

where k_{ij} , $i, j = \overline{1,N}$ are the correction coefficients, p_{ij}(t), $i, j = \overline{1,N}$ represent the expert-estimated probabilities of failures for subsystem i due to failures in subsystem j at the exploitation time t, and $P(t)$ is the expert-estimated probability of the vehicle's failure at the exploitation time t. The system of constraints for the coefficients k_{ij} takes the form (1).

It is important to highlight the significance of hardware (specifically installed sensors), as the more accurate the identification of a failure, the earlier it can be detected, allowing the preventive intelligent diagnostic system more time to reconfigure the network (e.g., reroute traffic). Here, it is essential to correlate the polling frequency of monitoring zones with the dynamics of failure progression, i.e., increasing the polling frequency proportional to the rate at which the monitored parameter approaches a critical value.

It is believed that the most suitable representation of the information model characterizing failures in a complex system is in the form of a neural network (network graph). In this case, the structure of the neural network should reflect the requirement that the resulting solutions consider variability associated with probability. Therefore, the following hypothesis can be proposed for the development of information models describing vehicle reliability: the behavior and technical state of a car as a complex technical system are determined by the structure of interactions among its component processes, which are inherently probabilistic or uncertain.

The importance of this becomes clear when we remember that explaining the mechanisms behind the system's behavior and its states involves determining which properties, to what degree, and under what conditions a given system possesses. Initially, the structure and properties of the system are defined using sets of models that vary in their organization. The concept for forming the methodological framework for studying the reliability of complex systems is illustrated in Figure 2.

Reliability analysis of IACTS elements can be conducted using a system approach. It should be emphasized that the conceptual foundation for applying this approach to reliability issues has not yet been fully established. However, having clear guidelines that validate certain decisions could substantially enhance the effectiveness of the method.

To address this issue, a neural network, modeled as a hierarchical graph of failures, can be developed during the second stage. Each branch of the neural network represents the probabilities of failures of individual elements (such as systems, parts, etc.) that lead to the overall system becoming non-operational, [3]; (Figure 3).

In this network, vertex *1* represents the influence of either the driver or the environment on vehicle failure, while vertices *2* through *N* correspond to vehicle subsystems. The flow values along the respective paths ($p_{i,j}$) denote the probabilities of subsystem *i* failing due to the failure of subsystem *j*. Vertex *B* symbolizes the sink, and the flow values along paths (p_i, B) indicate the probabilities of failure within the corresponding subsystem *i*.

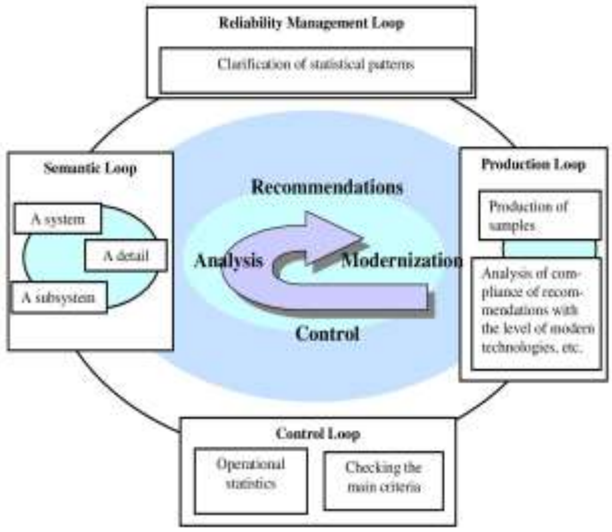

Fig. 2: Conceptual framework for applying a system approach to analyzing the reliability of complex systems and their key components (subsystems)

Each failure can be assigned a quantitative measure reflecting its contribution (weight) to the overall risk. Initially, parameter values are typically determined based on expert evaluations, implying subsequent use of a self-learning procedure for the developed neural network. Expert assessments can be provided by vehicle manufacturers or derived from established methodologies, [11], [12]. Given that the proposed system entails refining these estimates based on operational data from a statistical database of vehicle failures, relying primarily on manufacturer data is most advisable.

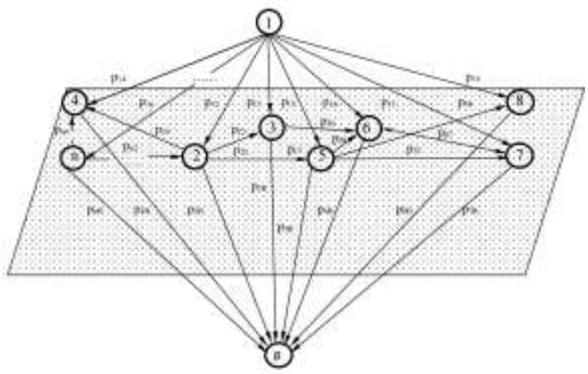

Fig. 3: Neural net for vehicle failures *(*p_{ij} – probabilities of subsystem *i* failure due to subsystem *j* failure)

A quantitative evaluation of the failure's contribution (weight) to the overall risk can be calculated for each failure. Initially, parameter values are commonly defined based on expert assessments, necessitating the subsequent application of a self-training procedure for the constructed neural network. Certain connections might be missing because the corresponding probabilities are zero.

It is evident that

$$\sum_{i,j=1}^{N} p_{i,j}(t) = P(t) \leq 1,$$

and the probabilities

$$p_{ij}(t) = \sum_{i,j=1}^{N} k_{ij} \cdot p_{i,j}^{\exp}(t)$$

themselves are independent. Each node in the graph represents a subsystem, so further analysis is conducted using a systems approach, assuming that the sum

$$\sum_{k,l=1}^{M} p_{i,j}^{k,l}(t) = p_{i,j}(t),$$

where $p_{i,j}^{k,l}(t)$ is the probability of failure of parts (components) in the corresponding vehicle subsystem.

Thus, the proposed neural network has a hierarchical structure.

All considered probabilities of vehicle failures ($P(t)$, $p_{i,j}(t)$, $p_{i,j}^{k,l}(t)$) in the proposed neural network are generally functions of time.

In many studies addressing reliability issues, it is assumed that the failure probability of a complex technical system follows an exponential distribution. This distribution describes exponential degradation, wherein the system progressively accumulates damage over time. It is believed that the anticipated pattern of product failures remains unchanged as long as the product continues operating. This property of invariance—whereby prior usage does not impact subsequent performance—strictly defines the boundaries of the distribution's applicability.

Therefore, as an initial expert assessment, it is reasonable to assume that vehicle failures follow an exponential distribution, with parameters determined by the expert assessment method. This method also sets the flows (probabilistic parameters of the neural network) (Figure 3), which serve as the initial dataset for the self-training of the neural network.

Identifying the technical condition based on time-series sensor readings may result in several errors due to potential discrepancies in how different sensors assess specific deviations. Additionally, this necessitates creating a database of vehicle failures during the system's self-training phase to determine the actual characteristics of the vehicle across its full range of operating modes (adapting the system to the vehicle).

The neural network operates as follows:

- When the technical condition of the system (part) is deemed "acceptable" based on sensor readings, the polling frequency increases;
- If an unfavorable trend in sensor readings is detected or the technical condition of the system (part) is classified as "dangerous," a request is sent to the CS to analyze the impending breakdown using a neural network. This analysis identifies both the potential causes and consequences of the failure. The remaining lifespan of the faulty component (part) is then calculated. If it approaches the critical threshold, a command is issued to redirect the vehicle to the outer lane. The collected failure data is utilized to fine-tune the parameter λ of the exponential distribution (Figure 4).

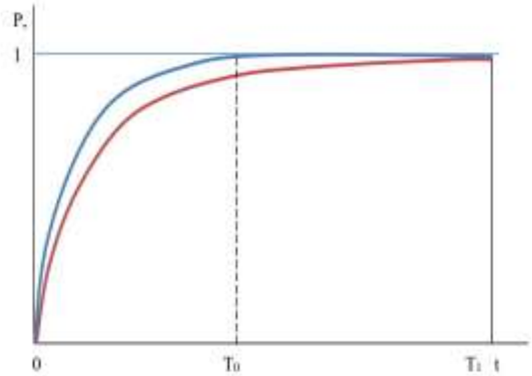

Fig. 4: Expert function of vehicle failure distribution (▬▬) and failure distribution function obtained after self-training of the predictive maintenance system (▬▬)

To fully implement a preventive maintenance system for monitoring the technical condition of vehicles within the IACTS, it is clear that we need to focus on utilizing artificial intelligence

4 Conclusion

The volume of road traffic is continuously increasing due to the rising number of vehicles and growth in trade activity. As a result, it's easy to foresee a scenario where traffic congestion reaches levels at which even minor obstacles like damages or repairs could trigger significant gridlocks. This not only wastes time and money but also severely impacts the efficiency of freight transport while exacerbating environmental issues. This problem becomes particularly acute in densely populated urban areas as traffic jams multiply the concentration of exhaust fumes. Hence, implementing advanced technologies capable of streamlining traffic flow through prompt responses to vehicle malfunctions has become imperative.

The advent of computer-controlled automotive systems has spurred the development and widespread adoption of sophisticated fault-detection electronics. The next logical step involves integrating these systems into Intelligent Automated Control and Transportation Systems (IACTS), enabling proactive monitoring of the technical condition of vehicles in road traffic.

The aforementioned approaches are extensively utilized, notably in the concept of establishing a Global Diagnostic Network, designed to integrate various diagnostic solutions worldwide (e.g., USA). These programs coalesce into a system that continually evolves under the supervision of intelligent diagnostics. Data collected by the system undergo processing, and subsequently, textual reports detailing the vehicle's condition, identified defects and prognostic indicators are conveyed to the user. The open architecture of the Global Diagnostic Network permits adaptation to emerging challenges by assimilating external information. Beyond diagnosis, the primary objective of the Global Diagnostic Network encompasses prevention. Thus, it holds the potential to evolve into a key component within the broader ecosystem of mobile network operator services. In the medium term, once statistical insights from deploying the Global Diagnostic Network become available, the insurance sector might emerge as another driving force behind this transformation.

One of the contemporary challenges is developing methods to warn about the stages and causes of defects in critical components of vehicles operating within the IACTS. Addressing this challenge includes incorporating these methods into the concept of an "intelligent" car. The evolution of artificial intelligence for vehicles relies on the establishment of neural networks.

The primary advantage of these networks lies in their rapid processing of information and swift decision-making capabilities. Consequently, neural networks are employed to handle data in real time and utilize it for predicting failures. However, a significant technical constraint in applying neural networks is the reliance on statistical data, whose analysis necessitates considerable resources.

Although the level of vehicle operational safety is improving daily, issues concerning the consideration of external factors (including the human element) and the behavior of transportation control systems (subsystems, parts) that contribute to hazardous situations remain largely unaddressed to date.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation translation of this work the author used GigaChat service in order to enhance the quality of translation. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

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