SUPPORT FOR TUNNEL SYSTEM DISPATCHER'S DECISION-MAKING USING FUZZY EXPERT MODULE

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Abstract: This article addresses the challenges operators face in decision-making during the operational management of tunnels and other transport systems. Operators of complex systems must process vast amounts of information and suggestions from various devices, subsystems, and both internal and external sources. In addition, they receive requests from multiple entities. This overwhelming influx of data and demands places significant pressure on operators to evaluate and respond swiftly and accurately, which is often crucial to ensuring smooth operation of the entire transport system. To assist operators in making better decisions, new approaches are being introduced, such as expert systems and artificial intelligence. These tools aim to enhance decision-making not only during crises but also for routine operations and more complex tasks related to controlling and monitoring transport systems. The article outlines components of an expert system that uses fuzzy logic to address the complexities of acquiring certain data, particularly from predictive maintenance, which cannot be easily interpreted through simple operational interventions by the operator. Predictive maintenance also relies on decision-making supported by advanced algorithms, which are integrated with the system's technology and control framework.

Key words: *expert system, HMI, operator attention, fuzzy logic, predictive diagnostics, transport system control, traffic system management, tunnel system, predictive maintenance*

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1. Introduction

The issue of ensuring reliable interaction between artificial systems and humans (HMI) remains unresolved despite increasing control of complex systems by automated systems. While the introduction of new technologies with AI elements reduces the likelihood of failures and extends the lifespan of such equipment, it simultaneously places greater demands on operator reliability. Operators must manage system complexity, evaluate new functions, and oversee automatic responses, which they may either influence or which are entirely autonomous, leaving the operator to react to subsequent events. In some cases, operators need predictions of system states to prepare, control, and operate effectively. Fully automated systems are increasingly used across fields like information technology, energy, the military, and particularly in transport. In transport systems, a combination of various advanced systems is often applied, which directly or indirectly affects the behaviour of road users and lower-level operators. This makes the transport system significantly more complex and some elements of autonomy significantly more difficult to implement [1].

We can examine the system from two key perspectives: the behaviour of the operator and the behaviour of the equipment, including monitoring its condition and estimating potential error rates. This article focuses on both of these critical viewpoints, highlighting an interdisciplinary challenge. On one side, we gather extensive data from the system, and on the other, we have an operator whose knowledge, reactions, and behaviour significantly impact the system's performance. Therefore, while we need to monitor and evaluate the equipment's condition and, where possible, operate autonomously or automatically, the operator's role remains essential, particularly in maintaining focus and ensuring the correct functioning of the system. In this context, the article uses tunnel systems as a specific example of interest [1, 2].

A tunnel system is a transport structure that forms part of critical infrastructure, which includes a number of devices and systems that function as a technological and technical unit. This unit significantly influences its surroundings, affecting vehicle traffic flow and driver behaviour in cities, urban areas, and on motorways [1–4]. The construction of tunnels also impacts other key systems, such as energy, transportation, safety, and others, which place significant demands on operators, not only during regular operations but also in emergency situations. These emergencies may arise from equipment failures, traffic flow issues (i.e., driver-operator-vehicle interactions), or external factors, such as crisis events requiring coordination with emergency services or national defence. Although much is described in regulations for tunnel constructions or for individual systems, certain areas are still being researched, developed, and tested, particularly with a view toward future applications of artificial intelligence and new approaches, etc. [5–9].

1.1 Operator's Influence on the Transport System

The issue of detecting operator behaviour and attention loss is one of the main challenges in controlling technical systems. The HMI (human-machine interface) is classified as a soft system, characterized by uncertainty and complexity, which makes it difficult to predict or interpret accurately, especially under extreme or boundary conditions. A typical example is a tunnel system dispatcher, who may rely on some automatic system responses, yet faces long-term stress, high levels of sensory input, emergency responses, and continuous monitoring of technical equipment all of which significantly impact their behaviour. By conducting direct or indirect measurements, it is possible to detect patterns that reveal whether an operator is thinking, resting, sleeping, or responding to environmental stimuli. To describe the different states the operator may experience more accurately, multiple measurements are performed simultaneously [10, 11].

An operator who works with complex and powerful systems is required, above all, to maintain a high level of focus on [12]:

- Maximum attention and concentration,
- Speed of response to the request,
- Correct resolution of emerging problems,
- Selection of the most relevant perceptions,
- A broad and high-quality range of perceived stimuli for informed decision-making,
- AI-based automatic assistance (in modern systems) to support decision-making.

Most often we refer to the reliability of information processing, psychophysiological reliability, and physical reliability. In technical applications where a person acts as an operator, the focus is usually on the reliability of information processing. In such scenarios, the human operator acts as a component of the system's structure, serving as a transformation link characterized by both amplification and delay. The other two aspects of reliability psychophysiological and physical evaluate the operator's mental and physical capacity to effectively participate in the operation of the hybrid system [11–14].

We will further explore the specific perceptions received from the tunnel system, which are critical for supporting decision-making. One example is predictive diagnostics, which using a partially expert approach based on fuzzy logic must enable the dispatcher to accurately assess the situation and decide on necessary corrective actions, evaluate the severity of impacts, and coordinate with other entities. Reliable methods for detecting the operator's condition include electroencephalography (EEG), as well as sequential testing of voice perception and reaction monitoring, with correlations drawn from both approaches. Additionally, other methods may also be used [13–15].

1.2 Diagnostics of the Transport System – Tunnel

A road tunnel is an appropriate example of a system that must operate continuously, except during closures for maintenance and repairs. To ensure the required level of operational safety, it is essential to monitor the current state of technical equipment, the functionality of the tunnel control system, and other subsystems.

New functions, such as simulators, tunnel simulations, custom tunnel models (digital twins), and the application of artificial intelligence—particularly in predictive diagnostics can be introduced. Predictive diagnostics, based on the life cycles of individual technical subsystems, would help identify potential errors and failures in advance, optimizing tunnel restrictions and minimizing closures. These advanced functions contribute to a more automated and autonomous approach, placing significant responsibility on the operator's knowledge and attention. Generally, tunnel functionality is well-documented in standards and technical literature. In this article, we focus on predictive maintenance, as it introduces a fundamentally new approach to dispatcher behaviour and highlights the need for an AI-based expert system to assist operators in decision-making [6–9].

An important requirement for applying predictive diagnostics is ensuring the reliability of data and information from devices and individual systems used in tunnels. For efficient and reliable maintenance with targeted service interventions, comprehensive documentation is essential. This is now being developed and implemented through building information modelling (BIM) and overall digitization, which greatly aids in navigating the tunnel and its technological systems. On one hand, technical documents clearly outline the correct functioning of equipment, while also supporting reliability detection and life cycle prediction based on the equipment's actual condition. The SCADA tunnel control system already enables simulations of system behaviour, including fault detection and alarms. This article presents an example of how various inputs, data acquisition methods, and parameter combinations are analysed, along with a methodological approach for predictive maintenance of tunnel technologies. This is linked to the operator's role in decision-making to ensure long-term operational efficiency [5, 9].

In addition to controlling and responding to transport and tunnel technologies, ensuring proper operation and maintenance is a crucial part of an operator's responsibilities. Continuous system monitoring is essential to verify that the system and all its components are performing their required functions. This verification can be achieved by assessing the degree of damage to materials, specific devices, or the entire system. The process of employing various detection methods to assess this is known as diagnostics. When detecting equipment failures, we can use direct methods where specific parameters are measured, such as changes in processes that directly impact the device's lifespan or performance, like temperature or undervoltage. Alternatively, indirect methods can be used, where defined parameters are measured, and the system's functional behaviour and life characteristics are calculated based on comparisons and evaluations [5–8].

The goal of diagnostics is to gather all relevant process data and evaluate it appropriately. By comparing historical data, manufacturer specifications, and current measurements, we can determine the system's current state and predict how its performance will develop over time. This allows us to compare the projected behaviour of the process or device with its actual lifespan, taking into account previously detected states and past experience with the equipment. To ensure the system's functionality, it is crucial not only to operate it correctly but also to identify faults, and most importantly to eliminate these issues to keep the system running smoothly. From the perspective of service life, equal emphasis must be placed on both system operation and its ongoing maintenance [2, 16].

According to the service life of selected technological equipment ranges from 10 to 25 years [8, 9, 17, 18]. For electronic systems, lighting control, and SCADA systems, the expected lifespan is around 10 years. Power and communication cables have a service life of 20 to 25 years, while ventilation and security equipment is estimated to last 15 to 20 years. Variations for these subsystems are typically within a range of 3 to 5 years. Maintenance should be standardized and optimized by considering failure predictions and the equipment's expected service life, which is further refined during regular inspections [5–9]. The goal of the system for analysing and diagnosing tunnel technology is to monitor the condition of individual devices and create predictive life cycles based on fault analysis, manufacturer data, and expert refinements during inspections. Given that the technological equipment in tunnels comprises various devices and subsystems [5, 8, 9], each with different lifespans, a different approach was adopted compared to the tunnel's structural components. For the initial verification of the predictive system, alarm messages and diagnostic information from the equipment were analysed and compared with the data provided by the component manufacturers.

The service life of components and equipment is well illustrated by the well-known bathtub curve, which may follow a slightly different pattern for mechanical and electronic elements but remains a fundamental model in reliability engineering, describing the frequency of failures over time (see Fig. 1). Our focus in predictive diagnostics is particularly on the "Maintenance" and "End of Useful Life" periods in the second half of the curve, especially the transition between them. This transition is significant by a higher number of component failures and increased operational interventions, which in turn lead directly to higher operating cost [5, 16–18].

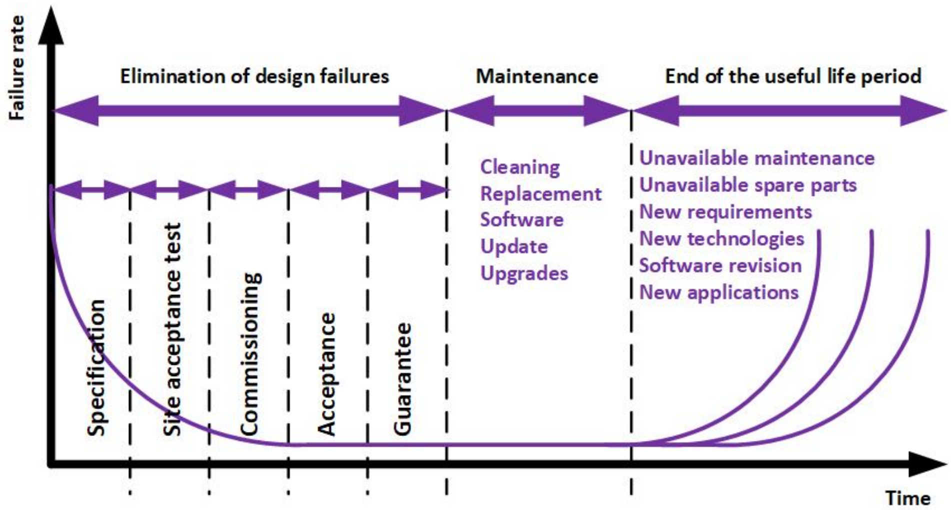

Fig. 1 *Bath curve of failure frequency [5].*

The main challenge in data analysis is that maintenance process data is not directly integrated into the control system, and much of this information is currently unavailable to operators. Service intervention records are often kept in either paper or electronic form in various documents. Manually reviewing and linking these service actions to specific devices is inconvenient and does not easily provide a comprehensive data model or valuable insights, such as the frequency of failures or the time intervals between them.

The history of service actions performed on each device would be recorded electronically and sent to the system with a time stamp. This record contains information on the history of the service as well as tracking the replacement and installation of new equipment for the forthcoming failure rate calculations. Based on this refined and automated data, it is possible to generate accurate predictions and analyses of the reliability of the equipment in the tunnel, leading to optimized maintenance and more efficient allocation of funding for the tunnel construction [5, 6].

2. Proposed Methods

Within the chapters and proposed methods, two new professional approaches are considered: monitoring integrated rescue system (IRS) service operators, power engineering personnel, transport systems operators, traffic controllers, and tunnel operators. Two key tasks are also addressed: monitoring the decline in operator attention through electroencephalography (EEG) and detecting changes in voice patterns.

Besides, the use of predicted data from the diagnostic module is proposed as a new approach for tunnel system dispatcher responses. This new input can significantly influence the operator's behaviour, attention, and reactions, and ultimately impact the success of managing transport systems or critical infrastructure, such as tunnel technology.

2.1 Operator Tracking

The methods used to assess the condition of the monitored individual or to detect a decrease in attention include, in particular [12–15]:

- Electrical activity of the brain,
- Breathing frequency,
- Heart rate,
- Eye movements,
- Change in skin resistance,
- Change in facial expression,
- Voice change detection.

All these methods for monitoring the operator can be found in literature sources [12–19]. Both the technical literature and those focused on the psychological or medical aspects of the monitored individual agree on the challenges and individuality of implementing a system capable of reliably detecting a decline in attention.

To detect decreased attention in operators, methods such as electroencephalography (EEG), combined with eye tracking (EOG) or facial expression monitoring, will be described below. Additionally, a new method using voice analysis will be introduced, which, in combination with EEG, represents a significant advancement in non-invasive techniques. While EEG requires electrodes to be placed directly on the head, the voice recognition method only requires a microphone positioned near the mouth [15].

Electroencephalography is a fundamental methodology for evaluating the condition of the monitored individual, also serves as a reference for other methods. The pre-processing of the measured data, using spectral analysis, categorizes the signals into distinct states based on basic frequency bands: delta – δ (1–3.5 Hz), theta – ϑ (4–7.5 Hz), alfa – α (8–13.5 Hz), beta – β (14–20 Hz). Based on these frequencies, the individual's state can be classified into four basic categories: vigilance (VG), thinking (TH), relaxation (RX), and sleep (SP). Fig. 2 illustrates examples of frequency spectra for each state according to this classification [12,13]. The state of vigilance can manifest in two forms: one with open eyes (OE) and another with closed eyes (CE), the latter closely resembling a state of relaxation.

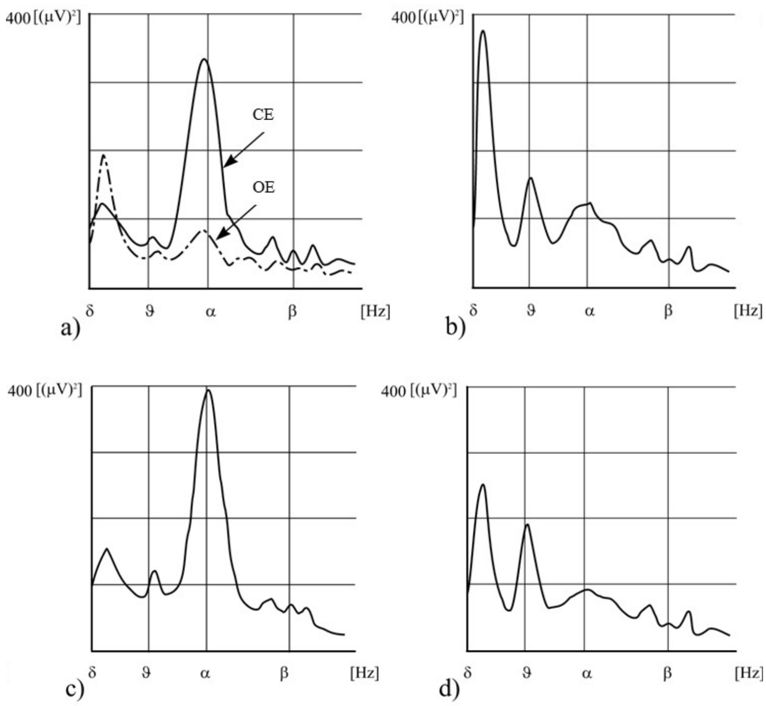

Fig. 2 *EEG spectrum for the state of a) Vigilance (VG – OE and CE), b) Thinking (TH), c) Relaxation (RX), d) Sleep state (SP) [12, 13].*

This division into four groups is partly subjective and serves as an indicative framework, though it has informative value based on static verification with a sample of over 200 operators. Each individual has their own unique EEG curve and specific distribution of parameters across the basic states.

On the other hand, EEG signals are unfortunately very weak and often affected by eye movements and muscle activity. Additionally, the EEG signals measured on the scalp are generated by multiple neural sources, each responsible for different cognitive functions [20].

As mentioned above, several methods have been developed to estimate operator fatigue levels. While some are highly accurate, they often rely on physiological measurements that require expensive or intrusive equipment. In safety-critical environments, where operators regularly engage in verbal communication, a fatigue estimation method based on speech analysis can offer not only an alternative but also a more cost-effective and less disruptive solution [21]. Automatic fatigue estimation systems are increasingly being used in such safety-critical environments.

A system capable of estimating speech-related fatigue would be valuable in domains where operators regularly engage in verbal communication as part of their duties, such as IRS units and traffic controllers. Previous studies on speech fatigue identification have been limited by their reliance on subjective assessments and the lack of comparison with other fatigue evaluation methods [15, 19, 21].

The production of speech sounds relies on precise coordination between the sensory and motor systems. Controlling vocal articulators is a biofeedback process that involves sensing and monitoring the vibrations of the vocal cords through the sound and sensations they produce. As fatigue increases or impairments such as alcohol consumption occur, this system becomes disrupted [15, 19, 22].

Several researchers have reported various speech-based manifestations of this disruption. Previous studies linking voice changes to fatigue have generally focused on discrete characteristics of the speaker's voice, such as pitch, word choice [23], and the timing between articulated sounds [15, 19]. Changes in the spectral parameters of the voice have also been associated with alcohol-related disorders [24]. Additionally, significant effects of circadian rhythms on vocal characteristics have been observed in multiple studies [15, 19, 23].

The development of reliable methods for predicting speech fatigue requires objective fatigue measurements for use in model training. However, previous studies on speech fatigue prediction have often relied on subjective assessments of sleepiness as an output parameter. These subjective evaluations do not always correlate well with objective measures obtained through behavioural tasks [21].

Identifying specific acoustic characteristics of the voice that are relevant to emotion recognition is a complex and not fully understood process. The existing literature offers numerous approaches to combining different acoustic properties for classifying emotions, but consensus on the most appropriate method has yet to be reached, and the field continues to evolve [25].

Despite the underwhelming performance of commercial vocal analysis software [26], the variables underlying these classifications hold promise for predicting fatigue if properly calibrated to specific environments. Previous research [27] supports the idea that voice can be a reliable and valid measure of emotion and deception, making it suitable for integration into future technologies, such as automated security checks and advanced human-computer interactions.

In this work, we explore the implications of using voice analysis to monitor the effects of fatigue on cognitive performance and validate its application as a tool for identifying and tracking fatigue in practical settings, particularly for transport operators, with a specific focus on air traffic controllers [15,19].

2.2 Fault Analysis of Technical Tunnel Equipment

The process of obtaining data can be represented using a design approach in the form of a diagram. From the defined set of signals within the Tunnel System, individual signals can be selected according to technology classes, with a separate determination of the status of each device within the system. By performing time-based correlations between the signal types and the devices themselves, an initial selection can be made to estimate the probability of failure. This allows for the identification of the most common failures in equipment and technology types, which can then be compared with other factors, such as service interventions, temperature measurements, and manufacturer or supplier recommendations. By analysing these factors over time, experts can more accurately determine the root cause of failures. Fig. 3 outlines a methodological procedure for data analysis and the identification of potential failures using an expert knowledge system. There are several reasons for this approach, the main ones being the lack of suitable historical data, difficulties in generalizing from other tunnel systems, and insufficient knowledge of similar equipment and component life cycle characteristics within the tunnel environment [5,9].

3. Analysis and Results

This chapter focuses primarily on the integration of operator state measurements in tunnel control systems with insights drawn from the latest approaches used by air traffic controllers, and the potential transferability of voice analysis compared to electroencephalography (EEG) for determining the specific operator state and detecting attention lapses. During the verification of operator behavior, certain edge conditions such as voice loss, illness, or other impairments, as well as artificial voice distortions, were not considered, in order to identify correlations with the operator's state. While the operator manages numerous tasks, they are currently not required to address potential malfunction scenarios; thus, the objective is to highlight this issue, which is expected to have a significant impact on the increasing demands placed on operators in the future. This trend is unlike those in transportation, energy, military, and telecommunications sectors, where these issues may not be relevant. However, the gradual advancement of technologies and the need for cost optimization and real-time response will increasingly influence the quality of complex system management by the operator. Although seemingly different aspects are being addressed, they are interrelated, as higher stress levels under increased workload have shown to push tunnel system operators towards a higher degree of concentration, closely resembling the performance standards of air traffic controllers.

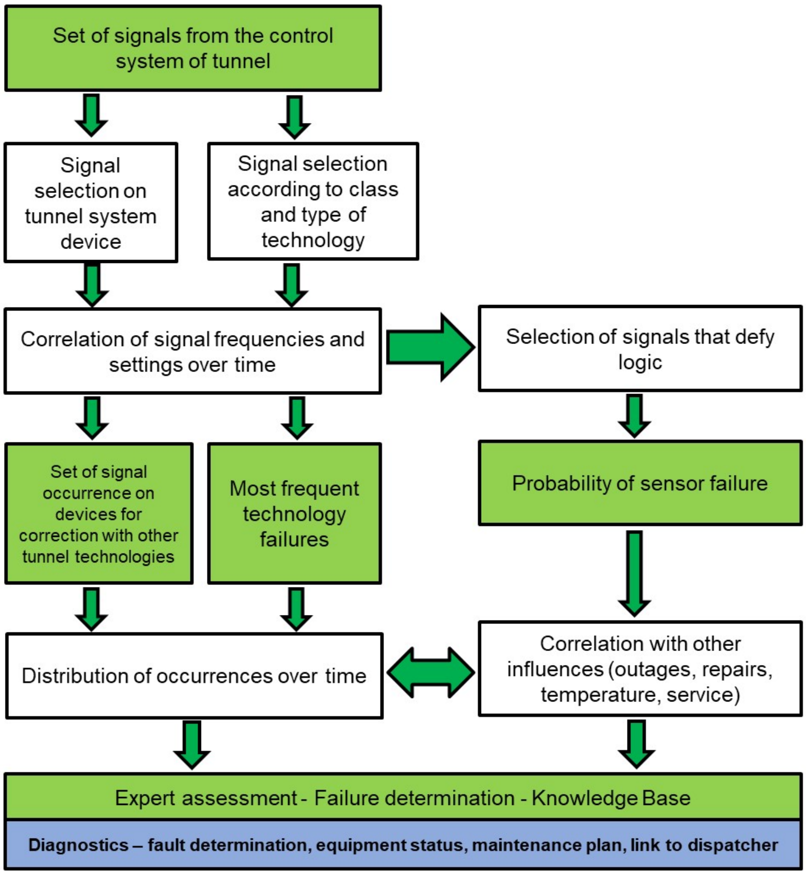

Fig. 3 *Graphical representation of the failure evaluation method [5, 9].*

3.1 Operator Measurements

For the initial processing of the electroencephalographic (EEG) signal, the TruScan software, developed by DEYMED Diagnostic s.r.o., was used. Seven basic states were identified, from which three-second segments of measured data were selected. The criterion for selecting a suitable graph was that it included all seven basic states, allowing for the identification of the proband's state and the measurement of reaction time. While reaction time is not a primary value in processing the data, it serves as a secondary component that aids in identifying individual states.

From the total dataset, 35 graphs (30 from men and 5 from women), representing individuals aged 22–55, were selected as complete and suitable for analysis. These graphs represent approximately 10–15% of the total measured data [12–14].

New interpretation of the data, EEG coherence was used, which reflects the degree of synchronization and similarity between two signals recorded from different sites on the scalp. It can be interpreted as an indicator of the functional connectivity between different brain regions. Unlike spectral analysis, EEG coherence is independent of signal amplitude and phase, allowing it to detect changes that may otherwise go unnoticed. The mathematical basis for this method is the calculation of the cross-power spectrum. The coherence value ranges from 0 to 1, where 1 indicates identical signals and 0 indicates completely different signals. This measure provides insights into the level of connectivity between neuronal populations in different brain regions [12–14]. The coherence is given by the formula found in [28].

$$coh(i,j) = \frac{|\psi(i,j)|^2}{\psi(i,i)\psi(j,j)}, \tag{1}$$

where $\psi(i,j)$ is the cross-power spectrum; $\psi(i,i), \psi(j,j)$ are the two power spectrums compared.

The TruScan SW tool from DEYMED Diagnostic s.r.o. allows the results of spectral analysis (FFT) and EEG coherence – coherent function (CF) of the spectrum to be displayed and expressed in the form of maps, where the intermediate points between the electrodes on the surface of the LBI were calculated by linear interpolation and the values were expressed in pseudo colours. The values for FFT are given by the square of the microvolts, the values for CF can be expressed as a percentage, where zero percent means no coherence between spectra, 100% means the identity of the spectre Fig. 4. For orientation, each map is accompanied by a colour scale with the indicated sensitivity. Map projection is called BM (brain mapping) or BEAM (brain electrical activity mapping) in the literature.

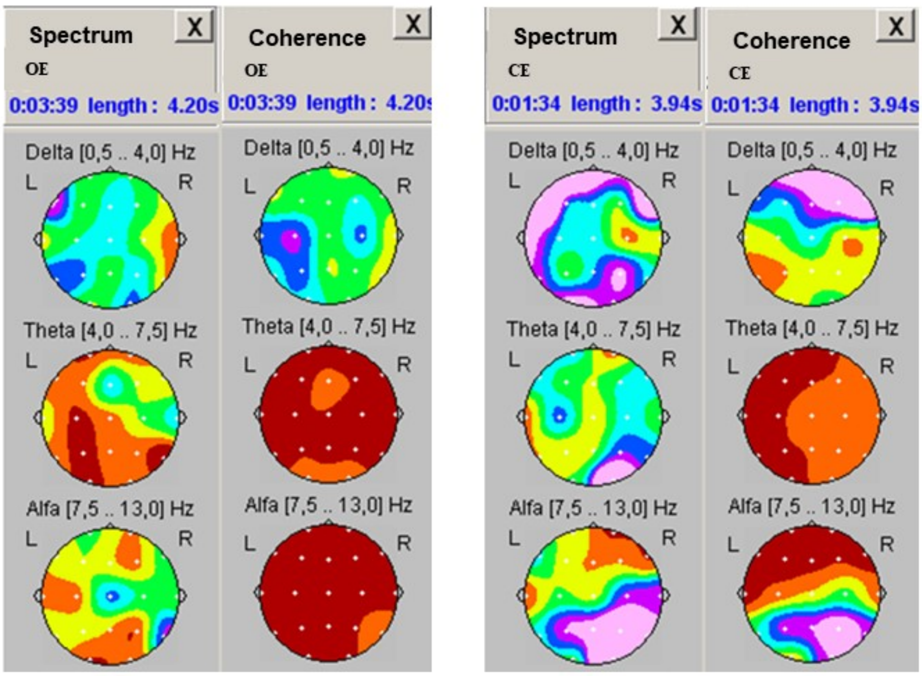

Fig. 4 *Spectra and coherence with open eyes (OE) and closed eyes (CE) of the operator [11].*

The length of the analysed section of the EEG curve ranged from 3 to 5 seconds and sections without biological and technical artefacts and corresponding to the conditions of frequency spectrum processing in which the measured subject may be located (vigilance – open eyes (OE), closed eyes (CE), thinking – the counting test, Raven's test, relaxation and sleep) were selected. [12–14].

The greater the mental exertion, the higher the delta activity observed. However, the amount of delta activity is determined by subjective effort rather than the objective difficulty of the task. An individual with a lower IQ exerts more effort on a simple test, resulting in higher delta activity. Conversely, an individual with a higher IQ exerts less effort even on a difficult test, leading to lower delta activity. Similar findings apply to coherence: the more challenging the cognitive task, the more pronounced the differences between the "islands" of maxima and minima in the multifocal arrangement [12–14].

We can thus conclude that EEG analyses, such as FFT (fast Fourier transform) and CF (coherence function), are highly effective in distinguishing not only serious organic issues but also subtle functional mental changes. These changes are often characterized by an EEG curve that appears optically flat and is almost indistinguishable to the naked eye, even when well-trained. This applies to states like wakefulness, falling asleep, mental activity, paradoxical sleep, and more. Notably, these methods are especially useful in discriminating between wakefulness, microsleep, and states of increased cognitive activity, such as deep thinking [12–14].

Participants' responses from each experiment were recorded and sent to advanced voice analysis software for processing. The voice recordings were captured using the recording and playback system (RRS), which recorded all participants. The data from RRS was anonymized to prevent identification of the measurement times and then forwarded to a representative of the manufacturer of the layered voice analysis (LVA) software (ANIS Group) for analysis. LVA technology was chosen due to its successful use at the flight school and its proven effectiveness in monitoring stress levels and development in trainees for air traffic controller positions. This technology, initially designed for operators, can also be applied to other transport system operators, such as tunnel operators [15].

The analysis was conducted using layered voice analysis (LVA) software, which operates across the full spectrum of vocal frequencies. It is user-friendly and can analyse voices both in real-time (while the subject is speaking) and offline (using recorded material). LVA processes the vocal signal by extracting and combining attributes to identify various types of stress, cognitive processes, and emotional responses. The original purpose of LVA technology was to measure multiple emotions, which, when combined, would allow users to assess whether a speech segment was at low or high risk of being deceptive. LVA software produces outputs based on different levels of analysis to support these conclusions [15, 19, 29–31].

The basic hypothesis established that attention levels would differ between the evening and morning measurements, with fatigue being significantly higher during the morning session. This would include a modified EEG spectrum coherence and lower scores in LVA parameters. A correlation between EEG and LVA was identified, as shown in Tab. I, where the correlation in the defined EEG spectra is evident [15, 19].

			Delta	Theta	Alpha	Beta1	Beta2	Gamma	SUM		
Average Voice Energy	Evening	SIM1	1	0	0	0	1	1	3	17	25
		SIM2	1	0	0	0	5	8	14		
	Morning	SIM1	1	1	1	0	2	2	7	8	
		SIM2	0	1	0	0	0	0	1		
Stress %	Evening	SIM1	2	3	1	0	0	0	6	26	37
		SIM2	6	5	7	2	0	0	20		
	Morning	SIM1	2	2	2	0	0	0	6	11	
		SIM2	2	2	1	0	0	0	5		
Upset %	Evening	SIM1	1	1	0	0	0	0	2	3	22
		SIM2	0	0	1	0	0	0	1		
	Morning	SIM1	0	0	2	2	0	0	4	19	
		SIM2	0	1	2	2	4	6	15		

Tab. I *Correlation of voice and EEG spectra [15].*

Furthermore, the relationship between voice analysis parameters and the established methods of fatigue detection is considered crucial. The expected positive correlation between EEG power spectra and selected voice parameters is evident. Based on the recommendations from the LVA software manufacturer, we anticipate a positive correlation between EEG activity in the beta and gamma bands and the voice parameters "Average Voice Energy – Upset%" and "Stress%," which has been demonstrated [15].

In conclusion, LVA is an emerging technology that has not yet been applied in the context of air traffic control. However, our research shows that voice analysis is capable of identifying differences in wakefulness and fatigue, as its results often correlate with EEG findings (voice changes frequently correspond to changes in electrical brain activity within certain frequency bands and electrodes) and other methods. Voice analysis holds great promise as a tool for fatigue detection and monitoring in various operational settings where voice communication is essential, and where traditional laboratory instruments may be impractical due to their disruptive nature and impact on operator comfort [15].

3.2 Measuring Data From the Tunnel

Data was collected from tunnels on Czech motorways as well as in urban areas. The proposed analysis was based on the experience from collected data and already performed analysis from the Lochkov Tunnel, located on the Prague Ring Road. The analysis was based on data archives over a 4-month period and includes several types of notifications, each with a specific meaning. These logs contain fault and error notifications, as well as operational and traffic information.

The notifications are split into the following groups [2, 5–8]:

- A0–A2 – alarm notification,
- D0–D2 – traffic events,

- E – energetics,
- Sys – system notifications.

Since the daily average number of notifications was quite high (around 10,000), the application of proposed approach could be applied and lead to quality enhancements.

The trend in notification frequency from previously performed analysis is below (see Fig. 5) [2, 5–8].

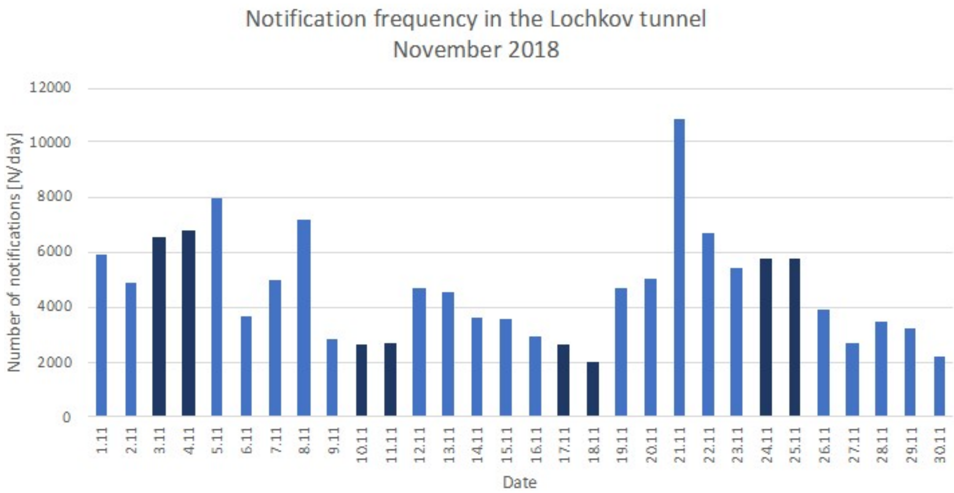

Fig. 5 *Frequency of notifications in the tunnel Lochkov [8].*

For the validation of functionalities, an effort was made to utilize additional datasets from the Lochkov Tunnel for the period 2019–2023. However, the volume and quality of the data significantly decreased, including issues with data retrieval, which is why newer data were not included or used for further analysis. Experiences were leveraged to obtain data from the Mrazovka urban tunnel in Prague during 2022–2023, which exhibits some similar conditions. However, a detailed analysis of tunnels in the Czech Republic indicated that, despite differences in technology, the detailed data can only be partially utilized, considering the number of alarms and their classification into the same categories. For subsequent, more detailed work, data from the Mrazovka Tunnel were considered due to the use of a similar tunnel control system supplier, who maintained consistent alarm labeling, and because certain technological components are sourced from the same suppliers. For each alarm type (A, D, E, Sys), not only the frequency of occurrence is verified, but also the potential severity and impact of the fault, assessed on a scale of $\langle 0, 1\rangle$. This results in a higher level of prioritization in the database records, which can be displayed to the operator as a potentially higher-priority alarm. Particularly, alarms labeled A0–A2 are primarily associated with specific tunnel technology devices and may be incorporated into a causality matrix, enabling a more accurate determination of both the likelihood and severity of faults. Repeated occurrences allow for state prediction, facilitating the anticipation of potential faults in the respective device. Devices whose faults can lead to tunnel closure (e.g., camera systems, lighting, ventilation systems etc.) are assigned higher significance, as these unexpected events require immediate active response from both the technology and the operator. Predicting such faults in advance is crucial for timely intervention.

In the example of the causality matrix shown in Fig. 6, the relationships between selected alarm events labeled 1–19 (col1) and their potential strong dependencies with other events (col2) leading to a fault event are depicted. For instance, if event 17 (power supply failure for barrier control) occurs, it triggers event 11 (failure to execute the command for the same barrier), and so on. Based on the number of alarms and monitoring of relationships with other systems and their behavior, as applied according to the described methods in Fig. 6, it is possible to estimate complex device status functions and potential faults from a sufficient number of events. This approach has led to various prediction methods currently under validation. However, due to the volume of data and the difficulty of transferring these methods between devices in different tunnels and technologies, a descriptive expert approach was chosen, for which fuzzy logic can be applied. The subsequent selection value of the device or system corresponds to a specific range, and the relevant function of the selected probability of fault value FNo is fed into the predictive model to provide a recommendation for the operator.

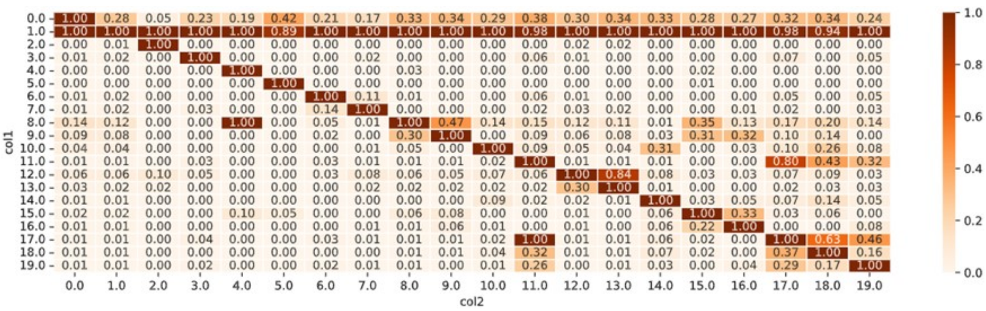

Fig. 6 *An example of the evaluation of the matrix of causalities.*

The operator requires qualified information from an expert model regarding potential failures or more accurate interpretations of certain conclusions. Artificial intelligence, implemented through an expert fuzzy model, should be capable of effectively analysing and aggregating large amounts of data, providing warnings of potential failures that could negatively impact the dispatcher's decision-making due to information overload. The goal is to present these outputs clearly, including insights into the technical conditions of the equipment in the tunnel. The prediction capabilities will enable proactive processing and timely responses to critical conditions, with potential applications in predictive maintenance [32]. The design of such a model and its integration into the tunnel system is discussed in the next chapter.

4. Proposal for a Complex System

It is evident from the above that presenting selected data is challenging, and making quick and accurate decisions based on the stimuli received by the operator from the traffic management system specifically tunnel technology during a given shift is equally difficult. Additionally, determining the status and behaviour of the operator is a complex task. Detecting a decrease in attention, whether through invasive or non-invasive methods, has technical limitations. However, monitoring the operator's behaviour is crucial for managing emergency situations.

For this purpose, simulators are used to replicate tunnel control behaviour based on predefined scenarios. These scenarios are derived from the tunnel's emergency cards (see Tab. II) [6, 9], which are part of the tunnel's operational documentation and outline the steps the operator should take during specific emergencies. These scenarios aim to cover all possible emergency situations arising from operations or external factors in the tunnels. If needed, additional scenarios can be implemented, and their functionality verified using the simulator.

Scenario number	Scenario
1	Man in the tunnel
2	Animal in the tunnel
3	Slow-moving vehicle
4	Stationary vehicle
5	Stationary dangerous vehicle
6	Object on the road
7	Chemical leakage (subject)
8	Chemical spill (cistern)
9	Demonstration in the tunnel
10	Threat of a terrorist attack (bomb)
11	Wrong-way vehicle
12	Entry of an oversized vehicle
13	Standing bus
14	Traffic accident (pedestrian collision)
15	Traffic accident (collision of an animal)
16	Traffic accident (collision of vehicles)
17	Traffic accident (subject)
18	Fire
19	Critical device or system failure

Tab. II *List of scenarios for simulation [6, 9].*

While the simulation of a scenario is performed within the model or directly in the control system, the operator's task during testing and verification is to respond to non-standard events (scenarios). Using the control system, which manages both transport and technological aspects, the operator can control various tunnel equipment. For instance, they can close individual lanes within the tunnel, close a section across the entire profile, or even shut down the tunnel completely. It is also possible to manage systems such as the ventilation fans. Additionally, the operator can respond to scenarios by dispatching a vehicle to the incident site to manage the situation.

For testing and verifying the operator's behaviour, a tunnel simulator is used to simulate selected situations and assess the operator's responses. The operator is supported by video detection systems that function as they would in real-world operations, with the option to adjust functionality or simulate malfunctions. These systems alert the operator to unusual events occurring inside or near the tunnel. When an event is detected, the camera displaying the affected area is shown. The simulator is a 3D model of the tunnel, accurately representing a real road tunnel. It provides detailed views of all tunnel sections, including the roadway and adjacent areas that impact traffic within the tunnel.

The complete system for tunnel technology, which can be adapted for use in other transport and related systems, is illustrated in Fig. 7 below.

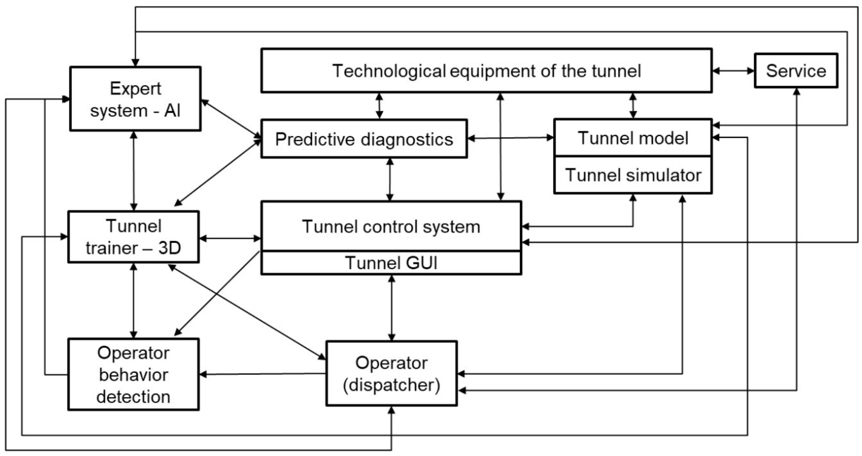

Fig. 7 *A comprehensive approach to supporting the decision-making process of tunnel system operators.*

Fig. 7 clearly illustrates the interconnection of key modules. On one side, there is data from the technology, which the operator must assess, evaluate, and respond to in a timely manner, contacting service or intervention units if necessary. The next part focuses on monitoring the operator's behaviour and knowledge, verifying their functional abilities, and evaluating stress levels, attention lapses, and other factors that may impact decision-making and reactions to events. To ensure comprehensive functionality, an expert system is introduced. This system not only evaluates data from the tunnel systems but also provides decision recommendations based on insights into the operator's behaviour. It assesses whether the operator followed the recommendation, adapts future recommendations accordingly, or evaluates inadequate behaviour. In case of a potential error, the system alerts the operator and suggests the correct intervention.

4.1 Expert System Based on Fuzzy Approach

For the fuzzy approach, a fuzzy model utilizing the Mamdani linguistic system was employed. Detection is based on defined rules derived from simulator experience and predictive diagnostics, as well as the operator's behaviour. The use of linguistic variables allows for a better understanding of fuzzy approximation by transitioning into a non-numerical domain, where basic elements and operations are defined when constructing linguistic descriptions of behaviour or system control [12].

The language variable L will be used to denote the ordered quintuple:

$$\mathrm{L} = \{\mathrm{PM}, \mathrm{T(PM)}, \mathrm{X}, \mathrm{G}, \mathrm{M}\},$$

where the meaning of each symbol is:

- PM – is the name of the variable or identifier (the state of the person being measured),
- T(PM) – is a set of language terms (very small, small, medium, large, very large),
- X – is the universe on which the individual terms are defined,
- G – is a syntactic rule (generative grammar for generating terms),
- M – is a semantic rule by which each language expression is assigned its meaning, which is a fuzzy set $\mathbf{A}_{\mathrm{F}} = (\mathbf{X}, \mu_{\mathrm{AF}})$,
- μ_{AF} is the fuzzy set membership function $\mathbf{A}_{\mathrm{F}}, \mu_{\mathrm{AF}} : X \to \langle 0, 1 \rangle$.

Based on the linguistic description, we can describe the states of the operator's behaviour using fuzzy sets. These fuzzy sets should make the interpretation of the states of the measured person more accurate. An example is a notation in the form of the inference rule IF (δ is small value) AND (ϑ is large value) AND (α is large value) THEN (O is SP). Similarly, it may determine approaches to fir states of a given system based on the defined 19 scenarios listed in Tab. II, as well as a causal approach to the device status based on A0–A2 alarms and significance determined by the type of device or system in evaluation of the matrix of causalities in Fig. 6.

To address vagueness, we can use fuzzy sets to describe uncertainty and then construct a fuzzy model. This model can be implemented into the design of a functional decision-making and evaluation block for detecting and assessing decreases in attention, stress levels, and linking these to system behaviour. The system would evaluate potential states or trends, such as equipment conditions or failures, in combination with the operator's mental state and behaviour.

The output fuzzy variable will produce a single value representing the current state of the measured person, while also indicating the relevance of the selected scenario (SNo). This value will fall within the range of $\langle 1, 19 \rangle$ (see Tab. II). Additionally, the variable will represent the probability of failure (FNo) in the given device, expressed as a probability within the range of $\langle 0, 1 \rangle$. Related to A0–A2 alarms of a specific device or system that have a critical impact on the functionality and failure of tunnel technology evaluation from the matrix of causalities (see Fig. 6).

For the output variable, we introduce a fuzzy set O, which will contain six fuzzy sets:

$$\mathrm{O} = \{\mathrm{VG}, \mathrm{TH}, \mathrm{RX}, \mathrm{SP}, \mathrm{SNo}, \mathrm{FNo}\}.$$

Fuzzy sets correspond to linguistic expressions and express:

- VG – vigilance,
- TH – thinking, stress,
- RX – relaxation, fatigue,
- SP – sleep,
- SNo – scenario value,
- FNo – probability of failure of the selected device or system.

The fuzzy classifier employs the Mamdani implication function, as shown by the formula, and the centroid method is used for defuzzification. The centroid is calculated similarly to the statistical mean value in a set and is the most common and widely recognized method for defuzzification [33, 34].

5. Discussion

The tunnel fulfils some characteristics where the causes of failures may arise due to various factors [2, 5–8]:

- Inappropriate operator intervention,
- Human factor behaviour – the user,
- Influence of aggressive environment – degradation of equipment and system,
- Overloading of certain elements, leading to degradation,
- Sudden malfunctions – accidents, etc.

For proper implementation, it is essential not only to evaluate the current situation and make forecasts, but also to address the root causes of failures. The causes of failures may differ from known statistical evaluations, and unexpected correlations can emerge. Typical examples include technological equipment where emergencies may occur [2, 4–6, 8]. Additionally, monitoring the attention and stress levels of operators significantly impacts the accuracy and speed of their responses to potential emergencies.

A clear benefit of predictive maintenance is the ability to troubleshoot constantly, well in advance of the actual failure or before reaching a critical failure state. This approach minimizes the cost associated with repair cycles, as it helps prevent emergencies, equipment shutdowns, or tunnel closures, along with the secondary costs these incidents entail. Downtime during preventive repairs can be minimized or appropriately planned. However, the disadvantage of this approach is the greater initial investment—requiring systems with not only sufficient diagnostics but also real-time data. Additionally, the equipment must be regularly monitored and evaluated to establish a reliable data history, which is necessary for accurately predicting failure thresholds. New BIM (building information modelling) approaches can be integrated during the design phase, creating the necessary data for future implementation and maintenance of the technology [5, 35, 36]. It is also advisable to implement novel and progressive technologies beyond standard tunnel systems, such as C-ITS and others [37].

Similarly, it is advisable to regularly train and assess the behaviour and condition of the transport system operator. Sustained attention and concentration can lead to a gradual decline in perception over time, which may result in inaccurate decision-making. Using multiple detection methods, such as voice analysis, EEG, and behaviour monitoring, can significantly help in accurately determining the operator's status, especially when dealing with complex tasks in a transport system that is part of critical infrastructure. By combining these insights, we can develop an effective AI-based expert system, utilizing fuzzy logic, which not only predicts the behaviour of the system but also that of the operator. This enables timely intervention suggestions for the system while optimizing the operator's time, attention, and overall performance.

The application of such a system can be extended to sectors like the military, energy, call centres, and other industries where high operator attention is required for managing complex systems or equipment. Expert systems providing "whispered" recommendations are already in use in various industries, although they are less commonly applied in control centres for transport system dispatchers and similar environments, etc.

In the context of further research, it is also possible to address boundary conditions such as operator illness and various other behaviors, including stress and voice distortion. Air traffic controllers rely significantly more on voice communication compared to tunnel dispatchers, operators in the energy sector, or military system operators, for example. Similarly, there is a need to assess advance information on potential malfunctions and the operator's response to such events, along with other essential perceptual inputs that require further validation and testing [38]. The focus of research should be on exploring the relationships between the volume of data outputs and the operator-dispatcher's behavioral responses. Future testing should demonstrate the utility and potential transferability of enhanced voice interaction with the tunnel system, including communication with auxiliary units, maintenance teams, etc. Voice analysis of the operator's state and interaction with future AI modules is expected to become a prominent trend in development, as it represents a non-invasive approach that is likely to be increasingly applied in practice.

6. Conclusion

This research addresses two primary tasks: detecting operator behaviour and implementing predictive diagnostics as part of the overall transport system control process. Operator behaviour was analysed in a sample of more than 30 individuals across various conditions, and these results were correlated with a selected sample of voice analysis. The combination of these methods has proven effective in reliably determining the operator's condition in terms of decreased attention, defined behavioural states, and stress levels, etc.

Similarly, efforts were made to gather the necessary data for predictive diagnostics of the equipment and to provide information not primarily intended for controlling the system. Predictive maintenance diagnostics were conducted in selected tunnels, involving a detailed analysis of data records and a review of the relevant documentation. Significant effort was made to allocate sufficient sources of relevant data for the selected tunnels [2, 5–8].

Subsequently, a comprehensive system was designed, including an expert system based on fuzzy logic, which will be further tested for reliability in selecting appropriate scenarios for controlling tunnel technology or identifying system states. This system also provides a potential probability of device failure. A key component is the assessment of operator status, offering assistance in selecting their current condition and providing support during system control, stressful situations, or emergencies. At this stage, further testing is required, as some data has proven to be insufficient, and certain settings may need to be individualized based on the person's unique profile.

Equally important is not only to have historical data but also to understand the relationships and connections between subsystems or sub-components. In summary, to implement predictive diagnostic and expert methods in the tunnel system, it is essential to further optimize and fine-tune long-term measurements, historical and statistically relevant data. In the future, the system can also be enhanced with cognitive functions that automate processes, reduce maintenance cost, minimize operator interventions, and extend the lifespan of the equipment or the entire system.

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References

[1] FABER J., NOVÁK M., TICHÝ T., SVOBODA P., TATARINOV V. Driver psychic state analysis based on EEG signals. *Neural Network World*, 2006, 16(1), pp. 25–39. ISSN 1210-0552.

[2] TICHÝ T., BROŽ J., BĚLINOVÁ Z., KOUBA P. Predictive diagnostics usage for telematic systems maintenance. In: *2020 Smart City Symposium*, Prague, IEEE Press: New York, NY, USA, 2020. ISBN 978-1-7281-6821-0, doi: 10.1109/SCSP49987.2020.9134051.

[3] RÁSTOČNÝ K., ŽDÁNSKY J., BALÁK J., HOLEČKO P. Diagnostics of an output interface of a safety-related system with safety PLC. *Electrical Engineering*, 99, 4, SI, pp. 1169–1178, 2017, doi: 10.1007/s00202-017-0624-1.

[4] RŮŽIČKA J., NAVRÁTILOVÁ K. Crisis management as the part of smart traffic control in cities. In: *Smart City Symposium*, (SCSP), Prague, Czech Republic, 2020, pp. 1–5, doi: 10.1109/SCSP49987.2020.9133818.

[5] TICHY T., BROŽ J., ŠMERDA T., BĚLINOVÁ Z. Application of Predictive Maintenanace in Technological Tunnel Systems. In: *XXVIIth World Road Congres*, Prague, 2023, pp. 1–13, ISBN 978-2-84060-837-0.

[6] TICHÝ T., BROŽ J., BĚLINOVÁ Z., PIRNÍK R. Analysis of Predictive Maintenance for Tunnel Systems. *Sustainability*, 2021, 13, 7, 3977. doi: 10.3390/su13073977.

[7] BORGHETTI F., DERUDI M., GANDINI P., FRASSOLDATI A., TAVELLI S. Safety in road tunnels. In: *Tunnel Fire Testing and Modeling.* SpringerBriefs in Applied Sciences and Technology, Springer, Cham, 2017, doi: 10.1007/978-3-319-49517-0_1.

[8] TICHÝ T., BROŽ J., ŠTEFAN J., PIRNÍK R. Failure analysis and data-driven maintenance of road tunnel equipment, *Results in Engineering*, 2023, 101034, doi: 10.1016/j.rineng.2023.101034.

[9] TICHÝ, T., ŠTEFAN, J., PIXA R., MIKLOŠÍK, I. System for technology control, diagnostics and simulation in tunnels. In: *14th international conference Underground construction*, Prague, 2019, pp. 1–8, ISBN 978-80-906452-3-3.

[10] BĚLINOVÁ Z., VOTRUBA Z. Reflection on systemic aspects of consciousness. *Neural Network World*, 2023, 33(5), pp. 397–412, doi: 10.14311/NNW.2023.33.022.

[11] FABER J., TICHÝ T. Vigilance and hypnagogium determination of drivers by EEG analysis, *Neural Network World*, 2008, 18(2), pp. 89–104. ISSN 1210-0552.

[12] TICHÝ T. Fuzzy nad expert approaches to detection of micro-sleep. *Neural Network World*, 2004, 14(1), pp. 97–108. ISSN 1210-0552.

[13] FABER J., PĚKNÝ J., PIEKNÍK R., TICHÝ T., BOUCHNER P., NOVÁK M., FABER V. Simultaneous recording of electric and metabolic brain aktivity, *Neural Network World*, 2010, 20(4), pp. 539–557. ISSN 1210-0552.

[14] NOVÁK M., FABER J., VOTRUBA Z., PŘENOSIL V., TICHÝ T. Reliability of Human Subject – Artificial System Interactions, In: *Acta Polytechnica*, 2002, 42, 3, pp. 31–40, ISSN 1210-2709.

[15] KOUBA P., TICHÝ T., ŠMOTEK M., KOPŘIVOVÁ J. Detection of air traffic controllers' fatigue using voice analysis – An EEG validation study, *International Journal of Industrial Ergonomics.* 2023, 95(103442), pp. 1–14. ISSN 0169-8141, doi: 10.1016/j.ergon.2023.103442.

[16] QUATRINI E., COSTANTINO F., DI GRAVIO G., PATRIARCA R. Machine learning for anomaly detection and process phase classification to improve safety and maintenance activities. *J. Manuf. Syst.*, 2020, 56, pp. 117–132.

[17] MENG Z., LI J., YIN N., PAN Z. Remaining useful life prediction of rolling bearing using fractal theory, *Measurement*, 2020, 156, ISSN 0263-2241, doi: 10.1016/j.measurement.2020.107572.

[18] MOTAGHARE O., PILLAI A.S., RAMACHANDRAN K.I. Predictive Maintenance Architecture. In: *Proceedings of the 2018 IEEE International Conference on Computational Intelligence and Computing Research* (ICCIC), Madurai, India, 2018, pp. 1–4, doi: 10.1109/ICCIC.2018.8782406.

[19] BEGUM S. Intelligent driver monitoring systems based on physiological sensor signals: A review. In: *16th International IEEE Conference on Intelligent Transportation Systems* (ITSC 2013).

[20] BARHAM M.P., CLARK G.M., HAYDEN M.J., ENTICOTT P.G., CONDUIT R., LUM J.A.G. Acquiring research-grade ERPs on a shoestring budget: A comparison of a modified Emotiv and commercial SynAmps EEG system. *Psychophysiology*, 2017, 54(9), pp. 1393–1404, doi: 10.1111/psyp.12888.

[21] GEVINS A., LEONG H., DU R., SMITH M.E., LE J., DUROUSSEAU D., ZHANG J., LIBOVE J. Towards measurement of brain function in operational environments. *Biological Psychology*, 1995, 40(1), pp. 169–186, doi: 10.1016/0301-0511(95)05105-8.

[22] TANAKA M., SHIGIHARA Y., FUNAKURA M., KANAI E., WATANABE Y. Fatigue-associated alterations of cognitive function and electroencephalographic power densities. *PloS one*, 2012, 7(4), e34774, doi: 10.1371/journal.pone.0034774.

[23] BRENNER M., CASH, J.R. Speech analysis as an index of alcohol intoxication–the Exxon Valdez accident. *Aviat Space Environ Med*, 1991, 62(9 Pt 1), pp. 893–898.

[24] LUBAR J.F., SWARTWOOD M.O., SWARTWOOD J.N., O'DONNELL P.H. Evaluation of the effectiveness of EEG neurofeedback training for ADHD in a clinical setting as measured by changes in T.O.V.A. scores, behavioral ratings, and WISC-R performance. *Biofeedback Self Regul*, 1995, 20(1), pp. 83–99, doi: 10.1007/bf01712768.

[25] ELKINS A. Evaluating the Credibility Assessment Capability of Vocal Analysis Software, 2010.

[26] DUVINAGE M., CASTERMANS T., PETIEAU M., HOELLINGER T., CHERON G., DUTOIT T. Performance of the Emotiv Epoc headset for P300-based applications. *Biomed Eng Online*, 2013, 12(56), doi: 10.1186/1475-925x-12-56.

[27] LOPES DA SILVA F.H., LEIROP T.H.M.T. VAN, SCHRIJER C.F., STORM VAN LEEUWEN W. Organization of thalamic and cortical alpha rhythms: spectra and coherences. *Electroenceph. clin. Neurophysiol.*, 1973, 35, pp. 627–639.

[28] MAYEW W.J., VENKATACHALAM M. The Power of Voice: Managerial Affective States and Future Firm Performance. *The Journal of Finance*, 2012, 67(1), pp. 1–43, doi: 10.1111/j.1540-6261.2011.01705.x.

[29] MAYEW W.J., VENKATACHALAM M. Speech Analysis in Financial Markets. *Foundations and Trends® in Accounting*, (2013), 7(2), pp. 73–130, doi: 10.1561/1400000024.

[30] DAMPHOUSSE K.R., POINTON L., UPCHURCH D., MOORE R.K. Assessing the Validity of Voice Stress Analysis (VSA) Tools in a Jail Setting in Oklahoma City (2008), Oklahoma, 2006 [distributor], doi: 10.3886/ICPSR20625.v1.

[31] HARNSBERGER J.D., HOLLIEN H., MARTIN C.A., HOLLIEN K.A. Stress and deception in speech: evaluating layered voice analysis. *J Forensic Sci*, 2009, 54(3), pp. 642–650. doi: 10.1111/j.1556-4029.2009.01026.x.

[32] CAO X., LI P., MING S. Remaining useful life prediction-based maintenance decision model for stochastic deterioration equipment under data-driven, *Sustainability*, 2021, 13, 8548, doi: 10.3390/su13158548.

[33] REMOALDO D., JESUS I. Analysis of a Traditional and a Fuzzy Logic Enhanced Perturb and Observe Algorithm for the MPPT of a Photovoltaic System. *Algorithms*, 2021, 14(24), doi: 10.3390/a14010024.

[34] BABUŠKA R. Fuzzy Modeling for Control; Springer: Dordrecht, The Netherlands, 1998, doi: 10.1016/B978-1-4832-1450-4.50065-1.

[35] BERAN V., TEICHMANN M., KUDA, F. Decision-Making Rules and the Influence of Memory Data. *Sustainability*, 2021, *13*, 1396, doi: 10.3390/su13031396.

[36] KUDA F., TEICHMANN M. Maintenance of infrastructural constructions with use of modern technologies. *J. Heat. Vent. Install*, 2017, 26, pp. 18–21, ISSN 12101383.

[37] LOKAJ Z., ŠROTÝŘ M., M. VANIŠ M., MLADA M. Methodology of Functional and Technical Evaluation of Cooperative Intelligent Transport Systems and Its Practical Application. *Appl. Sci.*, 2021, 11, 9700, doi: 10.3390/app11209700.

[38] NOVOTNÝ S., BOUCHNER, P. Advanced methodology for evaluation of driver's actual state with use of technical driving data. In: *Proceedings of the 8th WSEAS International Conference on Systems Theory and Scientific Computation* (ISTAC'08) – New Aspects of Systems Theory and Scientific Computation. Athens: World Scientific and Engineering Society Press, 2008. pp. 160–165. ISBN 978-960-6766-96-1.