VOLUME 13 NUMBER 2 BANJA LUKA, DECEMBER 2023 (57-120) ISSN 2232-9625 (Print) ISSN 2233-0194 (Online) UDC 004

Journal of Information Technology and Applications

(BANJA LUKA)

JITA

Exchange of Information and Knowledge in Research

APEIRON
АПЕИРОН

THE AIM AND SCOPE
The aim and scope of the Journal of Information Technology and Applications (JITA) is:
• to provide international dissemination of contributions in field of Information Technology,
• to promote exchange of information and knowledge in research work and
• to explore the new developments and inventions related to the use of Information Technology towards the structuring of an Information Society.
JITA provides a medium for exchanging research results and achievements accomplished by the scientific community from academia and industry.

By the decision of the Ministry of Education and Culture of the Republic of Srpska, no.: 07.030-053-160-4/10 from 3/3/2010, the journal „Journal of Information Technology and Applications" Banja Luka is registered in the Registry of public organs under the number 591. Printed by Markos, Banja Luka in 300 copies two times a year.

Indexed in: LICENSE AGREEMENT, 3.22.12. **EBSCO** Publishing Inc., Current Abstracts

ebscohost.com	road.issn.org
citefactor.org/contact	citefactor.org
scholar.google.com	cosmosimpactfactor.com
doisrpska.nub.rs	
crossref.org	

Printed on acid-free paper

Annual subscription is 30 EUR
Full-text available free of charge at http://www.jita-au.com

UDC 004

ISSN 2232-9625 (Print)
ISSN 2233-0194 (Online)

JITA

VOLUME 13 NUMBER 2 BANJA LUKA, DECEMBAR 2023 (57-120)

Contents

EDITORS:

ZORAN AVRAMOVIĆ, PhD
Editor-in-Chief

GORDANA RADIĆ, PhD

DUŠAN STARČEVIĆ, PhD

Dear authors,
Dear readers,

Welcome to the twenty-sixth edition of the Journal of Information Technology and Applications (JITA), published by Pan-European University APEIRON Banja Luka, that completes thirteen years of regular publication of the journal.

JITA is a research and professional information journal that aims to promise a forum for engineering, research and academics, universities and industry to showcase their scientific careers and encourage them to learn and explore.

The Journal of Information Technology and Application is honored to have a Distinguished Doctor of Engineering, Professor Efim Naumovich Rozenberg of the Research and Design Institute for Information Technology, Signalling and Telecommunications on Railway Transport (JSC NIIAS, Russia) as an editor of this issue.

Professor Rozenberg is the First Deputy Director General of JSC NIIAS. He leads research and development in train control and protection including signalling, train separation, automatic train operation, traffic safety, communication, cybersecurity. In 2018, he was appointed Chief Designer of JSC Russian Railways to implement train separation technology on Russia's railway network.

He is a recipient of the award of the Government of the Russian Federation in the field of science and technology. He was also awarded the title of Honored Designer of the Russian Federation, Best Innovator of JSC Russian Railways.

Professor Rozenberg is an author of about 300 research papers and about 400 patented inventions and is a fellow of the Academy of Electrical Engineering of the Russian Federation.

This issue of JITA is devoted to the application of information technologies in the railway sector, focusing on such areas as train control, functional safety and cyber security of intellectual railway systems. The authors of the papers are JSC NIIAS experts.

Gratitude

On behalf of the Editorial Board, we would like to thank the authors for their high quality contributions, and also the reviewers for the effort and time invested into the preparation of the Journal of Information Technology and Applications.

Acknowledgments

We would like to thank many who have read and/or commented on earlier versions of this journal including Leonid A. Baranov, Yuri M. Inkov, Alexey V. Ozerov, Nedim Smailović, Katarina Držajić Laketić and Dražen Marinković. However, any errors or shortcomings remain my full responsibility.

Conflicts of Interest

The author declares no conflict of interest.

Editor-in-Chief, Zoran Avramović
zoran.z.avramovic@apeiron-edu.eu
Editors, Gordana Radić, Dušan Starčević

Application of Artificial Intelligence Methods for the Prediction of Hazardous Failures

Igor Shubinsky, Alexey Ozerov

Research and Design Institute for Information Technology, Signalling and Telecommunications on Railway Transport (NIIAS), Moscow, Russia, a.ozerov@vniias.ru

Contribution to the State of the Art

https://doi.org/10.7251/JIT2302061S UDC: 007.52:004.42.032.24

Abstract: The availability of real-time data on the state of railway facilities and the state-of-the art technologies for data collection and analysis allow transition to the fourth generation maintenance. It is based on the prediction of the facility functional safety and dependability and the risk-oriented facility management. The article describes an approach to assessing the risks of hazardous facility failures using the latest digital data processing methods. The implementation of this approach will help set maintenance objectives and contribute to the efficient use of resources and the reduction of railway facility managers' expenditures.

Keywords: predictive analysis, maintenance, functional safety, Big Data, Data Science, risk indicators.

Functional safety of railway facilities as well as any technical facilities depends on the effectiveness of their technical maintenance and repair. The modern technical maintenance and repair strategy is based on predicting the state of functional safety and dependability of an object and the risk-oriented facility management [1]. This approach, focused on anticipating a negative event, is based on predictive analysis [2] and is implemented using dynamic predictive analysis models (categorization models) for infrastructure facilities and rolling stock [3].

When predicting functional safety of railway facilities it appears that the relative number of hazardous failures is small. At the same time, there are hundreds and thousands of objects and parameters that characterize these events. Moreover, only part of the data about the controlled objects is useful for decision-making when managing specific events. In this context, it is advisable to carry out categorization using Big Data and Data Science techniques, in particular machine learning. The capabilities of Big Data technology make it possible to predict the risks of hazardous failures of safety-related control systems, using data on multiple different factors. The Data Science algorithms enable dynamic object categorization models to be built. They are used to identify, assess, process and monitor early warning indicators of risk factors in respect to railway facilities, i.e. track, signalling, power supply, rolling stock.

Predictive analysis models solve the problem of object categorization for the purposes of:

1. Ranking of these objects in terms of early warning indicators of risk factors;
2. Ranking of the list of factors which indicators demonstrate an unacceptable level of risk;
3. Prediction of undesirable events for various planning time-frame.

The early risk indicators mean the result or attribute of the object state supervision, whose change or accumulation allows a certain analytical judgement to be made in order to identify the risk (audit orders, as well as the results of all types of revisions or audits).

The primary early risk indicator is the probability that a certain control system item will fail next month. The probability takes a value from the range [0; 1]. In accordance with the ALARP principle, this range is divided into four zones (Table 1) [4]:

[0; a) is the range of negligible risk;

[a; b) is the range of tolerable risk;

[b; c) is the range of undesirable risk;

[c; 1] is the range of intolerable risk;

where a = 0.5·Threshold_1, b = Threshold_1, c = 0.5·(Threshold_2+Threshold_3).

In turn, Threshold_1 is the lower probability threshold, Threshold_2 is the balanced probability threshold, and Threshold_3 is the upper probability threshold.

Table 1. *Risk zones as regards hazardous failure prediction*

Risk zone	Negligible	Tolerable	Undesirable	Intolerable
Probability	[0; a)	[a; b)	[b; c)	[c; 1]

Rather than a strict class value, the classifier of the predictive analysis model outputs confidence in the presence of a "positive" class that can take values from 0 to 1. For each item of the control system, the classifier calculates the probability that it belongs to a positive class, i.e. is a controlled item with a potential hazardous failure. For the purpose of final decision-making, the probability Threshold is defined. If the probability is below the threshold, the controlled item belongs to the negative class and is labelled '0' (an item with no hazardous failure). If the probability is above the Threshold value, the controlled item is labelled '1' (an item with a potential hazardous failure).

The numerical values of probability thresholds are determined in respect to the predictive analysis model (training algorithm) that suits the supervised item and the composite factors of this model.

The dynamic predictive analysis model covers the following tasks:

- requirements for the description of controlled objects;
- description of the controlled objects, including a set of object characteristics, data sources and those responsible for the operation/control of the objects;
- the procedure for generating risk indicators;
- risk assessment procedure;
- list of early warning indicators of risk factors, including risk owners;
- conceptual mathematical model for assessing the categorization of the controlled objects;
- conceptual digital mathematical model for assessing the categorization of the controlled objects as well as the model using procedure.

There are 4 stages to describe a controlled object:

1. Making a list of automated control systems that are the sources of data about the controlled object state (ACSs);
2. Setting the requirements for a list of controlled objects;
3. Setting the requirements for target attributes of controlled objects, which are early warning indicators of risk factors.
4. Setting the requirements for a list of controlled objects' characteristics.

There are 2 stages to make a list of controlled objects based on the analysis of ACSs.

Stage 1. It includes creation of a tree structure of controlled objects for each ACS. The tree is described in a matrix format. The first column should contain the largest object; the second column should contain the details of the large object, etc.

Stage 2. The list of controlled objects is created on the basis of the tree structure of controlled objects. Objects, for which categorization assessment models will be developed, are selected. Models are developed on the basis of early warning indicators of risk factors.

A target attribute should be determined for each object. The target attribute should indicate if there is an undesirable event, and have a time characteristic. The following can be selected as a target attribute: traffic safety violation; category 1 or 2 failure; hazardous failure; failure; a technological violation. If several target attributes are selected for one object, then an individual object categorization assessment model is developed for each such target attribute.

For each "object – target attribute" pair, a set of object characteristics should be defined, on the basis of which the values of the target attribute are predicted. The characteristics of the object should be time-homogeneous and have the same data storage depth. Time homogeneity means that if the values of one attribute characterize an object during a month (or another time period: year, day, date), then the values of other attributes should characterize an object for the same month (time period). The ACS-generated values of attributes are allowed to be converted in order to reduce them to time-homogeneous value. The minimum number of object attributes is 10. It is recommended to describe an

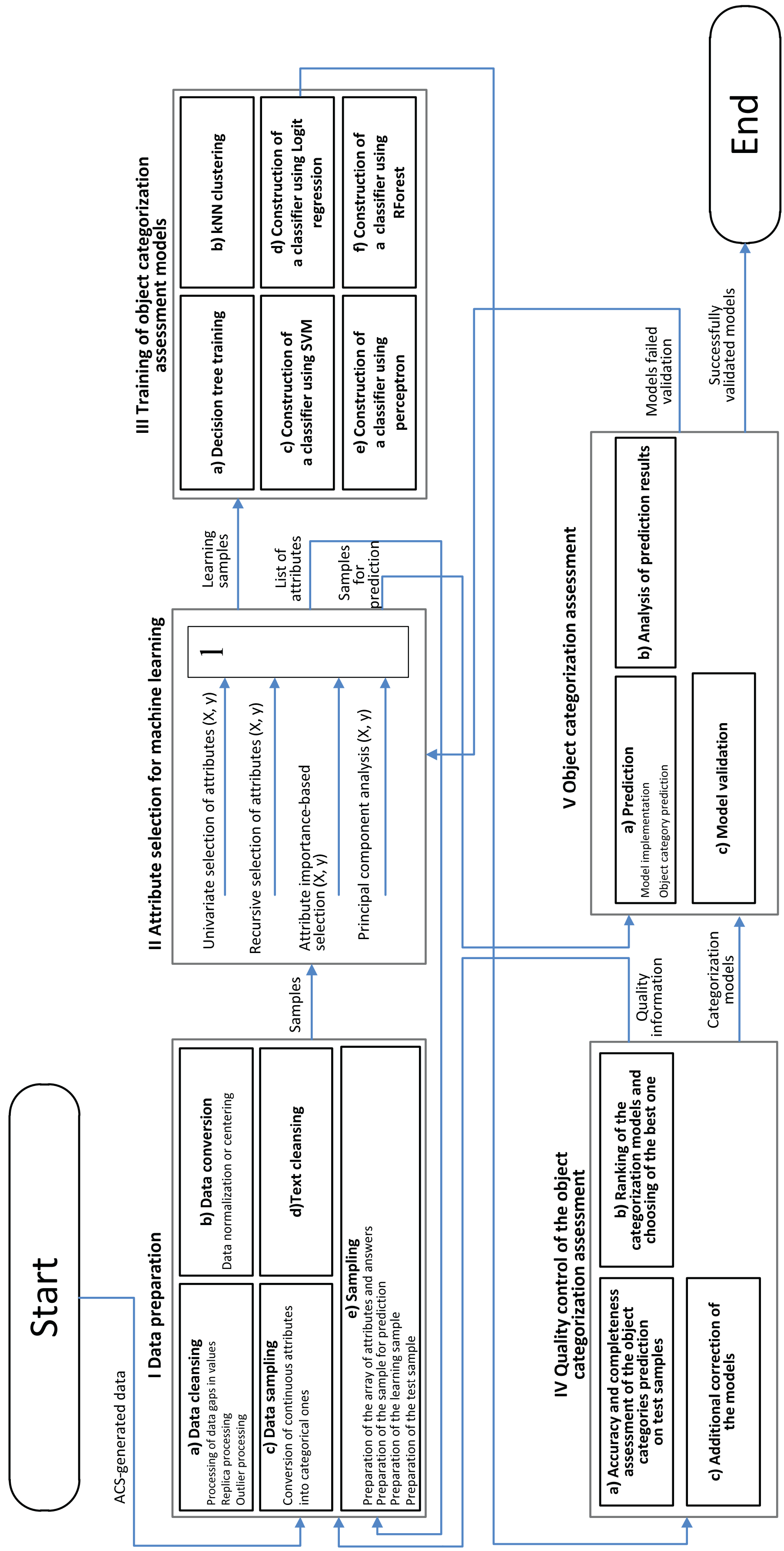


Fig. 1. Diagram of a conceptual mathematical dynamic model for predicting failures

object with 30 or more attributes. A time interval or a specific date is selected as a time characteristic, for which the value of the target attribute is to be predicted. Time characteristic should not be less than the time period during which the data on object characteristics is collected and exceed object characteristics storage depth.

Object categorization models should be developed using machine learning methods and statistics on the state of controlled objects. This will ensure minimization of the interval between the time when the data on the controlled object states enters the railway company's ACS and the time when a judgement on the object category is made.

Methods of machine learning can be subdivided into classical algorithms and deep learning methods. The main difference is the presentation level. The classical learning methods include XGBoost, AdaBoost, support vector machine (SVM), decision tree, RForest, logit regression, k-nearest neighbors algorithm (kNN), principal component analysis (PCA), etc. [5].

For example, in [6], the PCA along with the SVM were applied to a set of data on 31 objects collected on a US class I network for the purpose of detecting four types of surface defects. Deep learning algorithms based on neural networks are employed as the primary tool for detecting structural defects in rails.

Fig. 1 shows a diagram of a conceptual mathematical dynamic model for predicting failures based on early warning indicators of risk factors.

In 2020, the Russian Railways created dynamic models for the railway traffic control systems, which were tested on three regional railways.

For each of the railways, predictive analysis models were built on the basis of the following classification algorithms:

- XGboost;
- AdaBoost;
- Gboost;
- RForest;
- binary decision tree;
- SVM;
- kNN;
- Logit regression.

For all these models, the values of the early warning indicators are optimized. The table 2 shows the values of threshold for the prediction models with binary decision tree algorithm that is best suited for signalling facilities in terms of accuracy of hazardous events prediction. The threshold values are calculated for three regional railways.

According to the results of prediction for 3 regional railways, the best results for safety-critical railway signalling systems were obtained using the binary decision tree (89.9% and 87% convergence of the prediction of hazardous failure and actual occurrence). Further improvement of the prediction accuracy can be achieved not through more complex methods, but by improving the quality of input data. The input data can be extended by using other measurement tools, e.g. flaw detectors.

In general, the development of information systems allows us to get to a whole new level of ensuring functional safety. The experience in automation of data collection and management, and the application of Data Science methods make it possible not only to predict target events, but also to determine strategies for the development of data collection systems. After all, the reliability of prediction results ultimately depends on the input data. Moreover, recently we have dealt with the fact that the nature, volume and discreteness of the input data determine what kind of problem can be solved.

References

[1] Ozerov A.V. Dependability of railway control, command and signalling in the context of digitization. / A.V. Ozerov // Dependability. 2020; 2: 54-64 https://doi.org/10.21683/1729-2646-2020-20-2-54-64.

[2] Ozerov A.V. Predictive analytics using data science in railway transport. / A.V. Ozerov, A.M. Olshansky, A.P. Ku-

Table 2. *Optimized model hyperparameters for the three regional railways*

Name	Description	Railway 1	Railway 2	Railway 3
Threshold_1	Lower probability threshold	0.15	0.025	0.02
Threshold_2	Balanced probability threshold	0.5	0.5	0.5
Threshold_3	Upper probability threshold	0.75	0.59	0.55

ropteva // Railway Science and Technology; 2020; 4: 63-75.

[3] Shubinsky, I.B. Functional safety of railway control systems/ I.B. Shubinsky, E.N. Rozenberg. Vologda: Infra-Engineering; 2023; 360 p.

[4] Shubinsky, I.B. Safety-critical railway systems / I.B. Shubinsky, E.N. Rozenberg, L.A. Baranov // Reliability Modeling in Industry 4.0; 2023; 83-122.

[5] Shubinsky, I.B. Application of machine learning methods for predicting hazardous failures of railway track assets/ I.B. Shubinsky, A.M. Zamyshliaev, O.B. Pronevich, A.N. Ignatov, E.N. Platonov. // Dependability; 2020; 2: 44-54.

[6] Lasisi A. Principal components analysis and track quality index: a machine learning approach / Lasisi A., Attoh-Okine N. // Transp. Res. Part C Emerg. Technol. V. 91; 2018: 230–248.

Received: September 21, 2023
Accepted: November 11, 2023

About the authors

Igor Shubinsky is the Deputy Head of Integrated Research and Development Unit of JSC NIIAS, Doctor of Engineering, Distinguished Professor, expert of the Scientific Council for Information Security under the Security Council of the Russian Federation. His research interests include methods of analysis and synthesis of functional dependability and functional safety of complex systems, adaptive fault-tolerance of information systems, management of technical assets based on their dependability and safety status and risk assessment. He has authored 37 monographs and textbooks, over 400 papers and over 40 patented inventions.

Alexey Ozerov is the Head of International Department – Head of Intellectual Property Management Centre of JSC NIIAS. He has been working with JSC NIIAS for over 16 years in various positions related to research, signalling business unit and international cooperation. He is finishing his PhD in traffic management and has authored over 50 papers and 8 patents in the field of advanced railway signalling and traffic management.

For citation

Igor Shubinsky, Alexey Ozerov, Application of Artificial Intelligence Methods for the Prediction of Hazardous Failures, *JITA – Journal of Information Technology and Applications, Banja Luka*, Pan-Europien University APEIRON, Banja Luka, Republika Srpska, Bosna i Hercegovina, JITA 13(2023) 2:61-65, (UDC: 007.52:004.42.032.24), (DOI: 10.7251/JIT2302061S, Volume 13, Number 2, Banja Luka, December (57-120), ISSN 2232-9625 (print), ISSN 2233-0194 (online), UDC 004

The Dependability and Safety Indicators of a Train Driver-Machine System

Igor Shubinsky, Efim Rozenberg, Natalia Boyarinova

Research and Design Institute for Information Technology, Signalling and Telecommunications on Railway Transport (NIIAS), Moscow, Russia, n.boyarinova@vniias.ru

Contribution to the State of the Art

https://doi.org/10.7251/JIT2302066S UDC: 629.11:656.073.436

Abstract: The paper aims to assess the effect of the existing actions to assist a train driver in various operational situations, as well as to numerically evaluate the effect of such assistance on the resultant indicator of an error-free driver performance. The paper calculates and analyses the probability of at least one of the independent events or actions aimed at improving the quality of driver performance and reduction of the probability of error. The model of an environment was created, in which the probability of error-free driver performance is affected by a number of factors.

Keywords: safety of a man-machine system, increasing the probability of error-free transportation process performance, driver's operational environment.

Introduction

The driver is one a the key components in the process of train control and protection. Other noteworthy factors include the condition of the locomotive equipment and components, compliance with the rules and instructions, quality and dependability of equipment [1,2]. Such safety functions as observation of speed restrictions and correct train control are progressively being automated, yet in the majority of cases the final decision is still taken by the driver [3,4]. Today, the driver performs a host of tasks and bears great responsibility for the committed errors, therefore assisting the driver and reducing the probability of error associated with the performance of certain sets of actions is of relevance. The matter of the effect of the human factor on the railway traffic safety has been examined on many occasions. The probability of error of driver only operations is between 10^{-2} and 10^{-3}, while the probability of error-free performance is low [5], therefore the problem of ensuring stable and error-free driver performance is now of relevance. There is a number of methods of ensuring fault-free driver performance [6-8] and approaches to the evaluation of the effect of the human factor [9-11]. One of such approaches is the apportionment of the responsibility of the involved employees for incidents that caused a deterioration of the quality and efficiency of railway operations, violations of traffic safety [12]. Another approach is the evaluation of an employee's fitness for a specific professional activity for the purpose of targeted correction of professionally important qualities of employees and more efficient personnel selection [13,14]. Preventive measures aimed at reducing the probability of train control violations may be defined using a combination of methods of evaluating driver performance and prediction [6]. Another method of reducing the probability of violation is by observing the optimal ratio between periods of work and rest, granted the planned train schedule has been fulfilled [7,8]. Such approaches to the research of complex man-machine systems and human-human interactions primarily deal with the evaluation of the effect of professional and psychophysical properties of personnel on the operation of the system as a whole.

This paper examines the evaluation of the effect of the assistance to the driver's operations both by humans (traffic controller, instructing driver, etc.), and by hardware and software technical systems (train protection device, ATO systems, etc.)

The paper examines the following driver operating environment:

- in any difficult situation, the driver can immediately contact an instructing driver regarding malfunctions of the locomotive or train in order to confirm the grading of track or the methods of driving the train along a railway line;
- the physiological condition of the driver is monitored by a special device that protects against the onset of sleep and loss of attention;
- the driver receives the bulk of information on the operating situation from the onboard safety units;
- from each station, via the station duty officer, the driver receives information of the train route and emerging circumstances along the line;
- the level crossing duty officer communicates critical information to the nearest station's duty officer and the diver at the moment the train clears the station (flag), as the open line is the most hazardous facility;
- the whole travelled distance is recorded on an electronic storage device onboard the locomotive. All speed restrictions can be tracked automatically using the train protection device and visually by the driver;
- information is recorded into the electronic storage device from the speed restrictions server. Additionally, the system that tracks the locomotive location communicates real-time information to the locomotive to be displayed to the driver and for the purpose of automatic train operation. Train detection information is communicated to the traffic controller in real time. If necessary, it is also communicated to the driver via the radio channel. That is the procedure used in case infrastructure workers identify an emergency.

Adopted notations and assumptions:

1. The original sources of driver assistance shall be named "aggregators";

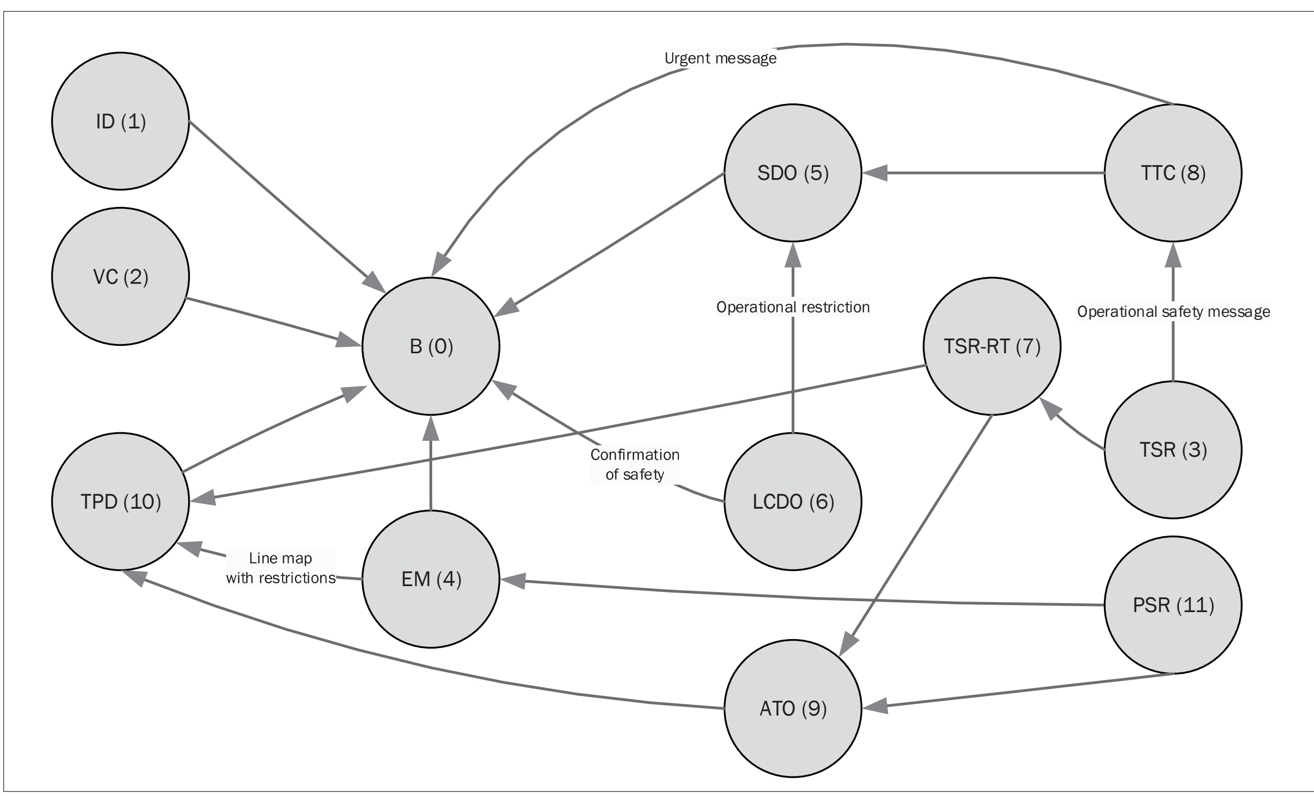


Figure 1. *Graph of interaction between a driver and the aggregators and actions aimed at improving the probability of error-free performance of train control actions*

2. The aggregators are mutually independent;
3. Each aggregator can generate one or more actions to assist the driver;
4. Each actions have a random effect of the reduction of the probability of driver error;
5. The effects of the aggregators on the probability of driver error are mutually independent;
6. The probability of error g_D is take as the quantitative measure of error;
7. Probability p_i , where i = 1,2,... m and m is the finite number of the effect of known actions aimed at reducing the probability of driver error is adopted as the quantitative measure of the effect of an action on the reduction of the probability of driver error;
8. The resultant measure of reduction of the probability of driver error is the product of the probabilities of the effect of all actions caused by the environment aggregators on the driver performance.

The diagram in Fig. 1 uses the following notations:

0, driver (D);

1, actions of the instructing driver (ID);

2. action of the driver vigilance control device (VC);

3. action of the automated system for track condition monitoring and generation of temporary speed restrictions (TSR). Temporary speed restrictions are displayed to the station duty officer and are transmitted to the train protection device (TPD) and ATO system. The ATO and TPD systems advise the driver on the optimal and safe clearance of the received restriction;

4. action of the electronic map of the line (EM);

5. action of the station duty officer (SDO);

6, action of the level crossing duty officer (LCDO);

7. action of the data of the TSR radio transmission to the locomotive (TSR-RT);

8. action of the train traffic controller (TTC);

9. action of the automatic train operation (ATO) system;

10. action of the train protection device (TPD);

11. action of the automated system for digital map generation and issuance of permanent speed restrictions (PSR). Permanent speed restrictions are loaded into the TPD and ATO databases, as well as the TSR. The TPD and ATO systems advise the driver on the optimal and safe clearance of the received restriction.

According to the diagram in Fig. 1 the finite number of known actions aimed at reducing the probability of driver error is m = 11.

In turn, the aggregators, i.e., original sources of data, are: 1, 2, 3, 6 and 11 nodes of the diagram.

The probability of error-free driver performance within the environment shown in Fig. 1 equals

$$p_D = 1 - G_D \tag{1}$$

The probability of driver error G_D is calculated using formula:

$$G_D = g_D W \tag{2}$$

where W is the resulting reduction of the probability of driver error as the result of designated actions within the examined environment.

In accordance with the diagram in Fig. 1

$$W = (1 - p_1) C_1 (1 - p_2) C_2 (1 - p_3) C_3 (1 - p_6) C_6 (1 - p_{11}) C_{11}, \tag{3}$$

where $C_1 = C_2 = 1$,

$$C_3 = (1 - p_8)(1 - p_8 p_5)(1 - p_7 p_{10})(1 - p_7 p_9 p_{10});\ C_6 = (1 - p_5);\ C_{11} = (1 - p_4)(1 - p_4 p_{10})(1 - p_9 p_{10}). \tag{4}$$

Thus, the probability of error-free driver performance within the environment equals

$$p_D = 1 - g_D (1 - p_1)(1 - p_2)(1 - p_3)(1 - p_8)(1 - p_8 p_5)(1 - p_7 p_{10})(1 - p_7 p_9 p_{10})(1 - p_6)(1 - p_5)$$
$$(1 - p_{11})(1 - p_4)(1 - p_4 p_{10})(1 - p_9 p_{10}) \tag{5}$$

It should be noted that in various operational situations the effect of the factors would differ. An example of evaluation of the effect will be examined in the following paper.

Let us analyse the deduced formula (5).

If none of the designated actions had an effect, then $p_i = 0$, i = 1,2,...,11 and the probability of driver error $p_D = 0$, as W = 1.

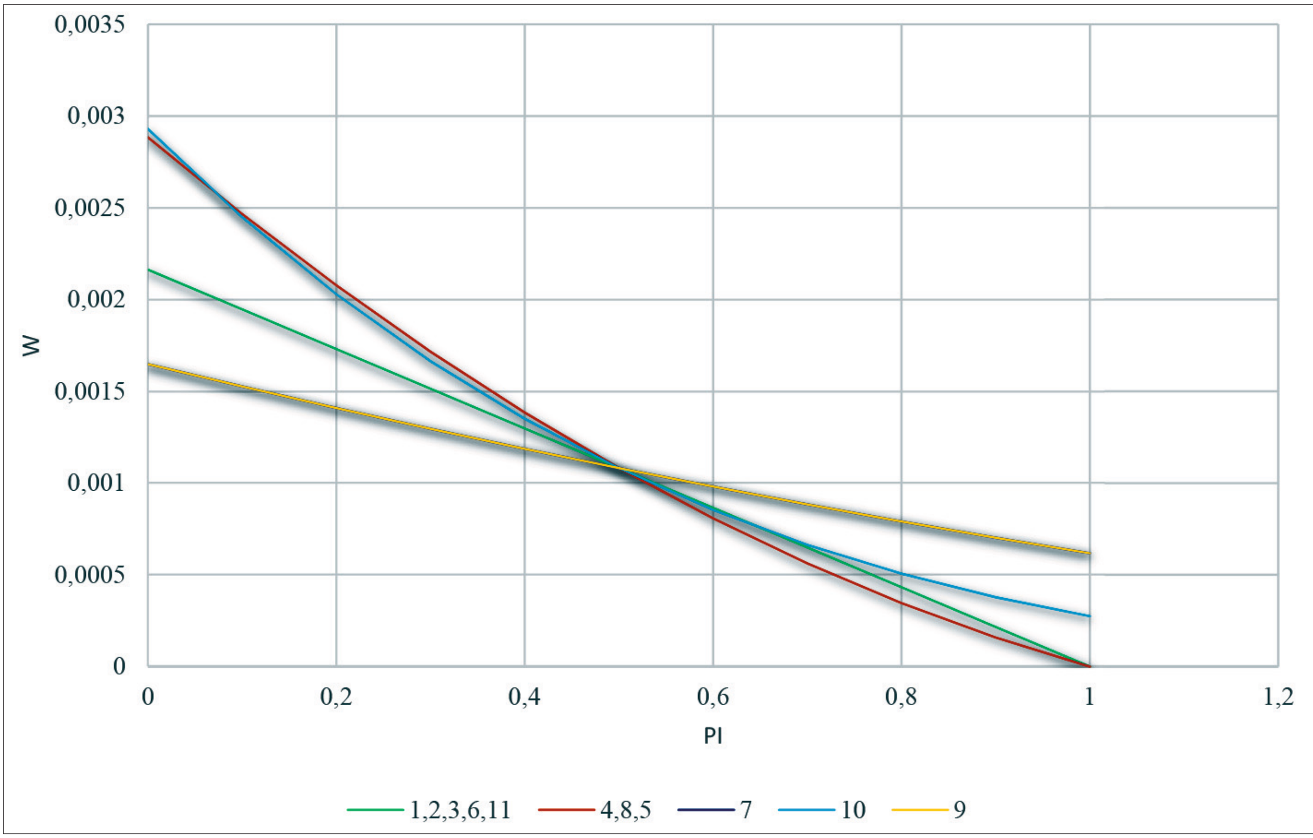


Figure 2. *Dependence $W(p_i)$*

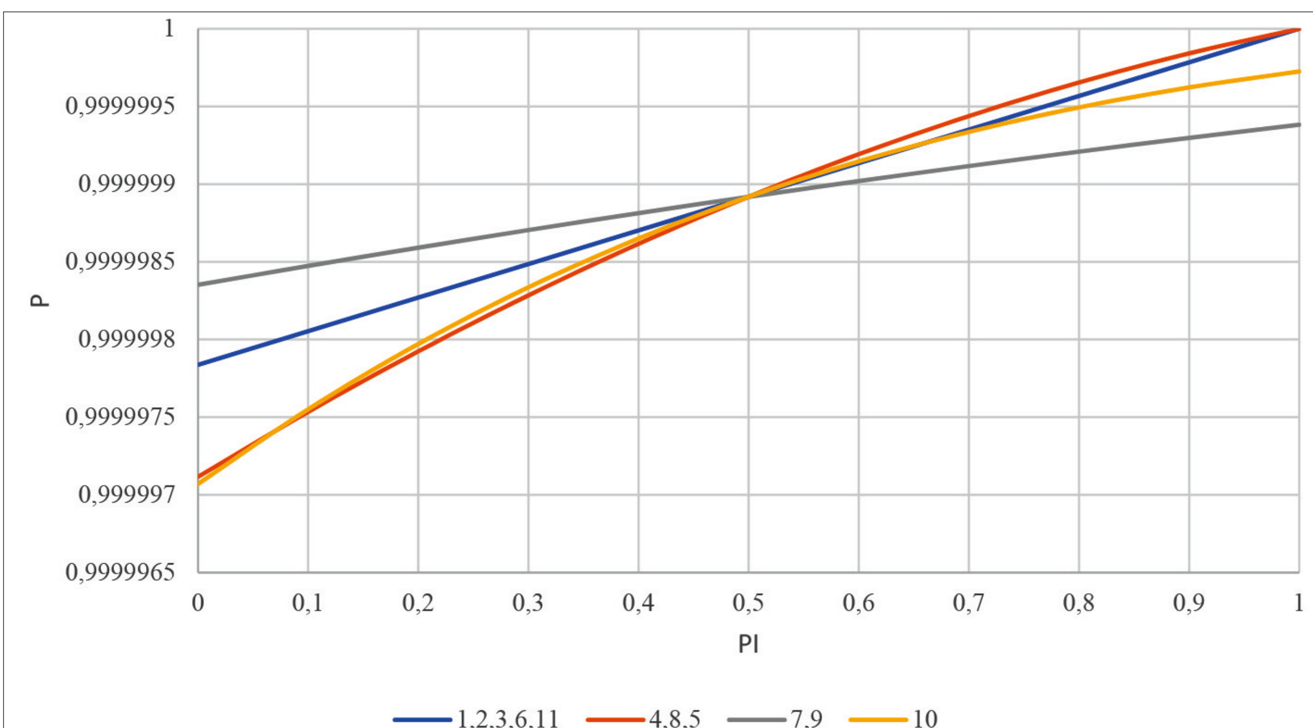


Figure 3. *Dependence and $p_D(p_i)$*

In turn, if at least one of the designated actions, in some cases in combination with others, produced a complete effect, i.e., one of the multipliers became equal to 0, then $p_D = 1$, as in that case $W = 0$.

Let us evaluate the effect of each action on the resulting probability of error. In order to identify the highest effect we will examine each probability p_i within the range between 0 and 1, while the remaining probabilities will be fixed at $p_i = 0.5$, $i = 1,2,...,11$. The probability of driver error will be adopted as $g_D = 10^{-3}$, that value being average [5]. The dependence graphs $W(p_i)$ and $p_D(p_i)$ are shown in Figures 1 and 2, respectively.

The graphs show that as the probability of successful driver assistance action increases the resulting probability grows. High values of TPD, TTC, SDO and EM have the highest effect on the final indicator. Under low probabilities the aggregators, TSR-RT and ATO have the highest effect.

Thus, if the values of error-free performance of the examined actions and aggregators are below 0.5 the highest effect is produced by the ATO and TSR-RT, while the TPD and other actions do not have a pronounced effect. However, if the probabilities are above 0.5, the situation changes dramatically. The lowest effect is produced by the ATO and TSR-RT. Between 0.5 and 0.7, the effect of the remaining factors is about the same. As the values near 1, the effect of the TPD somewhat decreases. As the probabilities of performance under normal conditions are above 0.5, it can be concluded that effort should be made to ensure the probability of correct performance of the TPD, TTC, SDO and EM, because they have a significant effect on the probability of error-free performance.

In the next article we will examine a case study involving the evaluation of the effect of each aggregator and action on the resulting probability of error-free driver performance in a specific operational situation.

REFERENCES

[1] Rozenberg E.N., Umansky V.I., Dziuba Yu.V. [Digital economy and digital railways]. Transport Rossiyskoy Federatsii. Zhurnal o nauke, praktike, ekonomike 2017;5:72. (in Russ.)

[2] Gapanovich V.A., Shubinsky I.B., Zamyshlyaev A.M. Mathematical and information support of the URRAN system. Dependability 2013;1:12-19.

[3] [PTE ZhD RF – Rules of operation of the railways of the Russian Federation approved by order of the Ministry of Transportation of Russia no. 286 dated 21.12.2010 (as amended on 25.12.2018)]. (in Russ.)

[4] Kirwan B., Gibson H. CARA: A human reliability assessment tool for air traffic safety management – Technical basis and preliminary architecture. In: The safety of systems. London: Springer; 2007. P. 197 – 214.

[5] Hinzen A. The effect of the human factor on the safety of railways. Institute of Transport Science. RWTH Aachen University; 1993.

[6] Kulagin M.A. [Intelligent system for analysis and prediction of train control violations: a Candidate of Engineering thesis.] Russian University of Transport; 2022. (in Russ.)

[7] Pereverzev I.G., Finichenko T.A., Balanova M.V., Gomelev V.V. [The role of the “human factor” in ensuring the safety of railway transportation]. In: Proceedings of the III International Science and Practice Conference Transportation and Logistics: Strategic Priorities, Technology Platforms and Solutions in a Globalised Digital Economy. Rostov-on-Don: Rostov State Transport University; 2019. P. 303 – 307. (in Russ.)

[8] Kulagin M.A., Sidorenko V.G., Markevich A.V. [The effect of the human factor on the train traffic safety]. In: Proceedings of the XXVII International Science Conference Problems of Safety Management of Complex Systems; 2019. P. 265 – 270. (in Russ.)

[9] Cooper S.E., Ramey-Smith A.M. A technique for human error analysis: Technical Basis and Methodology Description. USNRC: Washington, DC; 1996.

[10] Gertman D., Blackman H., Marble J., Byers J. The SPAR-H human reliability analysis method. US Nuclear Regulatory Commission 2005;230:35.

[11] Foreser J.A., Ramey-Smith A., Bley D.C. Discussion of comments from a peer review of a technique for human event analysis (ATHEANA). Los Alamos: Sandia National Laboratories; 1998.

[12] [Method of evaluating the effect of the human factor on the occurrence of injuries at work and apportionment of responsibility of the employees involved in the event]. Approved by Senior Vice-President V.A. Gapanovich no. 2777r dated 28.11.2014. (in Russ.)

[13] Zavialov A.M., Astashkina L.A., Zavialova Yu.V. [Ways of reducing the effect of the human factor on the traffic safety in the locomotive service of the railway industry]. In: [Modern approaches to ensuring hygienic, sanitary, and environmental safety in the railway industry: collected papers of researchers and experts of the transportation industry, II issue]. Moscow: VNIIZhT; 2016. P. 137 – 144. (in Russ.)

[14] Aksionov V.A., Zavialov A.M., Zavialova Yu.V., Siniakina I.N. [The role of the human factor in ensuring the safety of business processes in transportation]. East Ukrainian Volodymyr Dahl National University 2013;18(207):151 – 155. (in Russ.).

Received: September 28, 2023
Accepted: November 10, 2023

About the authors

Igor Shubinsky is the Deputy Head of Integrated Research and Development Unit of JSC NIIAS, Doctor of Engineering, Distinguished Professor, expert of the Scientific Council for Information Security under the Security Council of the Russian Federation. His research interests include methods of analysis and synthesis of functional dependability and functional safety of complex systems, adaptive fault-tolerance of information systems, management of technical assets based on their dependability and safety status and risk assessment. He has authored 37 monographs and textbooks, over 400 papers and over 40 patented inventions.

Efim Rozenberg is the First Deputy Director General of JSC NIIAS, Doctor of Engineering, Distinguished Professor. He is a recipient of the award of the Government of the Russian Federation in the field of science and technology. He was awarded the title of Honored Designer of the Russian Federation, Best Innovator of JSC Russian Railways. Professor Rozenberg leads research and development in train control and protection including signalling, train separation, automatic train operation, traffic safety, communication, cybersecurity. He is an author of about 300 research papers and about 400 patented inventions.

Natalia Boyarinova is a Senior researcher of Centre for Safety and Algorithmic Support of JSC NIIAS. In 2013, she graduated with honors from the Moscow State Transport University. Her areas of research interests are functional safety, risks in railways, autonomous systems, automatic control, methods for safety verification. She was awarded an honorary certificate for high professional competence, dedication and outstanding performance. She has authored 2 scientific papers and 1 patented inventions.

For citation

Igor Shubinsky, Efim Rozenberg, Natalia Boyarinova, The Dependability and Safety Indicators of a Train Driver-Machine System, *JITA – Journal of Information Technology and Applications, Banja Luka*, Pan-Europien University APEIRON, Banja Luka, Republika Srpska, Bosna i Hercegovina, JITA 13(2023) 2:66-71, (UDC: 629.11:656.073.436), (DOI: 10.7251/JIT2302066S, Volume 13, Number 2, Banja Luka, December (57-120), ISSN 2232-9625 (print), ISSN 2233-0194 (online), UDC 004

Evaluation of the Effect of Operational Scenarios on a Train Driver Performance

Igor Shubinsky, Efim Rozenberg, Natalia Boyarinova

Research and Design Institute for Information Technology, Signalling and Telecommunications on Railway Transport (NIIAS), Moscow, Russia, n.boyarinova@vniias.ru

Contribution to the State of the Art

https://doi.org/10.7251/JIT2302072S UDC: 656.073.436:629.11

Abstract: This paper aims to numerically evaluate the effect of existing actions to assist a train driver in various operational situations, as well as select the indicators of error-free operation ending on the form of activity and other factors. The effect of each individual examined factor on the resulting indicator was evaluated, operational situations were examined taking into account the proportion of times when the action has a positive effect. A few practical cases were examined, whereas the method can be used.

Keywords: safety of a man-machine system, increasing the probability of error-free transportation process performance, driver's operational environment.

In the previous paper we made an attempt to assess the effect of the existing actions to assist a train driver in various operational situations. Now let us analyse the effect of each aggregator and action on the resulting probability of error-free driver operation in a specific operational situation.

The probability of error-free human operation is affected by a number of factors. The most significant ones include the psychological and physiological factors of stress, types of situation and activity, time allowed for decision-making [1]. The probabilities of human error when performing various types of activities under various psychophysiological conditions differ.

Thus, [2] cites the following ranges of human error frequency depending on the type of activity:

Activity	Error frequency. Mean value range
Reaction to a signalling device	0.00005 – 0.001
Reading signals off of a digital screen	0.0005 – 0.005
Reading analogue instruments	0.001 – 0.01
Writing down more than three numbers	0.0005 – 0.005
Selection of the adjusting device on a functionally divided panel	0.0005 – 0.005
Switching a multiple-position switch	0.0001 – 0.1
Reading instruments with limiting markers	0.0005 – 0.005
Performance of a set sequence of actions	0.003 – 0.03

In [3], the following indicators of error-free human performance as part of various types of activities are given:

Activity	Coefficient of error-free operation
Reading manuals	(0.9901)
Reading electronic instruments	(0.9928)
Switching a multiple-position switch	(0.9940)
Reading a pressure gauge	(0.9952)
Setting switches into the "0" position	(0.9959)
Checking the time	(0.9966)

The probability of error depending on the type of activity associated with an exchange of information given in [4]:

Activity	Error coefficient
Speech acquisition	
Loudness and tone	
Significantly above the level of noise	$5*10^{-4}$
Insignificantly above the level of noise	$1*10^{-3}$
Practically equal to the level of noise	$5*10^{-3}$
Ambiguity	
Ambiguity allowed	$5*10^{-3}$
Definitely ambiguous	$5*10^{-3}$

Repeat	
No repeat	9*10^{-4}
Repeat	3*10^{-4}

[1] cites the following statistical data regarding the probabilities of human error:

Name of operation	Error probability
Perception of a verbal message (1 – 3 words)	0.0002
Issuance of a verbal message (1 – 3 words)	0.0002
Reading (1 – 3 words)	0.0010
Taking notes (1 – 3 words)	0.0003
Perception of alarm light, sign	0.0035
Perception of plates	0.0014
Perception of indicating meters	0.0072
Perception of digital device indications	0.0012
Pushing a button	0.0025
Pressing the required key	0.0050
Switch actuation	0.0020
Setting a selection switch into the required position	0.0044
Connecting cables	0.0032
Disconnecting a bullet connector	0.0009
Setting controller handle parameter	0.0094
Same for handwheel	0.0100
Same for lever	0.0150
Selecting out of several different switches	0.0001
Intense work with quickly changing situations	0.2 – 0.3

The probability of error significantly differs depending on the time allocated for decision-making and activity performance. In [1], the following indicators are given:

Time allocated for decision-making and activity performance	Probability of erroneous action of qualified personnel
Very short (less than 5 min)	0.1
Short (5 to 60 min)	10^{-3}
Long (more than 1 h)	3*10^{-4}

[5] cites the following frequencies of operator error when put under stress and depending on the time allocated for decision-making

Time to react	Probability of error
The action must be taken within the first 60 seconds upon the beginning of the stressful situation	~1.0
The action must be taken within the first 5 minutes upon the beginning of the stressful situation	9*10^{-1}
The action must be taken within the first 30 minutes upon the beginning of the stressful situation	10^{-1}
The action must be taken within several hours upon the beginning of the stressful situation	10^{-2}

The above results show that, depending on the type of action, presence of stress and availability of time for decision-making, the probability of human error may differ by 4 orders of magnitude. Having analysed the above statistical data, we can conclude that the presence of stress increases the probability of error by an order of magnitude, while the reduction of the time allocated for decision-making decreases this indicator by another order of magnitude.

In order to identify the probability of error in the course of interaction with

- an instructing driver (ID) p_1,
- a level crossing duty officer (LCDO) p_6,
- a line-level train traffic controller (TTC) p_8,
- a station duty officer (SDO) p_5,

let us use statistics on the frequency of human errors in the types of activity associated with the exchange of information, as the interaction occurs through verbal communication and issuance of commands and recommendations as to proceed along specific lines. Let us evaluate the effect of the factors by the lower bound, i.e., in the worst conditions out of those considered, namely the perception of speech under multitasking and high level of interference. Let us adopt $1 - p_1 = 1 - p_5 = 1 - p_6 = 1 - p_8 = 5 * 10^{-3}$ as the probability of error.

While evaluating the effect of a database error on the driver performance it must be taken into consideration that in most cases databases are populated by specialised personnel, and a population error is two orders of magnitude higher than the error of the system's electronic components in the process of data storage and communication that is about 10^{-5}, therefore the probability of error of temporary restrictions p_3 and permanent restrictions p_{11} will be taken equal to the probability of error of writing with the number of signs greater than 10 [6] $1 - p_3 = 1 - p_{11} = 4*10^{-4}$.

In order to identify the probability of error-free operation of electronic devices, including the vigilance control (VC) p_2, TSR radio transmission to the locomotive (TSR-RT) p_7, and automatic train operation (ATO) p_9, let us use the data on the dependability of single-channel SIL0 devices. The probability of failure per hour of such devices is 10^{-5}, therefore $1 – p_2 = 1 – p_7 = 1 – p_9 = 10^{-5}$. The safety integrity level of the train protection device and electronic map is SIL4, therefore $1 – p_4 = 1 – p_{10} = 10^{-9}$.

In order to identify the base probability of driver error let us take into consideration the time to react and presence of stress. In the examined operational situation the decision-making time is limited to several dozen minutes, as the situation is an emergency, it is assumed that the driver is stressed, therefore the base indicator of probability of driver error is taken to be equal to $g_D = 5*10^{-2}$.

Obviously, depending on the operational situation the set of auxiliary actions varies. Simultaneous assistance of all system components appears to be unlikely. In order to evaluate the effect, let us introduce an additional coefficient that takes into account the proportion of time when an action or an aggregator has a positive effect.

Then, formula (1) will become as follows

$$p_D = 1 – g_D (1 – p_1 k_1)(1 – p_2 k_2)(1 – p_3 k_3)(1 – p_8 k_8)(1 – p_8 k_8 p_5 k_5)(1 – p_7 k_7 p_{10} k_{10})(1 – p_7 k_7 p_9 k_9 p_{10} k_{10})(1 – p_6 k_6)(1 – p_5 k_5)(1 – p_{11} k_{11})(1 – p_4 k_4)(1 – p_4 k_4 p_{10} k_{10})(1 – p_9 k_9 p_{10} k_{10}) \quad (1),$$

where k_1 is the coefficient that takes into account the proportion of time when an action or aggregator may have a positive effect on the driver.

Let us examine the following operational situation:

The train protection device (TPD) has failed and the driver is to perform “removal of the train from the open line” subject to the time restrictions of the driver’s list of warnings (DU-61) and assistance of the instructing driver who has knowledge of the presence of permanent restrictions [7].

Let us calculate the probability of error G_D when moving on a section other than a level crossing:

$g_D = 5*10^{-2}$

$p_1 = p_5 = p_6 = p_8 = 5*10^{-3}$

$p_3 = p_{11} = 4*10^{-4}$

$p_2 = p_7 = p_9 = 10^{-5}$

$p_4 = p_{10} = 10^{-9}$

$k_1 = 1$, as in this operational situation the instructing driver completely monitors the operation and assists the driver;

$k_2 = 0$, as when the TPD fails, in this operational situation the instructing driver performs the function of vigilance control;

$k_3 = 1$, as the driver uses temporary speed restrictions from DU-61 and ATO;

$k_6 = 0$, as according to the conditions the driver does not move over a level crossing;

$k_8 = k_5 = 0$, as the operational situation is out of the competence of TTC and SDO;

$k_9 = 0$, as the automatic train operation does not enforce the allowed speed;

$k_{10} = k_4 = 0$, as according to the conditions the TPD and electronic map of the line (EM) have failed;

$k_{11} = 0$, as the electronic devices have no access to the database.

Thus, the probability of driver error when the train moves other than over a level crossing can be calculated as follows:

$$g_D = 0{,}05(1 – 0{,}995*1)(1 – 0)(1 – 0{,}9996*0)(1 – 0)(1 – 0)(1 – p_7\, 0)(1 – p_7\, 00)(1 – 0{,}995*1)(1 – 0)(1 – 0)(1 – 0)(1 – 00)(1 – 00) = 1{,}25*10^{-6}.$$

When the train moves over a level crossing the probability of driver error is

$$g_D = 0{,}01(1 – 0{,}995*0)(1 – 0)(1 – 0{,}9996*1)(1 – 0)(1 – 0)(1 – p_7\, 0)(1 – p_7\, 00)(1 – 0{,}995)0{,}5(1 – 0)(1 – 0)(1 – 0)(1 – 00)(1 – 00) = 1*10^{-7}.$$

Practical results:

1. The creation of a driver operational environment containing certain auxiliary actions and sources of additional information on a railway line and the restrictions in force allow reducing the probability of error and significantly improving the probability of error-free driver performance.
2. The TPD, TTC, SDO and EM have the highest effect on the indicator of fault-free operation. Of significant importance are the sources of data, including ID, VC, LCDO and database information on the temporary and permanent restrictions.
3. The effect of various actions and information depends on the operational situation.

References

[1] Aksionov V.A., Zavialov A.M., Zavialova Yu.V., Siniakina I.N. [The role of the human factor in ensuring the safety of business processes in transportation]. East Ukrainian Volodymyr Dahl National University 2013;18(207):151 - 155. (in Russ.)

[2] Swain A.D., Guttmann H.E. Handbook of Human Reliability Analysis with Emphasis on Nuclear Power Plant Applications", Draft (short version). Washington, DC: US Nuclear Regulatory Commission; 1979. Pages 20/38 onwards.

[3] Irwin I.A., Levitz J.J., Freed A.M. Human. Reliability in the Performance of Maintenance. In: Topmiller D.A., Eckel J.S., Kozinsky E.J. Human-reliability data bank for nuclear power plant operations. Volume 1. A review of existing human-reliability data banks. Nuclear Regulatory Commission; NUREG / CR-2744/1.

[4] Munger S.J., Smith R.W., Payne D. An index of electronic equipment operability. In: Topmiller D.A., Eckel J.S., Kozinsky E.J. Human-reliability data bank for nuclear power plant operations. Volume 1. A review of existing human-reliability data banks. Nuclear Regulatory Commission; NUREG / CR-2744/1.

[5] Hagen E.V. Monitoring and tools, nuclear safety. 1976;17(3).

[6] [STATUTE on the instructor driver of locomotive crews of the Motive Power Directorate]. Approved by order no. 707/r dated 09.04.2018. (in Russ.).

Received: September 23, 2023
Accepted: November 12, 2023

About the authors

Igor Shubinsky is the Deputy Head of Integrated Research and Development Unit of JSC NIIAS, Doctor of Engineering, Distinguished Professor, expert of the Scientific Council for Information Security under the Security Council of the Russian Federation. His research interests include methods of analysis and synthesis of functional dependability and functional safety of complex systems, adaptive fault-tolerance of information systems, management of technical assets based on their dependability and safety status and risk assessment. He has authored 37 monographs and textbooks, over 400 papers and over 40 patented inventions.

Efim Rozenberg is the First Deputy Director General of JSC NIIAS, Doctor of Engineering, Distinguished Professor. He is a recipient of the award of the Government of the Russian Federation in the field of science and technology. He was awarded the title of Honored Designer of the Russian Federation, Best Innovator of JSC Russian Railways. Professor Rozenberg leads research and development in train control and protection including signalling, train separation, automatic train operation, traffic safety, communication, cybersecurity. He is an author of about 300 research papers and about 400 patented inventions.

Natalia Boyarinova is a Senior researcher of Centre for Safety and Algorithmic Support of JSC NIIAS. In 2013, she graduated with honors from the Moscow State Transport University. Her areas of research interests are functional safety, risks in railways, autonomous systems, automatic control, methods for safety verification. She was awarded an honorary certificate for high professional competence, dedication and outstanding performance. She has authored 2 scientific papers and 1 patented inventions.

For citation

Igor Shubinsky, Efim Rozenberg, Natalia Boyarinova, Evaluation of the Effect of Operational Scenarios on a Train Driver Performance, *JITA – Journal of Information Technology and Applications, Banja Luka*, Pan-Europien University APEIRON, Banja Luka, Republika Srpska, Bosna i Hercegovina, JITA 13(2023) 2:72-75, (UDC: 656.073.436:629.11), (DOI: 10.7251/JIT2302072S, Volume 13, Number 2, Banja Luka, December (57-120), ISSN 2232-9625 (print), ISSN 2233-0194 (online), UDC 004

Study of Training Quality of Multilayer Artificial Neural Networks with Variable Signal Conductivity in Scheduling Problems

Alexey Olshansky

Research and Design Institute for Information Technology, Signalling and Telecommunications on Railway Transport (NIIAS), Moscow, Russia, a.olshansky@vniias.ru

Contribution to the State of the Art

https://doi.org/10.7251/JIT2302076O UDC: 004.032.26:556.131

Abstract: The paper studies approaches to railway scheduling problems using artificial neural networks (ANNs). The authors analyze traditional learning algorithms and difficulties for their application. The description of ANN's behavior is provided in the form of a phase portrait. New approaches and techniques are proposed for quality improvement of training of multilayer ANNs with variable signal conductivity.

Keywords: artificial neural networks, scheduling problems, learning algorithms, intelligent adaptive control.

Introduction

Scheduling tasks are of great importance and well known in railway transportation. The most common scheduling tasks are as follows:

- routing problems (combinatory optimization problems where a set of routes to several consumer points has to be found for a fleet of vehicles located at one or more source points);
- timetabling tasks (preparation of train timetables in such a way that they should meet all available time constraints);
- volume planning tasks (traffic distribution with the required volume of transportation taken into account);
- timetabling and volume planning (preparation of train timetables considering all possible constraints);
- volume planning and routing tasks (construction of train timetables and preparation of routes);
- other optimization tasks.

The main difficulties in solving these problems by strict methods are combinatory complexities, exhaustive searches, computer memory deficiency, and time-consuming computations to reach an optimal solution.

In this case a number of heuristic algorithms are used. For example:

- The Monte Carlo method. In scheduling problems, this method allows obtaining a series of approximated solutions, from which it is required to choose the best one. However, it is obvious that any verified change in the operation of a railway line will lead to necessarily changing the basic parameters of an algorithm, i.e. the type of a random value's distribution function, mathematical expectation, dispersion etc.
- Methods of dynamic programming (Bellman equation). The main idea of this method is the decomposition of a complex problem into a number of simple ones, whose solution is reduced to calculating a single variable. The method allows constructing a schedule using the optimality of any part of a schedule when it is optimal in general.

To sum up on the above methods, it should be noted that to achieve an optimal solution one needs to have numerous tests, and it increases time expenditures, while not giving any guarantee that an obtained solution will be close to optimality.

Approaches to scheduling problems using artificial neural networks

In this context, algorithms based on or constructed using ANN stand out. The reason is that artificial neural networks have a number of qualities inherent in a human brain and not available in classical computer architectures, capable of learning with and without a teacher, and consolidating accumulated knowledge.

Neural network solutions are applied to various types of scheduling tasks. There are various types of solutions.

David R. Martinelli and Hualiang Teng in [1] use a neural network to prepare a train formation plan. A train formation plan is the basis for further construction of freight trains' paths. They state the following task – for a given network of railway stations with existing routes, a table of requests and a given number of wagons one has to construct a train formation plan to satisfy requests.

The authors solve this problem using a multilayer perceptron. The input layer contains as many neurons as there are requests for transportation, the output layer contains as many neurons as there are possible combinations of "request – scheduled train". By training this network on existing training examples using the method of error back propagation, one can have new solutions satisfying these constraints.

The disadvantages of the method are the dependence of a neural network on the available options of a train formation plan and the necessity to retrain it every time the configuration of wagon flows changes.

For instance, papers [2-3] are based on the use of Hopfield networks. The paper [4] considers the issue of scheduling using Hopfield networks applied to the distribution of tasks across several processors. However, the method also has its drawback that is represented by a repeated use of heuristics and necessity to solve complex equations to obtain a schedule, even when some equations are already available.

To avoid problems associated with the use of Hopfield neural networks, such as long working hours and the amount of memory required, the authors of [4] propose to use the competition of neurons. The simulation results show that a competitive neural network with the constraints taken into account in the proposed energy function provides a more suitable approach to solving such a class of planning problems as traveling salesman problems.

Paper [5] considers timetabling classes at university using neural networks. The authors have adapted the Hopfield methodology to the task of timetabling classes: a neural network interpretation of the task is given, specific constraints of the energy function are considered, and the neural network is synthesized. The timetable of a certain number of classes that should be distributed by class rooms with constraints taken into consideration is presented in the form of integer piecewise-constant functions of time. As in the papers described above, the design of a neural network is selected and its energy function is configured. The authors note that they only developed an approach to construction of class timetables. They don't calculate the coefficients of the obtained function, they don't consider the issues of achieving its minimum and, respectively, they don't evaluate the quality of the resulting neural network solution.

A Hopfield neural network is often used in scheduling tasks. However, it is only used with the following restriction – of importance is only the final distribution of resources (free / busy). This network can't be applied in the following cases:

- It matters how the state of these resources changed;
- The state of a resource at a given moment of time should be equal to the state of a resource at the previous moment of time;
- These sequences should be memorized as well as shifted in a two-dimensional coordinate space (e.g. time-distance).

As it is seen, the analyzed papers reflect the implementation of a Hopfield network for processors, class timetables, but not for the systems in which the previous behavior determined the behavior at subsequent moments, and a railway line being that type of a system.

Let us consider some more materials where neural networks are applied to transport problems. In [6], neural networks, as one of the methods, are used to predict congestion of roads in the city.

The application of Hopfield neural networks to optimize airport operations (aircraft landing scheduling) is given in [7].

As a target function for an airport with different aircrafts the paper considers the minimization of a landing time interpreted as a time interval between the arrival of the first and the last aircrafts.

For this purpose, possible modes of aircraft landing – sequences – are encoded as chains. The classical function of Hopfield networks is used as an energy function, where one of the parts implies constraints (such as the impossibility of two planes to land on the same strip at the same time), and the second minimizes the landing time (using pairs of integer binary values of the output signals of Hopfield neurons).

As soon as the Hopfield network has come to a stable state, mutation is applied to the individual outputs and the process of calculation of the energy function is repeated.

This task is more like the task of constructing a schedule for a single-track railway line, however, since not all planes are connected to each other upon arrival, and the behavior of a subsequent train on a single-track line depends on the behavior of a previous one, there are substantiated assumptions that the form of an energy function when constructing a railway schedule can be different from that indicated in [7].

For instance, V. A. Kostenko and A. V. Vinokurov in their paper study the issue of scheduling by using Hopfield networks [4] applied to the distribution of tasks across several processors. A number of problems should be solved to obtain solutions for combinatory optimization problems using neural networks of this class:

- To translate a task into the "language" of neural networks means to find correspondence between the states of neurons and the values of optimized parameters.
- To construct a network energy function given the constraints and the target function. The energy function of a network at the minimum points of the target function should also have minimum points. If the constraints are violated, there should be fines increasing the value of the energy function.

There arise two complex controversial issues:

1. How can we establish correspondence between the members of a network energy function and the members of the general form of network energy?
2. How can we calculate weighting factors for penalty functions?

The author of the paper obtains coefficients for penalty functions using heuristics, noting that their values are subject to future research. Analyzing the influence of the number of processes and processors on the number of correct decisions obtained, he comes to the conclusion that the optimal algorithm for constructing a timetable will be:

a. obtaining a schedule using a heuristic algorithm;
b. obtaining bindings by the Hopfield network, provided that there are no restrictions on the order of the processes using the schedule obtained in paragraph 1, as an initial approximation;
c. obtaining order by a heuristic algorithm of local optimization.

The disadvantage of this method is the repeated use of heuristics and the need to solve complex equations to obtain a schedule, even taking into account the existing restrictions.

In addition to the use of neural networks to solve schedule tasks per se, let us consider such an aspect as modifying the designs of neural networks in terms of rebuilding internal elements and modifying the entire or partial network structure.

Multilayer artificial neural network with variable signal conductivity

One of the attempts to overcome these shortcomings in the subject field of railway transport is the development of a multilayer artificial neural network with variable signal conductivity (abbreviated as MANN VSC) to the issues of scheduling. This was first done in 2015 [8], and is currently the main source for research in the field of improving the quality of education.

MANN VSC is a hybrid neural network that combines the characteristic features of a multilayer perceptron, the Wilshaw-van der Malsburg network with the Hopfield network.

In the paper by Ignatenkov A.V. [9] the following explanations are given: "... from the point of view of the architecture of artificial neural networks, it is important to note one feature the developed neural network must satisfy: the importance of not only the value of the network error function on the output layer, but also the importance of the path from the start neuron through the layers to the final neuron of the network ...". This aspect is considered in the topology below.

The topology of the special neural network with variable signal conductivity described in [10] is given in Fig . 1

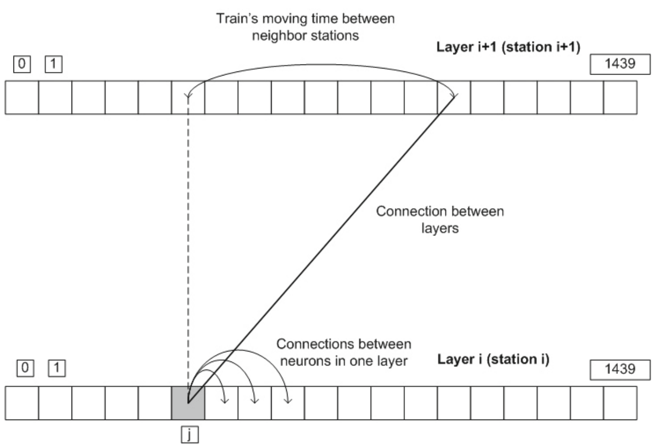


Fig 1. *The topology of MANN VSC*

The number of layers is equal to the number of railway stations. Each layer has 1440 neurons, which is equal to the number of minutes in the period of twenty-four hours.

From each neuron of the *i*-th layer, there are connections to each neuron of the next layer (a total of 1440 links). In addition, each neuron is associated with several neurons on the left (i.e., with neurons with a smaller number) and on the right (with neurons with a larger number).

Each matrix of weights W between two layers with numbers i, i+1 is a square matrix with the number of rows and columns equal to 1440.

$$W_{i,i+1} = \begin{pmatrix} w_{0,1} & \cdots & w_{0,1339} \\ \vdots & \ddots & \vdots \\ w_{1339,0} & \cdots & w_{1339,1339} \end{pmatrix},$$

where W_{ij} is the weight value on the link connecting the neuron with the i-th layer number and the neuron with the j-number of the adjacent layer.

Possible states of the neuron are: "active" – the input signal can be received at the input of the corresponding neuron, "sleep" – the value of the potential of the given neuron is zero, "off" – the neuron cannot receive signals from the previous layer. The states of "sleep" exist for both even and odd directions.

Weights of constraints are initially specified randomly by real numbers from zero to 0.1. Later they change as the neural network is trained. The transit of the signal through the connections between the neurons of neighboring layers displays the process of the train running along the path between the stations. Note that all weights of links from a neuron with number j from 0 to $j+t$ (where t is minimum travel time) are taken equal minus infinity. These weights never change.

Under normal conditions this network is trained according to several algorithms based on error back propagation and featuring some specifics:

1. MANN model for calculating the output vector of the network based on the competition of links for signal transit. Note that the values of the network's output vector and the vector defining the state of the network are different in their physical sense, i.e. the input and the output of the network illustrates the points of entry and exit of a signal, while the values of neurons activation don't have any explicit physical sense.

2. Special learning algorithms for MANN with alternate changing of weights, i.e. the weights which help to reduce MANN's errors increase while the weights preventing the reduction of errors are reduced.

Unlike existing learning algorithms, a fixed initial learning speed is used and an increase in the learning speed of the network is proposed depending on the past number of epochs. In addition, the ratio between the rate of increase of weights and the rate of decrease of weights is regulated by a special function.

When testing and using the resulting network on simulation models of railway lines in 2015-2019, various schedules were obtained with the load level of 185 processes per day. The computational complexity of the neural network is $O(m^2n) + O(mn^2)$ for m neurons in the layer and n layers.

Therefore, the issue of improving the quality of training is relevant. Some main principles of modelling control strategies for such objects were briefly described in [10]. To this end, many attempts have been made, and their results will be shown below.

Training of MANN in terms of digital signal processing

In a particular case when the error function could be described as a sum of sinusoidal harmonics with different frequencies and amplitudes we may use the results obtained in [11]. In a general case we are not sure in this signal error representation.

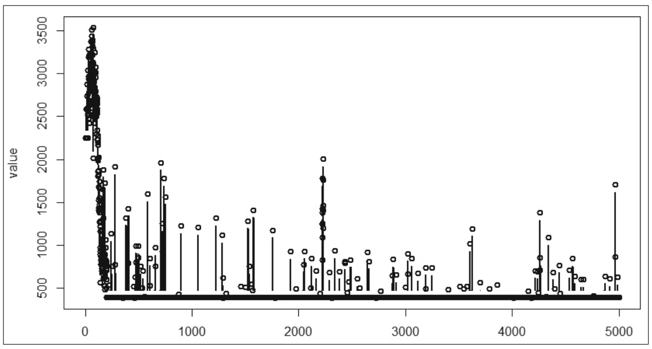


Fig. 2. One example of error function

To analyze the behavior of the error function we plot its autocorrelation function (Fig. 3).

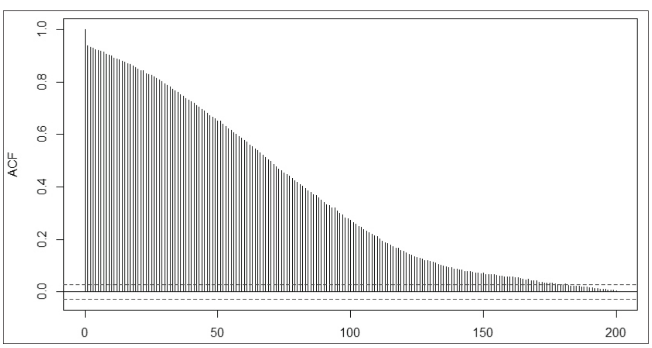


Fig. 3. ACF of the error function

It gave us an assumption that it is possible to decompose the signal. The goal of this decomposition is to filter the main components of the error function. After filtering we should try to implicate the decomposition for a rational control scheme to train the network.

According to the useful practice in stochastic market signal processing, we have successfully implicated LOESS techniques [12] to decompose the signal of the neural network error function. It was found that the analyzed signal consists of three perceptible components: a trend part, a periodic signal and irregular components.

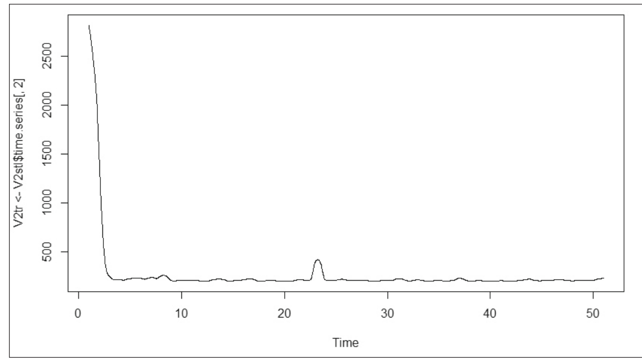


Fig. 4. An example of STL-decomposition of the error function (trend)

The trend curve of the neural network error function provides guides for synthesis of the rational control.

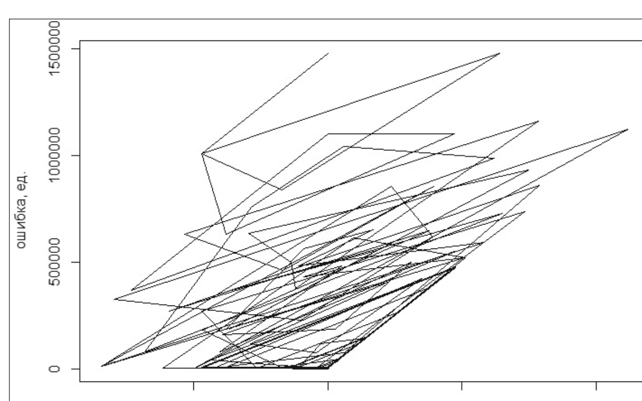
In terms of desired MANN's output this behavior can be considered as acceptable, however, the authors faced the following problem: the need to implicate one control curve using 10^{5-6} weight coefficients on average, which is computationally difficult and requires additional laborious studies in the dependence of the error function on dynamics of each weight coefficient.

Therefore, despite the controllability of such a network, as illustrated in [13], the authors developed a number of techniques for its implementation.

Post-Training Technique

To develop this technique, we carried out a generalized analysis of signal change trajectories in phase coordinates (Fig. 5).

Additionally, in order to study the behavior of the ANN as a system, phase portraits of the error of the artificial neural network in the coordinates (dE(t)/dtE(t)) for a converged and non-converged network were constructed.



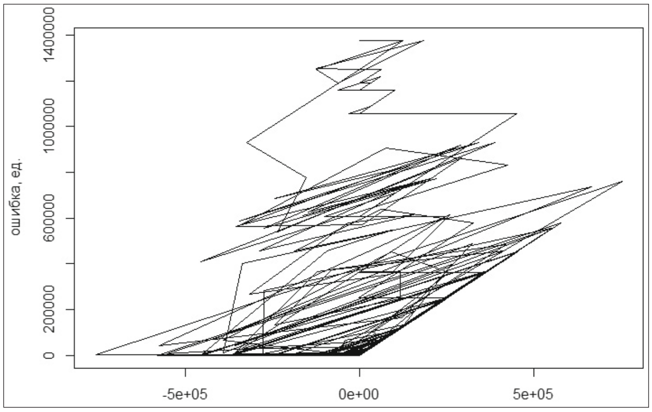


Fig. 5. *Phase portraits (left – converged network)*

There is a certain similarity of portraits, i.e. the presence of certain quasi-stable cycles and points with a low error value, which are not part of the stable cycles. In this case, the rate of change of the error changes, while being on the indicated trajectories with an increase in the total error.

In the behavior of a multilayer artificial neural network [8], sharp jumps are observed both in the error itself and in the rate of change of the error. The reason for this is the network structure and the principle of choosing the maximum connection when calculating the output. When an even signal propagates through the connections between neurons, then at the moment of activation of the neuron, according to the conditions of the problem, a dead zone occurs. The odd signal propagating through the links finds the maximum odd link, which can lead to an “off” neuron. In this case, the signal doesn’t go through the given connection but uses the next largest weight connection. And this connection can be far from the point of the desired network output by a significant amount (network connections are initialized when it is created randomly). Thus, a sharp increase in the output error signal occurs.

To mitigate this effect, the model for determining the width of the training links bundle for each neuron was changed according to formula

$$s = \sqrt{E(t) + (E(t) - E(t-1))}, \quad (11)$$

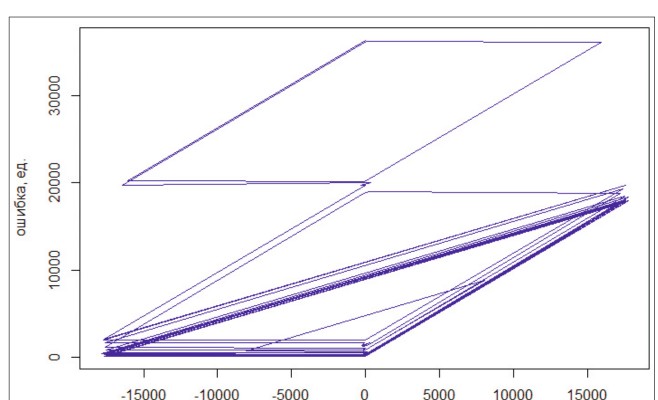
where s is the magnitude of the bundle of neuron connections for training, E (t) is the error, t is the number of the epoch.

Thus, the behavior of the network is controlled not only by an error, but also by its change in the previous step. If the network tries to increase the error, the width of the bundle of connections increases.

The essence of post-training is as follows: during the first epoch of the MANN displays primary errors and writes them as control ones. In subsequent epochs, current errors change, but before output, they are compared with the results of control errors of the previous epoch. In the case when the error of the new epoch turns out to be greater than the control error of the previous epoch, the retraining and lowering of the error value is started, thereby the network tries to reduce the error to the minimum value, simultaneously striving for a quasi-stable position. In the case when the errors of the new epoch become less than the control errors of the previous one, the control errors are rewritten. After a certain number of epochs, the ANN comes into a quasi-stable state, but jumps also occur that on average happen once per 275 epochs. Post-training is carried out 25 times, and afterwards a researcher deals with error results changed during the process.

Despite the fact that it was not possible to completely eliminate the oscillatory behavior of the network, significantly lower error values are observed and the network has been near them for a long time. This allows us to stop training such a network at the right time and get a solution for a smaller number of epochs (1.7-2 times) than it is achieved with a classical network.

The results are presented in the graphs below in Fig. 6.



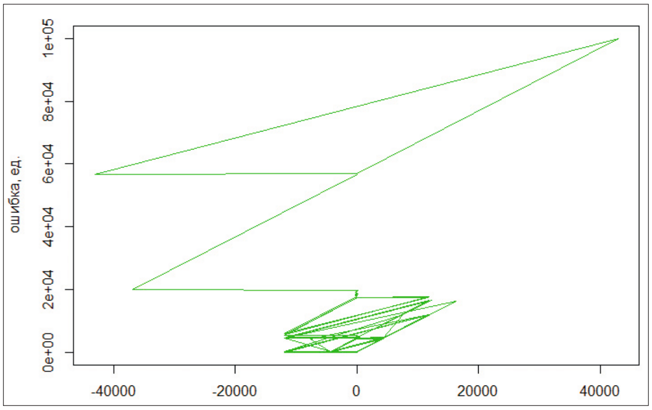


Fig. 6. *Phase portrait of a network with post-training (blue – even error, green – odd error)*

If phase portraits are compared before and after post-training, one can see that post-training leads to reduction in random fluctuations. However, for a signal of even errors there are two modes, with one of them being replaced by another, and for odd errors portraits give oscillations within a predefined region of the phase space.

Note that the initial design of the MANN did not have post-training, i.e. in fact had no memory. Control errors and post-training were introduced as one of the types of implicit memory. The program began to memorize the current error, then started a new epoch, received an error, and compared if it became better than the previous one. In the case of getting worse results, the retraining procedure was started until optimal results were obtained, but no more than a predetermined number of steps in post-training.

Unlike the first series of tests that were carried out on simulation models of railway lines sections, post-training was applied to the operation of the ANN on real lines of Russian Railways in the Eastern region for a network of 1920 neurons with 27 layers and a load of 170 trains per day.

The received error signal after changing the training scheme is given in Fig. 7 (1250 training epochs).

Its autocorrelation function is shown in Fig. 8.

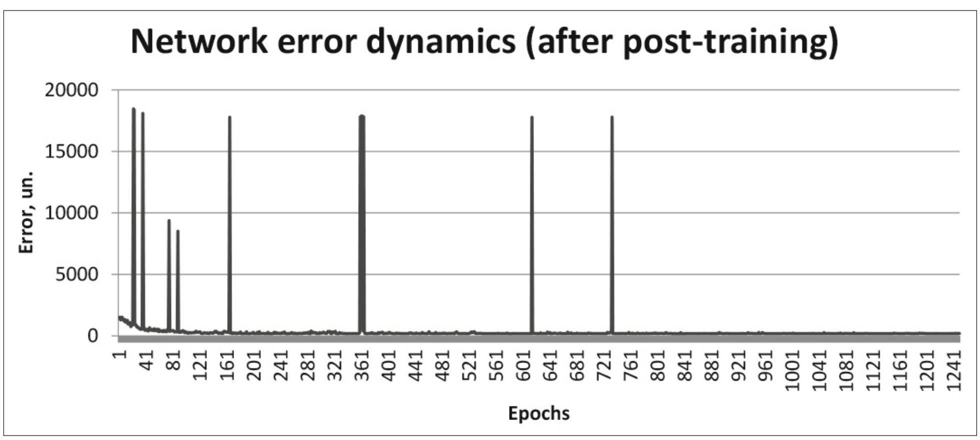


Fig. 7. *Network error signal after the introduction of post-training*

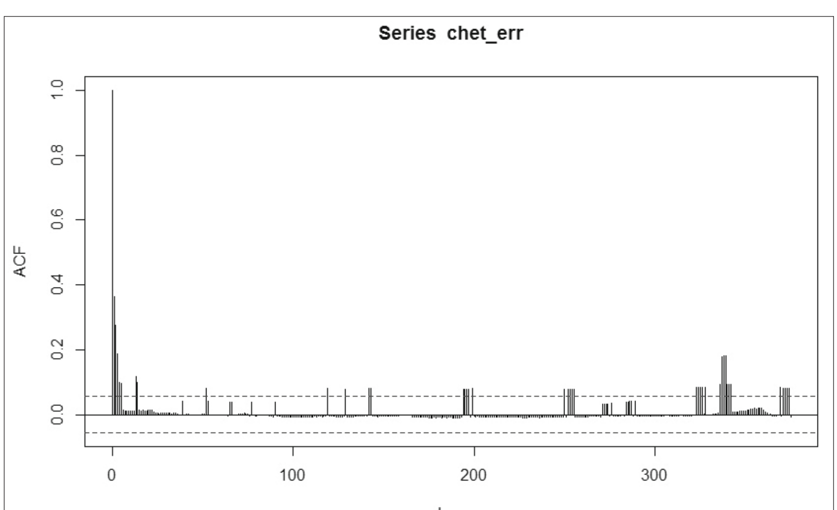


Fig. 8. *Autocorrelation function of the network (with post-training)*

As it can be seen from a comparison of Fig. 2 and Fig. 8, the following changes occurred in the behavior of the error signal:

- The severity of the correlation of the error signal with itself sharply decreased for time intervals of 0-60 epochs.
- Not strong, although distinct peaks are observed at intervals 13-14, 39, 52-53, 62-63. In their absolute value, they speak of an extremely weak degree of correlation.
- In general, which is confirmed by Fig. 3, the nature of the error signal became smoother, and in epochs with a significant number almost without sharp deviations and outliers.

The received new error signal was decomposed according to the LOESS method (Fig. 9) in the RStudio software environment. This method extracts the trend, periodic and residual random component from the error signal.

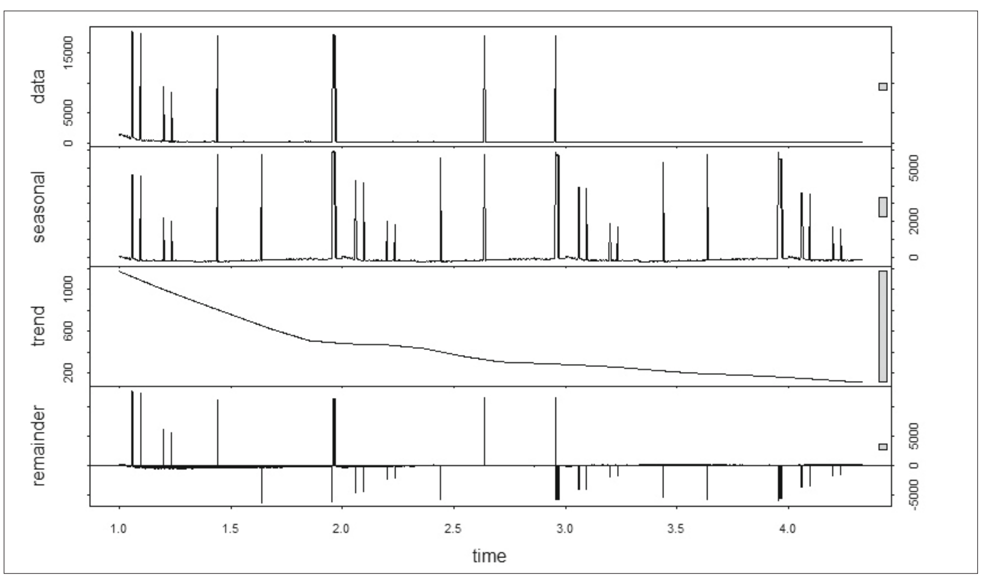


Fig. 9. *STL-decomposition of the error signal after ANN's post-training*

After receiving the results of errors of 1250 epochs, the authors conducted their analysis, built a graph, and displayed a trend. If we compare the graphs of the dynamics of the error of a multilayer ANN before and after post-training, then we can immediately note a decrease in the dynamics of the spread of an error, a transition to a more stable position of the network, stable points. Then the graphs were decomposed using the "STL" function of the "RStudio" software environment for a more detailed study, determination of the frequency of error occurrence, and identification of the causes of a sharp jump in error growth even from relatively stable positions.

It is seen that there is a significant correlation between the overshoots of the error signal in a number of decomposition residues and in the periodic component. At the same time, the contribution of the trend is low (1/15 at the beginning of training).

In this regard, it is necessary to create a mechanism for controlling the state of the ANN, which, without fixing a complete set of bond weights in each epoch, would eliminate the influence of the periodic and residual components. Such a problem can be solved, for example, using approaches to the synthesis of optimal regulators.

PID control

The application of a trend component to control such an ANN consists in the fact that its values can be used at the stage of training the network in question as the reference values of a control error, which will reduce the training time and improve the quality of constructed timetables.

In search for various ways to control the error signal, the idea was proposed to apply a PID controller that would correct the output signal trying to reduce the error of the output data and reducing the possibility of scatter and jumps.

PID control of the ANN error signal is implemented according to the following formula:

$$G(s) = K_1 + \frac{K_2}{s} + K_3 s'$$

where *s* is the argument of the transfer function, K_1 is the coefficient of proportional regulation, K_2 is the coefficient of integral regulation, K_3 is the coefficient of differential regulation.

The PID controller algorithm is implemented in the programming language R in the RStudio environment.

As a setup, the approximation of the network error signal is set by an exponential function of the form Ae^{-kt}, where *t* is the number of the network operation epochs, *A* is the initial value of the network error with which training starts, and *k* is the coefficient of the degree of error attenuation. The choice of such a setting function is due to the fact that it corresponds to the most common form of error reduction in the training of traditional neural networks.

For the MANN, consisting of 27 layers and 1920 neurons in each layer and with 175 schedules as a load, the error signal without control changed according to Fig. 10.

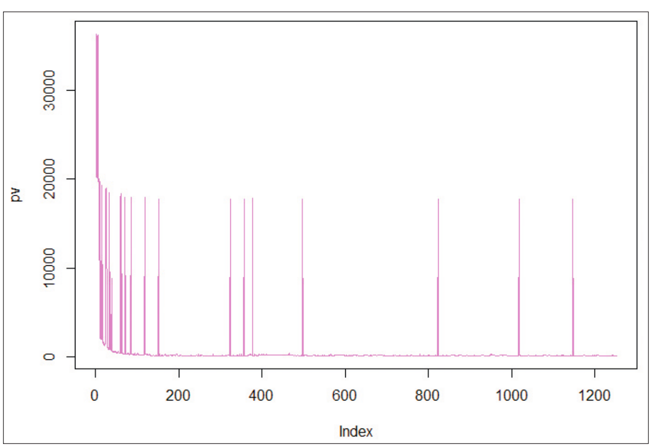


Fig. 10. *Network error signal*

The desired error change signal is shown in Fig. 11.

Application of PID controller to the error signal with parameters $K_p = 10$, $K_i = 1$, $K_d = 0.01$ showed that the control curve for the network error signal should look like this (Fig .12):

The algorithmic implementation of such control is carried out using the built-in techniques of the ANN and special techniques, including post-training etc.

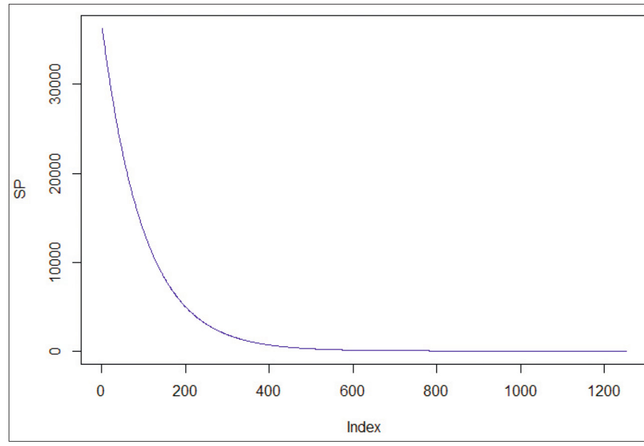


Fig. 11. *Setup change*

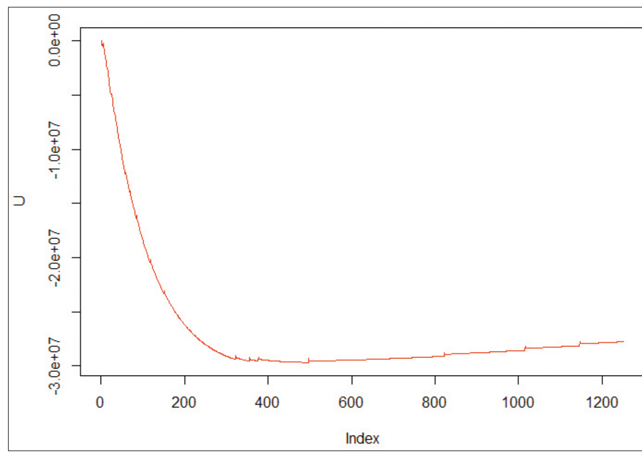


Fig. 12. *Control curve for a given network*

An analysis of Fig. 12 shows that the control found is quite adequate to the existing behavior of the ANN error.

A promising development of this control is the introduction of decomposition and prediction of an error signal in real time in combination with the applied PID controller.

For the developed control system, the price of sustainability will be performed as follows. For each epoch, an additional perturbation is introduced into the error signal in the work of the MANN. The magnitude of this perturbation is within [5 ... 100] and changes with step 5. The parameters of the PID controller during testing (Table 2, Columns 2,3) were initially set as:

PID controller of even error:

$$K_p = 0.1, K_I = 10, K_D = 0.5$$

PID controller of odd error:

$$K_P = 0.3, K_I = 30, K_D = 0.5$$

Table 1.

The magnitude of the disturbance, units/ epochs.	Test Series No. 1				Test series No. 2			
	Even		Odd		Even		Odd	
	% dist	% resp	% dist	% resp	% dist	% resp	% dist	% resp
1	2	3	4	5	6	7	8	9
5	0.31	101.83	0.4	104.15	0.28	100.42	0.33	98.8
10	0.56	103.01	0.74	105.53	0.55	101.91	0.65	102.00
15	0.89	104.19	1.23	106.91	0.88	102.76	0.95	105.01
...								
95	5.18	120.95	7.16	140.09	5.15	119.11	5.80	122.85
100	5.24	122.88	6.89	144.24	5.53	120.81	6.09	128.46

The second series of tests (table 2, article 4.5):
New *controller coefficients for an even error:*

$$K_P = 0.5, K_I = 30, K_D = 0.5$$

New *controller coefficients for odd error:*

$$K_P = 1.5, K_I = 30, K_D = 0.5$$

The results are presented in Table 1.

Table 1 will be read as follows. The value of 0.31 in the column "%" returns indicates that when a disturbance value of 0.31% of the average error is added to the error signal, its output value in the column "% resp" increased by 1.83% from the average.

This was done for error signals in the even and odd directions.

Compared to the first series of tests, in the second series, the average response to disturbance decreased by 2%, which is insufficient.

To assess the stability value, let us introduce the stability coefficient (quality), which is calculated by the formula below:

$$K_{st} = \frac{K_{dist}}{K_{resp}},$$

Where:
K_{st} – *coefficient of stability (quality),*
K_{dist} – *coefficient of disturbance,*
K_{resp} – *coefficient ofresponse.*

The results are presented in Table 2.

The quality factor should be no more than 1, which means that the disturbance provided led to a response not exceeding in strength. Such modes with controller parameters $K_P = 1.5$, $K_I = 30$, $K_D = 0.5$ are observed in 2 cases out of 20.

For the purpose of identifying the most effective training modes of the network with the PID controller, a second series of tests was carried out, during which the disturbance applied to the network input for 4 error signals varied from 0 to 55 with the step of 5, and the PID controller coefficients changed according to the following scheme:

- K_P: from 0.1 to 1 in increments of 0.2;
- K_I: from 10 to 40 in increments of 10;
- K_D: from 0.1 to 4.1 in increments of 1;

As in the first series, the values of the stability coefficients and the disturbance coefficient were calculated.

Table 2.

The magnitude of the disturbance, units /epochs	Even (small)	Odd (small)	Even New	Odd New
1	2	3	4	5
5	5.96	10.45	1.49	-3.69
10	5.39	7.48	3.48	3.07
15	4.70	5.64	3.14	5.29
...				
85	4.66	5.96	3.6	7.20
90	4.09	5.83	3.9	5.18
95	4.04	5.60	3.71	3.94
100	4.37	6.42	3.77	4.67

The best solutions for even and odd errors are shown in the figures below (Fig. 13 and Fig. 14).

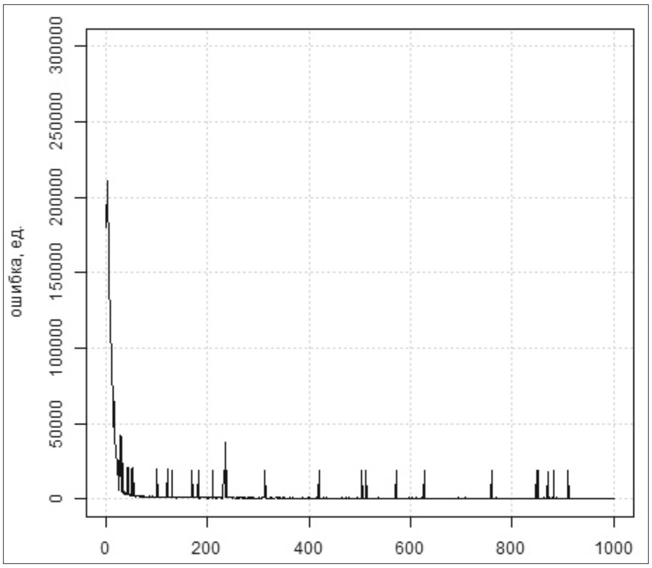


Fig. 13. *Dynamics of a clear network error with the parameters of the PID controller*
$K_P = 0.1$, $K_I = 40$, $K_D = 2.1$ with disturbance of 5

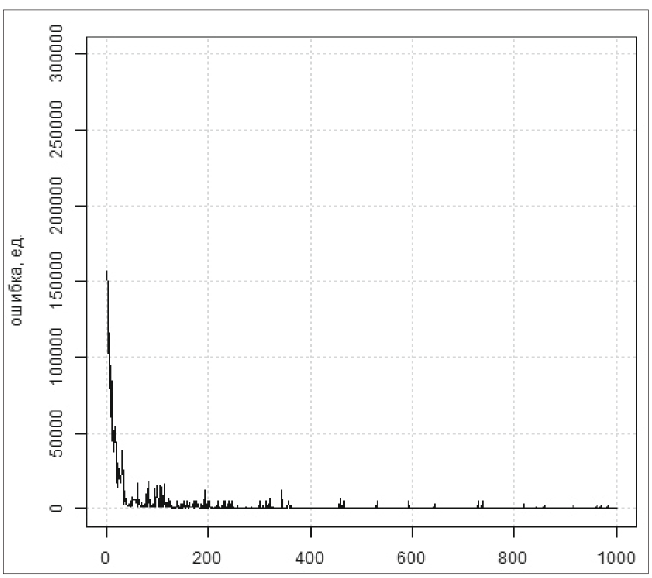


Fig. 14. *Dynamics of an even network error with the parameters of the PID controller*
$K_P = 0.1$, $K_I = 40$, $K_D = 2.1$ with disturbance of 5

Thus, we can draw the following conclusions:

1) A total of 1100 launches were carried out, of which 136 were sustainable;

2) The behavior of this network with a PID controller can be considered stable only for weak disturbances, the magnitude of which does not exceed 10-15% of the final steady-state network error;

3) The most stable mode under disturbance of 5 is the regime with the following coefficients:

- for an even controller, $K_P = 0.1$, $K_I = 40$, $K_D = 2.1$;
- for an odd controller, $K_P = 0.3$, $K_I = 10$, $K_D = 2.1$.

In addition to the PID controller and post-training with control errors or with a floating range of the links bundle for training, an alternative approach to training of such networks is proposed.

MANN control using a three-layer perceptron

[14] describes the idea of training an ANN through parallel training of two networks at once, in which the second ANN runs through a lot of epochs, calculating errors, comparing them with the given parameters. If the results are satisfactory, then these values are transferred to the first ANN. In this case, the second ANN acts as an invisible duplicating neuron in the main network, in which all calculations and determination of the best result are performed.

For the presented ANN design, such an algorithm is depicted in Fig.15.

We will implement this scheme in practice with a slight change using direct or inverse training of one neural network (MANN) using a multilayer perceptron.

The control ANN learns from a set of triples (“Error at the time” - “Status at the last moment” - “Control signal from the past at the given time”) or (“Error at the past” - “Error now” - “Control”).

The error output and the error itself (with a delay) are fed to the trained control network. The response of the control network is fed to the residual error and to the executive algorithm. Subsequently, the residual error integrator provides a signal to the control ANN as well.

As a practical implementation of the control found, we can use any of the algorithms (PID, post-training) to transmit a control signal. The error at the moment of time plus the magnitude of the control signal is the target error transmitted to the actuator.

Figures 17-18 present the graphs of an error under direct neurocontrol provided that the MANN is used separately for different flows of a software system – for freight and passenger flows.

Compared to the previously developed post-training techniques, the number of overshoots and their frequency, as well as the absolute value of the

Fig.15. An *enlarged algorithm for simultaneous training of two networks*

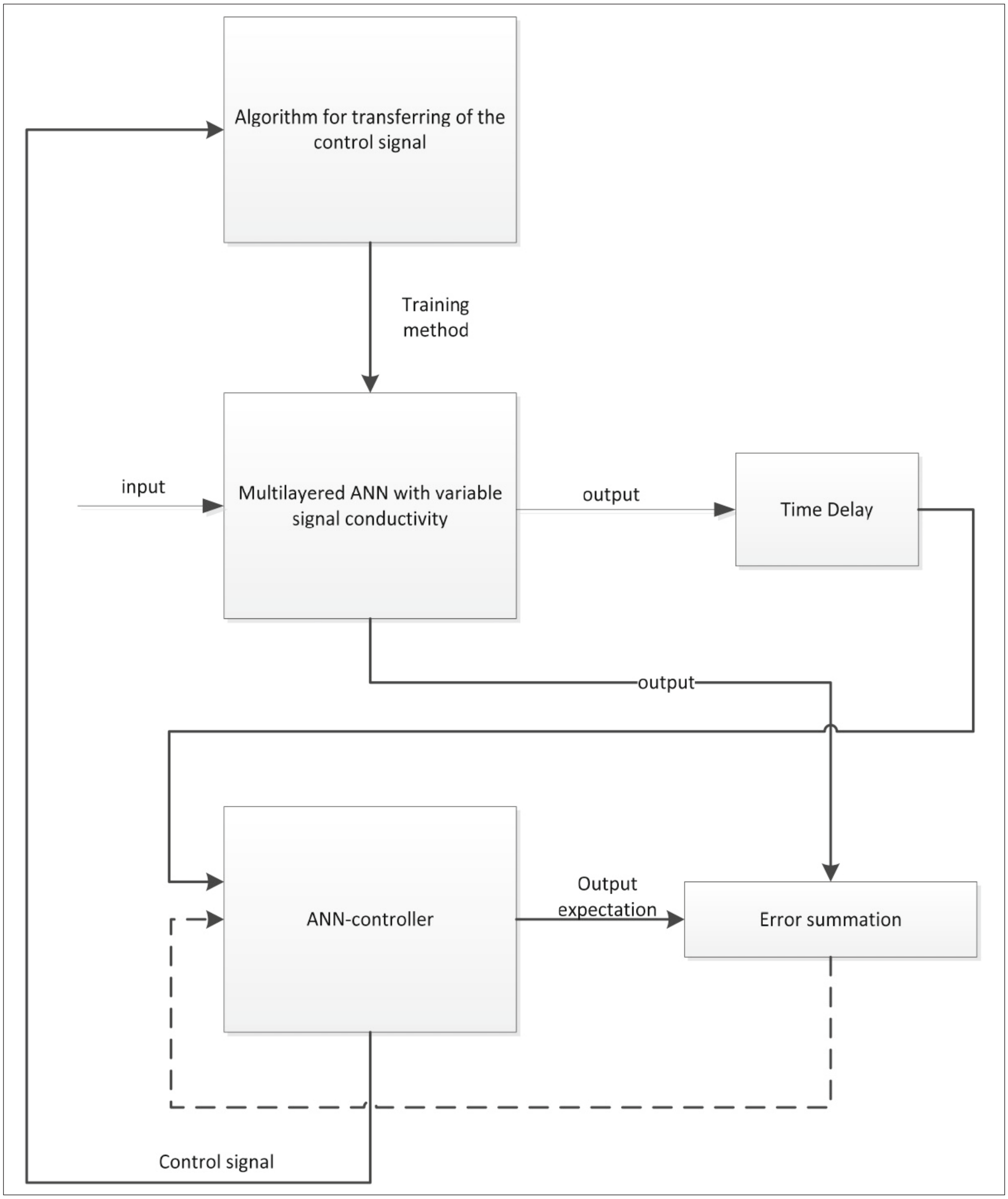


Fig. 16. *Neurocontrol scheme*

error values during overshoots were significantly reduced.

In some cases, a gain of the control signal is applied as:

$$K(t,E) = K_0 \pm \alpha * E(t),\ u(t) = K(t,E) * U(t)$$

where $E(t)$ is the magnitude of the current error, α is the proportionality coefficient, K_0 is the initial gain, $U(t)$ is the change in the error signal predicted by the multilayer perceptron, $K(t,E)$ is the resulting gain, u(t) is the final control signal.

As before, for testing of such approaches we chose the timetable for the line, where there are 185 trains, 27 stations and 24 hours.

Comparison shows that the introduction of amplification in neurocontrol in some cases reduces the amount of residual errors in the steady state mode of ANN operation. However, this decrease is not so great to speak about the significant difference between the control techniques in question.

In general, the comparative effectiveness of MINS training methods is given in Table 5:

Table 3. *Comparison of neurocontrol techniques (perceptron) for a multi-layered network for passenger trains*

Error	No gain		Linear gain	
	Even	Odd	Even	Odd
Median	152	54	155	53
Average	967	1070	1200	1225
Maximum	37050	56280	37040	56230
Minimum	152	0	152	0

Table 4. *Comparison of neurocontrol techniques (perceptron) for a multi-layered network for freight trains*

Error	No gain		Linear gain	
	Even	Odd	Even	Odd
Median	210	76	218	80
Average	756	717	746	802
Maximum	37040	56300	36940	56370
Minimum	184	38	185	32

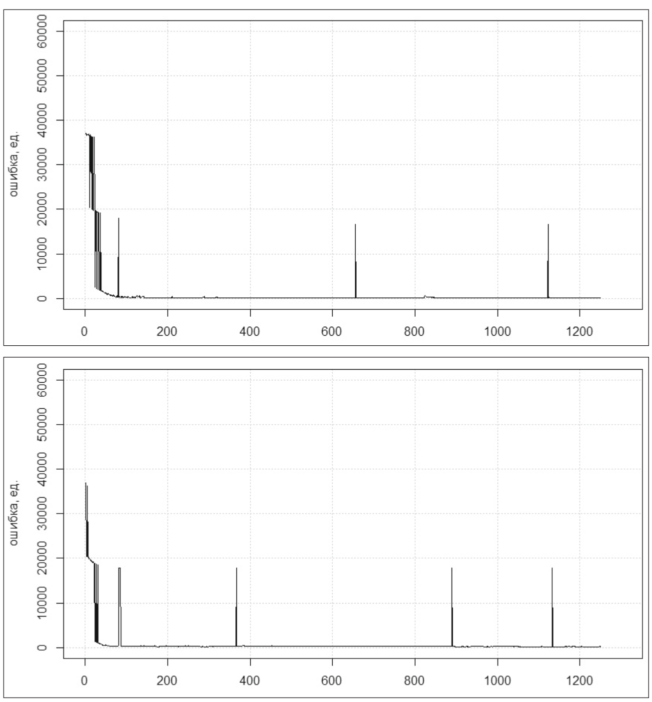


Fig. 17. *Network error dynamics (even error signal)*

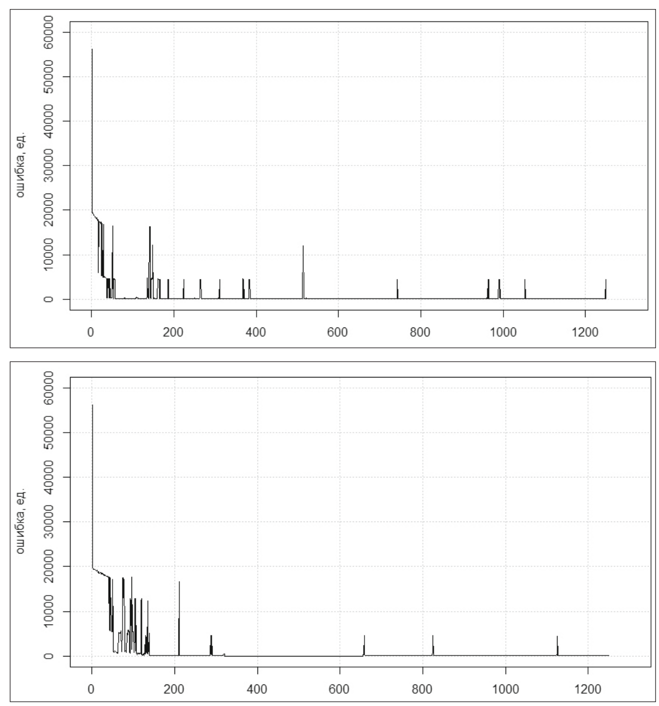


Fig. 18. *Network error dynamics (odd error signal)*

Table 5. *Comparative effectiveness of teaching methods MINS*

Indicator	Common Learning Algorithms	Post-training	PID controller	ANN (direct neurocontrol)
Minimum	75	0	362	193
Maximum	134795	54392	211585	57895
Median	5469	265	471	210
Average value	16548	1240	1830	384
SD	6687	4621	4485	1180
Burst Frequency for 100 epochs	50	3	15	0.4

Conclusion

1. The article shows the application of an artificial neural network with variable signal conductivity for solving the schedule problem.
2. The authors developed additional algorithms for managing the learning of a multilayer ANN with variable signal conductivity. The most effective from the standpoint of convergence to the solution are direct neurocontrol and post-training.
3. Direct neurocontrol also gives the smallest spread in the dynamics of error signals and the smallest value of the median error, i.e. 50 per cent of all estimates are in the range from 0 to 210.
4. A comparison of the methods showed the advantages of direct neurocontrol; however, in order to develop the most rational network operation modes, computational experiments for different tasks and network sections are required.

References

[1] Martinelli D.R. Optimization of railway operations using neural networks / D.R. Martinelli, H. Teng // Transpn. Res.-C. - 1996. - Vol. 4, No. 1. P. 33–49.
[2] Hopfield J. J. "Neural" Computation of Decisions in Optimization Problems / J.J. Hopfield, D.W. Tank // Biological Cybernetics. - 1985. - Vol. 52, Issue 3. - P. 141–152.
[3] Hopfield J.J. Neural networks and physical systems with emergent collective computational abilities / JJ Hopfield // Proc. Natl. Acad. Sci. USA - 1982. - Vol. 79, No. 8. - P. 2554–2558.
[4] Kostenko, V. A. Local-optimal scheduling algorithms based on the use of Hopfield networks / V. A. Kostenko, A. V. Vinokurov // Programming. - 2003. - No. 4. - P. 27–40 (in Russian).
[5] Yakovlev, V.V. Solution of the task of timetabling classes at university using neural networks /V.V. Yakovlev, Yu. G. Vasiliev, B.M. Kalmykov // Bulletin of the Chuvash University. - 2008. - No. 2. [Electronic resource]. - URL: http://cyberleninka.ru/article/n/reshenie-zadachi-sostavleniya-raspisaniya-zanyatiy-v-vuze-s-pomoschyu-neyropodobnyh-sete y
[6] Cavaliery S. Optimal path determination in a graph by Hopfield neural Network / S. Cavaliery, A. Di Stefano, O. Mirabella // Neural Networks. - 1994. - Vol. 7, No. 2. - P. 397–404.
[7] Agafonov, A. A. Mathematical models and adaptive methods for short-term forecasting of traffic parameters: Thesis: 05.13.18 / Agafonov Anton Aleksandrovich. - Samara, 2014.- 164 p. (in Russian).
[8] Olshansky A.M., Ignatenkov A.V. One approach to control of a neural network with variable signal conductivity // Information Technologies and Nanotechnologies (ITNT-2017). - 201.- P. 984 -987.
[9] Ignatenkov A.V. Neural network modeling and streamlining of traffic flows on railway lines. Abstract of Thesis, 05.13.18. - Mathematical modeling, numerical methods and program complexes // Penza, PenzGU, 2018.-20 p., P. 14 (in Russian).
[10] Rozenberg Yefim, Olshansky Alexey et al. Some approaches to improving the quality of artificial neural network training// https://ceur-ws.org/Vol-2667/paper7.pdf, pp.27-29.
[11] IgnatenkovA.V. Model iskusstvennoy neyronnoy seti dlya postroeniya graphika dvizheniya poezdov na dvukhputnom uchastke / A.V. Ignatenkov // International Scientific Conference Proceedings "Advanced Information Technologies and Scientific Computing". - Samara, Samara Scientific Center of RAS Publishing, 2016 - P.619-623. - ISBN 978-5-93424-758-5 (in Russian).
[12] Olshansky, A. M., Ignatenkov, A. V. Development of an artificial neural network for constructing a train schedule // Bulletin of the Ryazan State Radio Engineering University (RGRU-2016). - 2016. - No. 55. - P. 73-80 (in Russian).
[13] Cleveland RB et al. STL: A Seasonal-Trend Decomposition // Journal of Official Statistics. - 1990. - T. 6. - No. 1. - P. 3-73.
[14] Géron Aurélien. Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow. O'Reilly Media, Inc., 2022.

Received: September 7, 2023
Accepted: November 21, 2023

About the authors

Alexey Olshansky is the Head of Centre for Mathematical and Computer Simulation of JSC NIIAS, PhD in Engineering. His areas of interest are system analysis, theory of automatic control of socio-economic systems, artificial neural networks and heuristic methods for designing control systems. He is the author of over 150 scientific papers and 20 patented inventions.

For citation

Alexey Olshansky, Study of Training Quality of Multilayer Artificial Neural Networks with Variable Signal Conductivity in Scheduling Problems, *JITA – Journal of Information Technology and Applications, Banja Luka*, Pan-Europien University APEIRON, Banja Luka, Republika Srpska, Bosna i Hercegovina, JITA 13(2023) 2:76-90, (UDC: 004.032.26:556.131), (DOI: 10.7251/JIT2302076O, Volume 13, Number 2, Banja Luka, December (57-120), ISSN 2232-9625 (print), ISSN 2233-0194 (online), UDC 004

Big Data-Based Methods for Functional Safety Case Preparation

Efim Rozenberg, Alexey Olshansky, Alexey Ozerov

Research and Design Institute for Information Technology, Signalling and Telecommunications on Railway Transport (NIIAS), Moscow, Russia, a.ozerov@vniias.ru

Contribution to the State of the Art

https://doi.org/10.7251/JIT2302091R UDC: 004.42.032.26:007.52

Abstract: The paper aims to overview the opportunities, approaches and techniques of studying and ensuring functional safety of transportation systems, including those driverless, with the use of Big Data. Examples are provided of machine learning/Big Data application in analysing the functional safety of complex control/management systems in railway transportation. The paper proposes the concept of application of supervised artificial neural networks combined with model checking. The following methods were used in the preparation of the paper: system analysis, logical and comparative analysis and historical principle. Updated requirements are defined for transportation systems using artificial intelligence as part of adaptive train schedule management and autonomous train control. That will ultimately allow developing an entire line of research from AI-based system functional safety estimation and machine learning to safety case preparation of intelligent supervised control/management systems based on formal verification.

Keywords: functional safety, safety case, code verification, supervised artificial neural networks (SANN), machine learning, Big Data, driverless control systems, train schedule, Markov chains.

Introduction

The modern technology that underpins next-generation transportation systems that operate in ever-evolving conditions, with significant numbers of passengers, requires modified control systems design. With the growth of agglomerations, many suburban and urban systems merge, and the headways approach those of the subway. In this context, man-machine systems are transforming into automatic ones with varied degrees of automation (from GoA1 to GoA4). Failures and delays that occur within such transportation systems cause significant disruptions that affect thousands of passengers and require the mobilization of infrastructure and technical assets. In the above scenarios of transportation system operations, it becomes impossible to use the conventional approaches to traffic schedule redesign and to transportation service planning using algorithms for static problem optimization (which, no doubt, can well be used in long-term planning).

Mitigating the above challenges requires solving the following primary tasks:

1. Improving the adaptive quality of the planning and management processes, in particular, in terms of schedule design/redesign;

2. Improving the resilience of the transportation system and its technical component to unsafe behaviours, failures and disruptive effects.

The significantly increasing costs of both an hour of time and infrastructure resource for companies, and trains and infrastructure assets favour the transition to computer simulation and formal analysis of all possible situations in the transportation system that is enabled by modern approaches and methods for developing adaptive and functionally safe management. In the context of the above problems, the conventional methods [1, 2, etc.] have quite limited capabilities.

Definition of the scope of research

Drawing on the existing standardization guidelines, we should consider the concept of "umbrella standard", i.e., a basic, high-level standard. In case of functional safety, that is IEC 61508 *Functional safety of electrical/electronic/programmable electronic safety-related systems*. IEC/GOST 61508 is a basic functional safety standard applicable to all industries.

According to IEC 61508, for the purpose of ensuring functional safety, first, the safety functions are to be defined that are required for reducing the risk associated with the controlled equipment, as well as for achieving and maintaining the safety of such equipment (e.g., emergency shut down function). It is very important that, according to the standard, a control system is to possess the property of so-called safety integrity, by which IEC 61508 means the probability that the system will correctly perform the safety functions under all specified conditions, within the specified period of time.

In practice, along with IEC 61508, industry-specific functional safety standards are used as well. For instance, in railway transportation, there is GOST 33433-2015 *Functional safety. Risk management on railway transport* that specifies the approach and general rules for managing risks in railway transportation associated with the functional safety of infrastructure and rolling stock. In addition, there is GOST 33432-2015 *Functional safety. Policy and program of safety provision. Safety proof of the railway objects* that defines the purpose of the "Safety Policy", "Safety Program" and "Safety Case", as well as specifies the primary requirements for the structure and content of those documents and the procedure for their development.

The following primary methods for safety case preparation are identified [3]:

- expert, based on expert evaluation of technical and design documentation;
- computational, based on analytical computations;
- simulation, based of experiments with computer models;
- experimental, based on experimental tests with a trial system (laboratory tests);
- full-scale testing that involves testing the system in actual operation conditions at the stage of commissioning and run-in, certification tests;
- information-based that involves the collection of statistical data on failures in the course of long-term operation of a single system or a number of same-type systems.

The choice of one or several specific methods depends on the developer's qualification and used regulatory framework.

The specificity of railway operations today

Currently, there is a number of distinctive features of the 1520 mm gauge railways that should be pointed out. In railway transportation, freight traffic is concentrated on certain lines. The primary load is on about 10 percent of its operational length. Historically, in the Russian Federation, about half of the total freight turnover is ensured by 1/6 of the railways. The situation is similar in passenger transportation.

Due to this uneven distribution of operations throughout the railway network, its certain parts become extremely busy, which ultimately affects the entire network. The primary cause of such "bottlenecks" is the insufficient capacity of the operational regions. Railway lines may also experience loads outside of the permitted capacity in case of insufficient traction power supply and length of receiving, marshalling, turnout and departure tracks at intermediate, line and marshalling stations. That reduces station capacity, causes train delays at entrance signals and generally reduces the service speed of passenger and freight trains.

In practice, improving the theoretical and practical capacity of lines subject to the existing limitations involves a comprehensive approach that requires significant investment. That includes the construction of main tracks, station tracks, delivery of modern locomotives, electrification, improvement of traction power supply, signalling upgrades (e.g., implementation of moving block sections). At the same time, improvements to the transportation management process allow reducing capital expenditures if local solutions are used that are adapted to specific facilities and sites.

In this context, point technological solutions should be used for the purpose of increasing the theoretical and practical capacity in the short term until the completion of major infrastructure projects and to ensure the performance of the development program.

For instance, the last decade saw widespread deployment of digital telecommunications, process automation and remote data collection and management technology in railway transportation. Managing railway operations through the use of sensors and microcontrollers, as well as programmable and remotely controlled railway signals and switches, has resulted in increased system efficiency as well as operational flexibility. However, the use of network connectivity made railway data communications vulnerable to cyber-attacks. Today, an increasing number of railway data transmission networks are cyber-physical systems with interconnected physical, computer and communication components. Cyber-attacks against such systems can potentially cascade through those interconnections and cause significant damage. These systems are critical to safety due to the great financial implications and, more importantly, potential threats to human life. Therefore, safety and reliability requirements for such systems are to be taken into account at the very beginning of their design [4].

Thus, an accelerated adoption of new technology requires new approaches to safety case preparation and safety assurance. Most importantly, that involves the development of alternative and target schedules for large regions of operations and stations, especially, with possible large-scale application of unmanned vehicles in passenger transportation and shunting operations. Due to their complexity, all such new technical solutions require intelligent control elements. The solution may be in the artificial intelligence and deep neural networks along with big data processing as a more advanced computational method for functional safety case preparation.

Big Data-based safety case process for systems with artificial intelligence

One of the difficult aspects of a safety case is the identification of abnormal scenarios that may potentially cause a specific accident. At this difficult stage of safety assessment, experts are to be able to understand, among other things, the specificity of the artificial intelligence technology.

For example, [5] suggested an ACASYA-based model for calculating hazardous scenarios of automatic railway device operation. The software tools presented in this paper have two main functions. First, to record and store the experience associated with safety analysis. Second, to help those involved in system development and evaluation, as well as in solving the complex problem of evaluating safety trials. Currently, those tools are at the prototype stage, yet safety experts have noted the strong potential of the proposed approaches.

The approach chosen in this paper is based on several capabilities of artificial intelligence and, in particular, on the use of the following methods:

- accumulation of railway safety information, including potential accident scenarios;
- training through concept classification for the purpose of grouping accident scenarios into homogeneous classes associated with train collisions or derailments;
- rule-based machine learning (RBML) for automatic identification – based on a database of historical scenarios (experience feedback) – of appropriate safety rules that are often difficult to extract manually;
- knowledge-based system (KBS) that is filled with the process rules previously derived using machine learning for the purpose of creating a knowledge base for a functional safety analysis support tool.

Thus, the approach to railway transport safety assessment used in this paper is a hybrid method based on a classification algorithm, rule-based machine learning (RBML) and a knowledge-based system (KBS).

As shown in Fig. 1, the railway safety analysis and assessment methodology consists of 11 stages. The first eight steps are performed by the scenario classification module (CLASCA), while the last three are performed by the scenario evaluation module (EVALSCA).

Advanced information technology is increasingly employed as part of controlling and controlled equipment, whose correct operation might have an effect on the life and health of people. Information security is vital to ensuring comprehensive functional safety, therefore efficient methods for safety evaluation and safety case preparation are required [6].

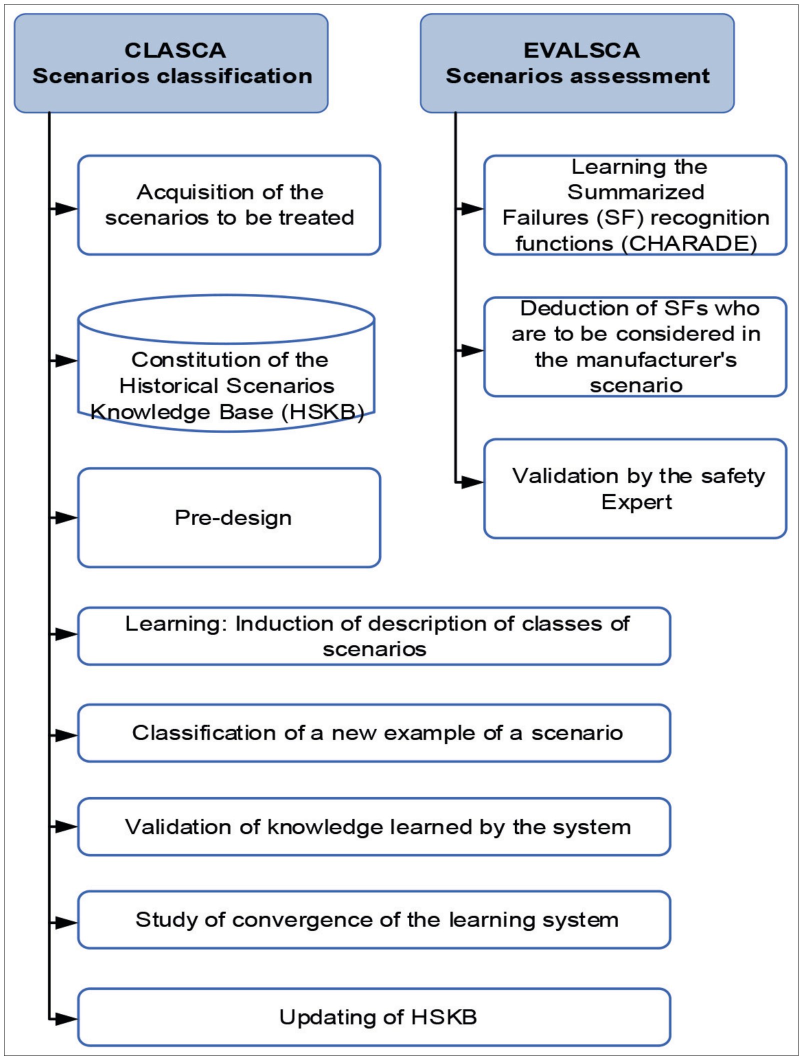


Fig. 1. *Safety analysis and assessment method*

Thus, [7] examined the process of safety case preparation of a complex information system using artificial intelligence.

Convergence indicators, speed and accuracy of the inverse error distribution (BP) neural network algorithm, particle swarm method (PSO), genetic algorithm, GA-PSO and PSO-BP algorithm were compared in the study of information system operation risks (Fig.2).

As a result of the simulation experiment, the error of the PSO-BP algorithm in predicting information system risks is practically 0, the error of the conventional BP algorithm is 3.87, while the maximum error of the PSO algorithm is 1.12 units.

However, it should be noted that a significant drawback of the proposed method consists in the requirement of prior knowledge of the possible risks for the examined system, whose insufficient availability is noted by the authors.

In general, the use of safety case assessment methods for systems with artificial intelligence is arguably a poorly studied domain that should be based on both the experience of successfully implemented standards, and new developments [8].

Today, the issue is particularly pressing for driverless cars. It is also common in the application of artificial intelligence for direct equipment control, where documents regulating the methods of safety assessment are lacking. There are many works dedicated to this topic, including comprehensive studies ([7], etc.) that suggest ways to solve the problem of shortage of safety assessment methods, yet they do not address the matter of safety integrity demonstration for artificial intelligence.

Let us examine how the matters of safety management can be implemented in the train schedule

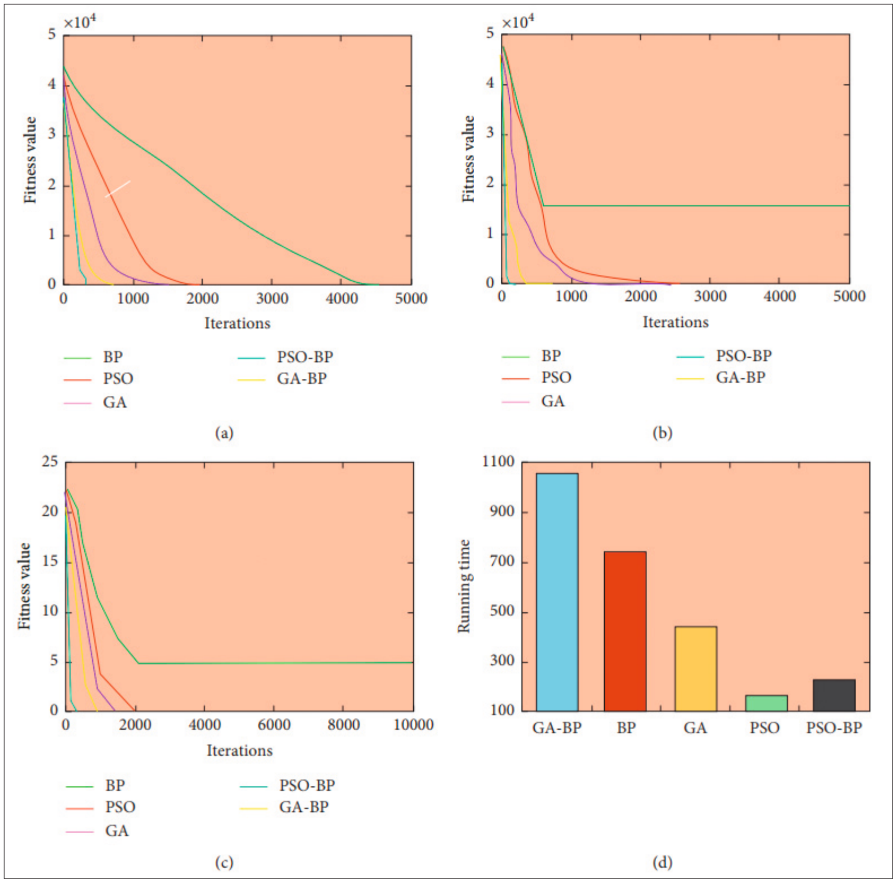


Fig. 2. Convergence measures of five algorithms: (a) First training; (b) Second training; (c) Third training; (d) Time.

process. It should be noted that the International Union of Railways (UIC) regards the transition to adaptive train schedule and its life cycle-based management as a most important component of the railways' digital transformation [9].

The notion of train schedule life cycle includes an entire set of phases from the concept, definition of operating conditions to the actual information implementation and logging of the schedule performance, each of which refers to the corresponding information fields involved in the associated information model.

These parameters may be defined by regulatory means (from the corresponding database) or by analysing the input information using an intelligent algorithm, including with the use of machine learning examples and historical context.

Up until now, literature has not considered the relationship between the phases of the train schedule life cycle and the matters of its functional dependability and safety. Although, essentially, each of the parameter values in the train schedule phases actually defines a certain level of safety on the line.

The set of automation devices, data communication and man-machine systems (operation of traffic controller, train driver, station duty officer) are elements of functional scenario trees, each of which results in an assessment of the risk of technology or process-related failure.

As a result, at each phase, a hazardous failure scenario can be defined and protection measures can be foreseen for a train schedule. Here, the term "failure" should be interpreted broadly, including a wide class of situations, in which the safety level is not below standard, yet the line capacity does not allow handling the specified train traffic [10].

In this situation, Markov chains may prove to be the most efficient method. For each scenario branch, Markov chains are thus formed with specified state transition rates that are compactly written in matrix form.

The URRAN methodology would be very applicable in this area [1]. That will enable a comprehensive approach to managing the functional safety and dependability of train schedules, in which key indicators, i.e., the transition rates, will be evaluated using Data Science.

Thus, the transition to a trinity of models is possible, i.e., a historical, a dynamic and a predictive data landscapes, built on common principles that allows handling information data models in relation to different time horizons and in accordance with local goals. Evidently, obtaining reliable results requires that the data generated using Big Data methods are cleared of noise, validated and submitted to other standard procedures.

Today, train schedules are implemented in the form of specific management of assets: train routing, section and switch location occupancy supervision, etc., that are associated with specific time parameters. The fact that changes in the asset status have no effect on the target schedules that are modified no more than once a day represents a particular difficulty. The migration towards adaptive train schedules with continuous replenishment with data generated using Big Data-based methods will enable a shorter transition process caused by the normalization of the operational situation in case of certain disturbances. Currently, under the existing process that does not involve Big Data-based methods, the schedule is largely unable to keep up with the evolution of asset statuses.

In [12], the matter of supervised artificial neural networks was examined given their application in process management for the purpose of ensuring the required functional safety of systems.

Control and management systems are conventionally assessed for Lyapunov's stability. In this case, the behaviour of a stable system can with a 100% probability be predicted in the neighbourhood of the ε-tube [13].

For the examined supervised systems, in which stability is ensured through the introduction of a supervisor algorithm, speaking of a strict Lyapunov's stability would not be correct.

Let us consider the operation of the above diagram (see Fig. 3). At the first step, an external signal is fed to the input of the supervised ANN. The latter operates as an output-controlled system. The output of the network (with the addition of feedback control) is formally verified. If the solution belongs to the set of acceptable processes D, such signal is fed to the actuator and further to the controlled item (which may include the network). If the output signal is outside the set of acceptable processes, the limiter is triggered. The limiter is the history of processes and reactions to a specific implementation (managerial decision-making algorithm with no clear indication of the nature of such algorithm). The algorithm suggests a decision (in terms of the output vector) with confidence P%. If the decision is deemed belonging to the set of acceptable processes, it is fed to the actuator.

In order to clarify the specificity of the proposed diagram, let us note that, firstly, SANN has latency (if a correct decision is not produced at the second step, then between the duration of 2 steps and indefinitely, until it is abruptly interrupted by the DM using the time control unit), and secondly, the algorithms

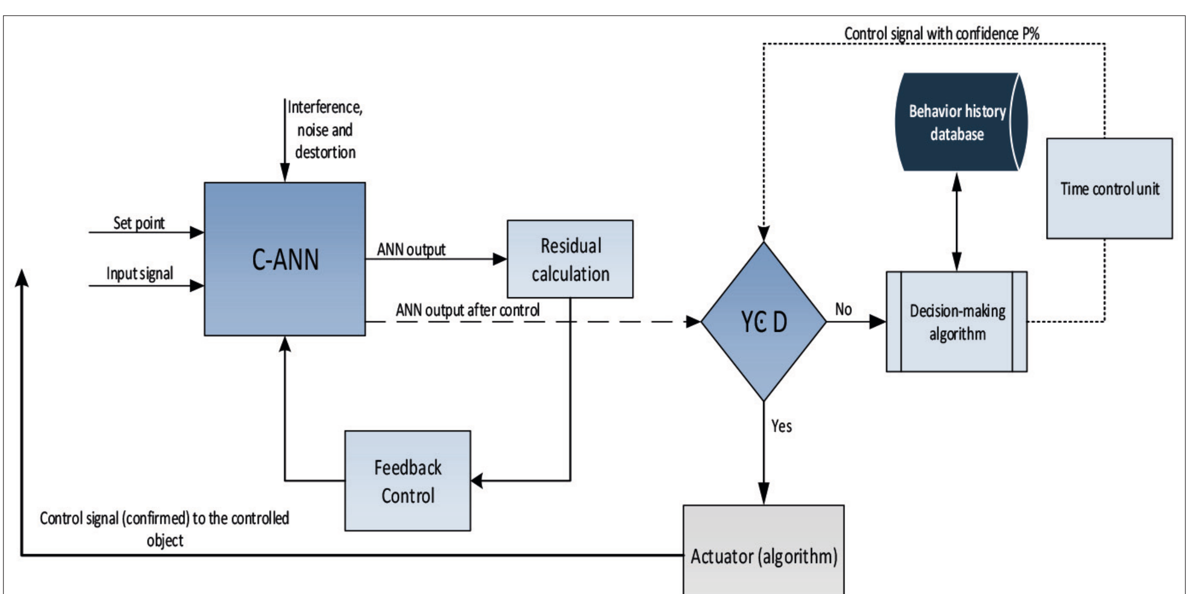


Fig. 3. *Block diagram of the supervised ANN*

for acceptability evaluation and development of decisions in the supervisor are to be sufficiently fast, so that the total latency was reasonable. In addition, the confidence level P will always be less than 100%.

The diagram should also verify whether the output values belong to the set of acceptable processes D. The evaluation of the boundaries of domain D, continuous adjustment of the boundaries of the ε-tube of stability, and identification of the limiter's behaviour are to be done using Big Data-based algorithms and methods.

The extension of this practice (application of SANN and, more generally, supervised machine learning algorithms) to train schedule data processing enables the transition to functionally dependable and adaptive scheduling. This hypothesis is to be further studied, as it is required to:

1. Prove the controllability of algorithms and methods of information processing at least "at the output".
2. Synthesize a practically implementable method of control and evaluate its stability.

Such approach allowed examining the possible implementations of partially controlled intelligent systems in [10]. In literature, partially controlled (output) ANN with variable signal conductivity were first described in papers funded through the Russian Foundation for Fundamental Research grant no. 17-20-01065 *Development of the Theory of Neural Network-Based Control of Railway Transportation Systems* [14, 15]. The provisions on ANN control defined therein may, in principle, be extended to other machine learning algorithms. Only after those studies have been completed, specific software and hardware implementation should commence.

It should be noted that the idea of algorithms that are supervised in this manner may apply not only to ANN, but other intelligent algorithms as well. At the same time, the currently used rules and principles of strict verification of model checking algorithm branches should not be unconditionally rejected [16].

Scope of practical application of the findings

Unmanned train control systems are being rapidly deployed in the Moscow Central Circle and the Luzhskaya station. The most complicated issue is the safety case preparation, since the key component is the convolutional ANN-based machine vision. Using the methods proposed above, approaches have already been developed for specific engineering implementations that are undergoing trials both on specially designed laboratory benches, and in the field [17].

Additionally, future development of such intelligent systems will be ensured by in-depth research of signal recognition technology (sound analysis, machine vision, self-diagnosis systems, etc.). Matters of sensor interpretation, sensor elements and associated decision-making systems are in close relation with the proposed algorithms. In [18], a single safety case system is proposed for each intelligent autonomous transportation system. Within such system, a zone is defined that is not covered by SIL-4. That is the Intelligent Train Protection zone that is characterized by the uncertainty of system behaviour or partial observability. In these conditions, one of the ways to overcome these gaps may be to apply Big Data processing techniques to controlled algorithms (including the controlled ANNs described above). These techniques may prove to be especially useful for MAPE (Monitor – Analyse – Plan – Execute) signal processing. Identifying and eliminating abnormal signals will allow more clearly defining the boundaries of the set of acceptable processes D, thus, in some cases, increasing the speed of the decision algorithms by disabling an entire branch of unfavourable scenarios.

Given the developed and above-described approaches, as well as the papers on the examined matter, model checking is to be used in any case.

Conclusion

Thus, this paper analysed the current requirements for transportation systems, including those that use artificial intelligence, for the most promising areas, i.e., adaptive train schedule and unmanned systems, which allows defining an entire new line of research, i.e., assessment of the functional safety of systems using AI and machine learning.

A design is proposed that is promising in terms of further computer research, i.e., supervised ANN. The authors also substantiate further lines of research in the area of intelligent supervised systems, including the transition to the preparation of such system's safety cases based on formal verification of the developed control systems.

REFERENCES

[1] Gruntov P.S. [Centralized systems for automated railway management in market economy conditions]. Minsk: BelGUT; 2011. (in Russ.)

[2] Osminin A.T. Problems and ways of their scientific solving on the issues of railroading. *Bulletin of JSC RZD United Academic Council* 2015;4:41-54. (in Russ.)

[3] Fedukhin A.V. Mukha Ar.A., Sespedes Garsiya N.V. [Safety case of a computer system]. *MMS* 2016;3:93-101. (in Russ.)

[4] Neema H. Simulation testbed for railway infrastructure safety and resilience evaluation. In: Proceedings of the 7th Symposium on Hot Topics in the Science of Security. Association for Computing Machinery; 2020. P. 1-8.

[5] Hadj-Mabrouk H. Contribution of Artificial Intelligence to Risk Assessment of Railway Accidents. *Urban Rail Transit* 2019;5:104-122.

[6] Shubinsky I.B., Schäbe H., Rozenberg E.N. On the functional safety of a complex technical control system with digital twins. *Dependability* 2021;21(1):38-44.

[7] Zhang J., Li J. Testing and verification of neural-network-based safety-critical control software: A systematic literature review. *Information and Software Technology* 2020;123.

[8] Shubinsky I.B., Shäbe H., Rozenberg E.N. On the safety assessment of an automatic train operation system. *Dependability* 2021;21(4):31-37.

[9] Ozerov A.V., Lysikov M.G., Olshansky A.M. Timetable as part of next-generation adaptive management system. *Nauka i tekhnologii zheleznykh dorog* 2021;5(1):50-64.

[10] Ozerov A.V., Olshansky A.M. [Approaches to the assessment of the functional safety of a driverless automatic train control system]. In: International Scientific Conference Proceedings "Advanced Information Technologies and Scientific Computing". Samara; 2021. P. 504-509. (in Russ.)

[11] Gapanovich V.A., Shubinsky I.B., Zamyshlyaev A.M. Mathematical and information support of the URRAN system. *Dependability* 2013;1:12-19.

[12] Ozerov A.V., Olshansky A.M. Safety model construction for a complex automatic transportation system. *Dependability* 2021;21(2):31-37.

[13] Dorf R., Bishop R. Modern control systems. Moscow: Lab. Bazovykh Znaniy; 2004.

[14] Rozenberg E.N. et al. [Hybrid neural network-based management of transportation systems]. *Automation, Communications, Informatics* 2017;12:2-5. (in Russ.)

[15] Ignatenkov A.V., Olshansky A.M. About neural network error control as an optimal control problem. *Izvestiya Samarskogo nauchnogo centra Rossiyskoy akademii nauk* 2016;18(4-4):733-738. (in Russ.)

[16] Clarke E.M., Henzinger T.A., Veith H., Bloem R., editors. Handbook of model checking. Vol. 10. Cham: Springer; 2018.

[17] Okhotnikov A.L., Popov P.A. Self-driving: yesterday, today and tomorrow. *Automation, Communications, Informatics* 2019;8:12-17. (in Russ.)

[18] Flammini F. et al. A Vision of Intelligent Train Control. In: Proceedings of the 4th International Conference on Reliability, Safety and Security of Railway Systems (RSSRail-22). Springer LNCS; 2022. (preprint 2022)

Received: September 10, 2023
Accepted: November 1, 2023

ABOUT THE AUTHORS

Efim Rozenberg is the First Deputy Director General of JSC NIIAS, Doctor of Engineering, Distinguished Professor. He is a recipient of the award of the Government of the Russian Federation in the field of science and technology. He was awarded the title of Honored Designer of the Russian Federation, Best Innovator of JSC Russian Railways. Professor Rozenberg leads research and development in train control and protection including signalling, train separation, automatic train operation, traffic safety, communication, cybersecurity. He is an author of about 300 research papers and about 400 patented inventions.

Alexey Olshansky is the Head of Centre for Mathematical and Computer Simulation of JSC NIIAS, PhD in Engineering. His areas of interest are system analysis, theory of automatic control of socio-economic systems, artificial neural networks and heuristic methods for designing control systems. He is the author of over 150 scientific papers and 20 patented inventions.

Alexey Ozerov is the Head of International Department – Head of Intellectual Property Management Centre of JSC NIIAS. He has been working with JSC NIIAS for over 16 years in various positions related to research, signalling business unit and international cooperation. He is finishing his PhD in traffic management and has authored over 50 papers and 8 patents in the field of advanced railway signalling and traffic management.

FOR CITATION

Efim Rozenberg, Alexey Olshansky, Alexey Ozerov, Big Data-Based Methods for Functional Safety Case Preparation, *JITA – Journal of Information Technology and Applications, Banja Luka*, Pan-Europien University APEIRON, Banja Luka, Republika Srpska, Bosna i Hercegovina, JITA 13(2023) 2:91-98, (UDC: 004.42.032.26:007.52), (DOI: 10.7251/JIT2302091R, Volume 13, Number 2, Banja Luka, December (57-120), ISSN 2232-9625 (print), ISSN 2233-0194 (online), UDC 004

Computer Vision as Part of an Advanced Train Control System

Alexey Ozerov, Andrey Okhotnikov

Research and Design Institute for Information Technology, Signalling and Telecommunications on Railway Transport (NIIAS), Moscow, Russia, a.ozerov@vniias.ru

Contribution to the State of the Art

https://doi.org/10.7251/JIT2302099O UDC: 656.073.436:004.42

Abstract: The article addresses the key issues related to the application of computer (machine) vision as part of an advanced train control system. The authors describe the architecture of a multi-layered train control system that uses computer vision as a key element of autonomy and automatic detection of obstacles on track ahead the train. The article provides some overview of computer vision sensors, key stages of dataset preparation for onboard perception, and some issues related to sensor calibration.

Keywords: automatic train control system, computer vision, artificial intelligence (AI), machine learning (ML), datasets, RAMS, SIL, sensor calibration.

The basic principles of the development of advanced train control and protection systems were defined as early as at the beginning of the XXI century. In terms of safety and infrastructure access requirements, they are based on the RAMS (Reliability, Availability, Maintainability, Safety) principles described in the IEC 61508 and EN 50128 standards. In that sense, the train control systems are quite conservative and are designed according to the "safety above all" principle. This approach is based on the method of evaluating the risk of failure per each safety function and defining target failure indicators (both random and systematic) based on the criteria of probability and severity of consequences. The failure targets are conventionally named SIL (Safety Integrity Level), where the highest requirements are specified for SIL 4, for which the probability of wrong-side failure is between 10^{-8} and 10^{-9} [1].

Currently, technological innovations are widely tested and deployed as part of train control systems (TCS). Those include artificial intelligence-based control elements as part of unmanned train control systems that do not completely comply with the adopted RAMS methodology, which requires its possible modification along with a whole number of regulations and operating instructions. Despite the certain conservatism of the railway industry the migration from niche solutions to a mass use of COTS appears to be inevitable, as otherwise it is impossible to reduce the time and cost of innovation deployment [2].

Today, development, testing, and deployment of such innovations are conducted as part of the general digital transformation of the railway industry, one of the key elements of which is the evolution towards robotised train control processes (cyber physical transportation systems) that implies the minimisation of human involvement in the business processes and complete replacement of humans in routine operations [3]. The objective is the transition to command and control 4.0, meaning that all trains are covered by a single broadband communication network, while each smart train continuously calculates its own safe distance to go and controls its speed accordingly based on precise knowledge of its current coordinate and information on the operating situation (location of other trains, status of track and signalling assets) received from a smart TMS [4].

The key point is the migration of the railway infrastructure functionality onto on-board trains (the concept of "smart train"). For instance, while in the past the absence of obstacles and foreign objects on the track ahead of a train could only be guaranteed (partially) by fencing the tracks, now that can be done through the use of a computer (machine) vision system installed at the head end of the train and additionally, if necessary, on the track itself in particularly hazardous locations [5].

The computer vision system (CVS) is to ensure timely detection and classification of foreign objects ahead of a train for the purpose of making a decision as regards the appropriate reaction of the onboard train control system (whistle, speed reduction, emergency braking, etc.). The CVS can play the role of a smart assistant if a human driver is present in the cab or of the primary automatic obstacle detection facility. Over the last few years such systems have been tested in several locations in Russia and other countries.

The onboard CVS consists of a set of sensors of varied nature and purpose, as well as high-performance, large-memory computer systems that process the signals of such sensors in real time using machine learning algorithms (Fig. 1). The above sensors include lidars, video cameras, 3 – 7 and 7 – 14 um thermal cameras, short range ultrasound sensors. Cameras and lidars are used at different ranges, i.e., short (up to 50 – 100 m), medium (up to 500 – 600 m) and long (up to 1000 – 1500 m). The settings are chosen depending on the function of the rolling stock. Shunting engines operate within a short range, commuter trains operate within the medium range, while long-range trains are additionally outfitted with long-range sensors. The sensors operate in various ranges of the electromagnetic spectrum, have their advantages and drawbacks that can manifest themselves under different conditions of lighting, humidity, etc.

Despite the active testing and application of the above systems a whole number of open questions remains regarding the use of computer vision as part of advanced train control systems. For instance, the question remains as to the method of proving the safety of an CVS as part of an TCS, including the definition of SIL for such a system. Obviously, the application of artificial neural networks does not allow classifying a CVS as a system with a high safety integrity level (SIL4). Meanwhile, the many tests conducted on CVS show that the capabilities of machine vision definitively surpass those of a human eye in terms of obstacle detection at various distances and under different lighting conditions.

For the purpose of ensuring safety and certifying a TCS that includes a computer vision system, some experts suggest dividing such TCS into a safe part (safety kernel) in the form of an onboard safety device that operates within a safety envelope, and a computer vision subsystem that operates within a separate control loop (see Fig. 2) [6].

Meanwhile, a TCS can be complemented with an additional element that fulfils the function of super-

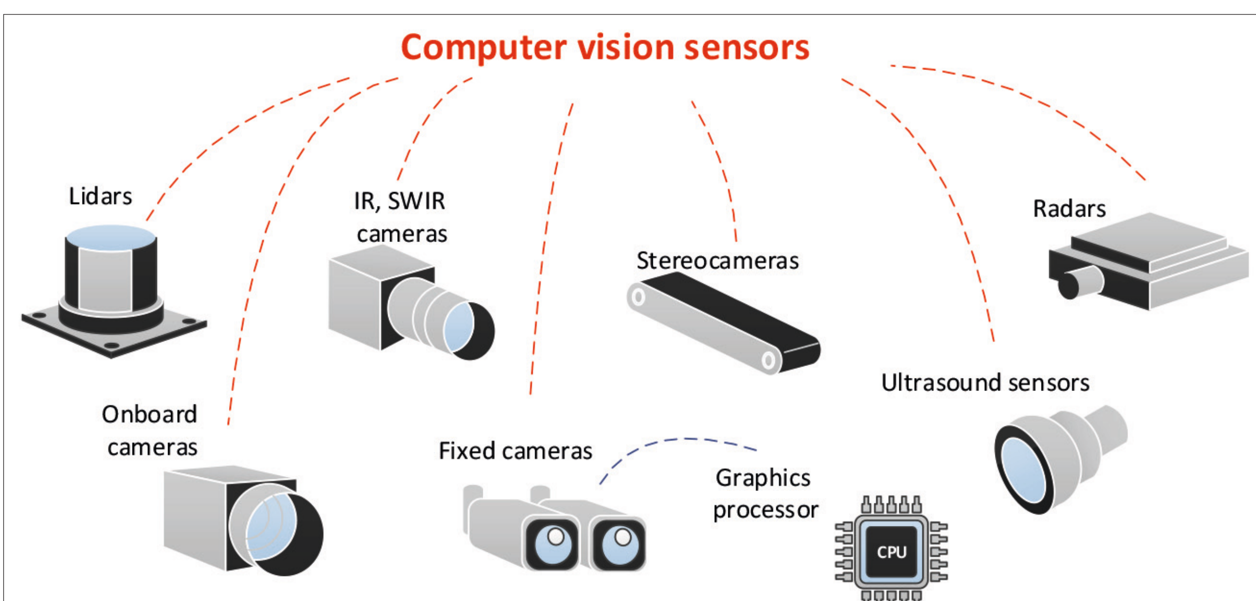


Fig. 1. *Computer vision system with various types of sensors*

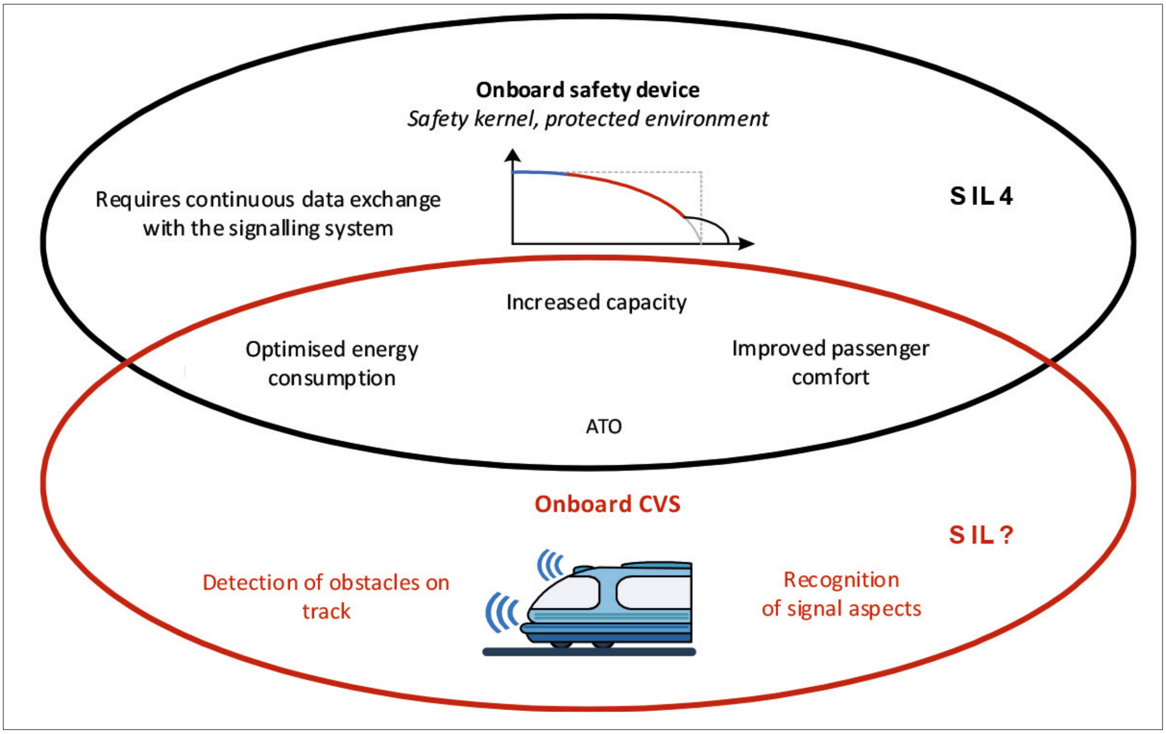


Fig. 2. Diagram of an advance TCS with smart control

vision and restriction. In most cases, a remote operating driver is considered as such an element that makes decisions in case of disparity of data between the control loops, yet other, completely automatic, solutions are examined as well [7].

As an example, let us consider the diagram of the TCS implemented on the Moscow Central Circle (MCC). The MCC TCS is designed as a multi-loop control system that supports two control modes, "autonomous" and "remote control". In Fig. 3, the red

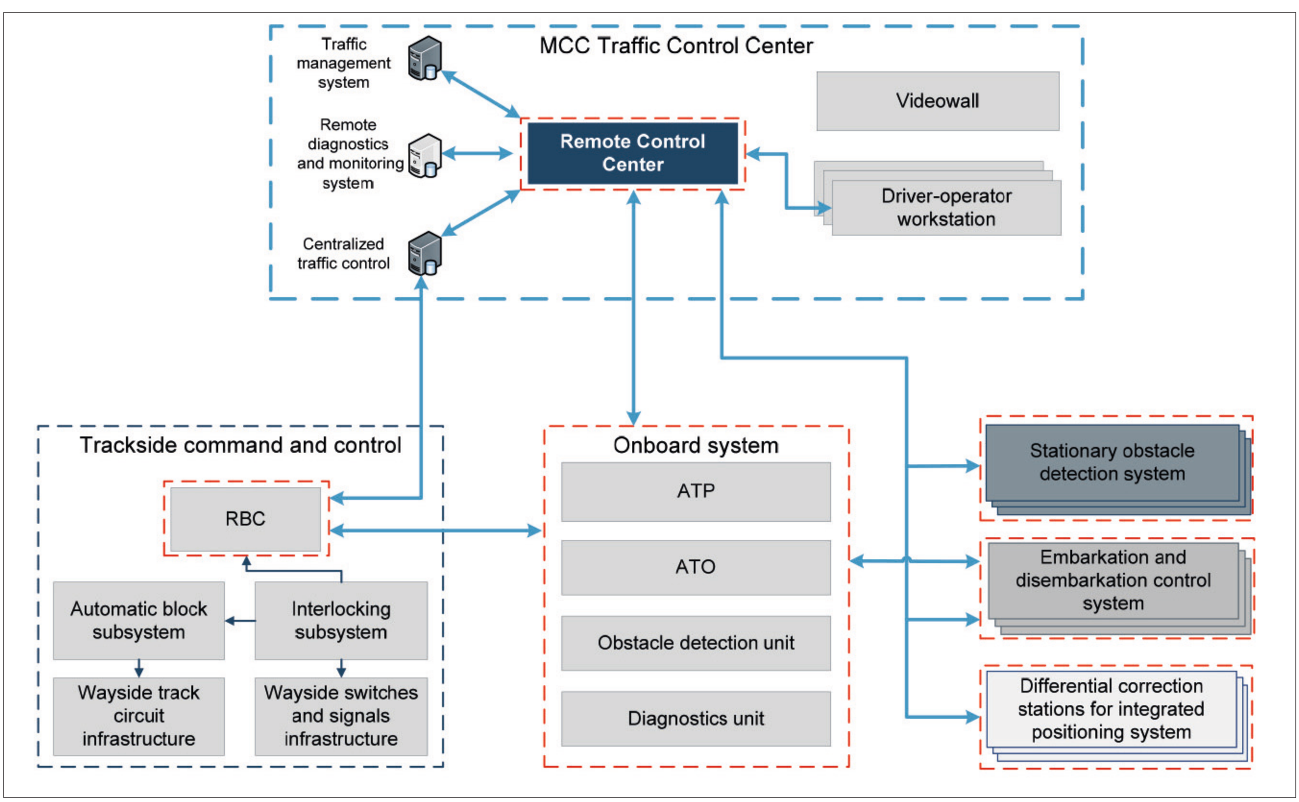


Fig. 3. General diagram of the MCC TCS

dashed line shows the subsystems that constitute the safety envelope of the GoA3/4 mode [8]:

The MCC TCS, besides the conventional coded track circuit-based automatic cab signalling, implements radio-based interaction between the trackside and onboard train control systems. Additionally, within a separate control loop, obstacles are automatically detected using onboard and fixed visual detection devices using artificial neural networks with the communication of the collected information to the Remote Supervision and Control Centre (RSCC).

Standardisation and automation of the preparation and verification of datasets for CVS sensors, as well as selection, testing and calibration of machine vision devices remain a question [4].

The process of dataset preparation for CVS includes the creation of digital models of railway lines and training of an artificial neural network to recognise objects. Normally, digital models are created by processing arrays of data obtained using laser scanning and video recording of railway lines during test rides. Besides input data obtained from the sensors, datasets contain target output data. Supervised learning aims to identify the required correlations between the input and output data. A CVS is to recognise not only infrastructure assets, but nonstationary objects (both static, and dynamic) at different distances and in different configurations and positions, namely, people of different age and gender, animals, trees on the track, vehicles, etc.

In case of unsupervised learning, the machine learning algorithms are used for the purpose of analysing and clustering of sets of unlabelled data. The creation (the so-called “annotation” or “labelling”) of correct target output data (labelled data) is normally done by people, which is labour-intensive. Various ways of automating data labelling for CVS are being examined [9].

Correct identification and semantic segmentation of objects (people, cars, trees, buildings, etc.) affects the operational safety of unmanned railway transportation. Reliable and efficient operation of CVS also requires accurate setting, calibration and continuous verification of the machine vision sensor outputs. The existing calibration methods are largely inefficient and unreliable and often cause reduced accuracy and increased error in the operation of the sensors. If CVS are mass-deployed as part of TCS, a whole number of issues will need to be resolved that deal with the organisation of the calibration and verification of CVS sensors as a measuring instrument with the development of an industry-wide method in accordance with GOST R 8.879-2014 [10].

One of the key difficulties as regards the calibration is the comparison of the data collected by sensors of different nature: a set of spatial points collected by a lidar and images collected by cameras. Therefore, calibration requires a special calibration stand including one or several calibration objects (markers) and equally well-identifiable both on a visual image, and within a point cloud, which will allow using its acquisitions as input data for calibration. A synchronised verification of data collected by all types of sensors – video cameras, lidars and thermal cameras – is to be provided for as well, including when an autonomous train operates in automatic mode.

The use of machine vision as part of advanced TCS is becoming a key and long-lasting trend in the development of modern control systems, which defines a wide range of engineering problems that require a comprehensive approach. Their efficient solution will define the mass migration towards completely automatic train control (with no driver) that is primarily enabled by the guaranteed level of safety that is at least not worse than the current one.

References

[1] Ozerov A.V. [On the methods of ensuring functional safety and dependability of railway control systems]. Nauka i tekhnologii zheleznykh dorog 2021;5,2(18). P.74-81. (in Russ.).

[2] Ozerov A.V., Marshova A.S. [Machine vision as part of automatic train control systems]. In: [Proceedings of the International Science and Technology Conference Future Information Technology]. Samara: Samara Science Centre of the RAS; 2022. P. 201 – 205. (in Russ.).

[3] Okhotnikov A.L., Tsvetkov V.Ya., Kozlov A.V. [Algorithms of a cyberphysical transportation system]. Zheleznodorozhny transport 2021;12:49 – 53. (in Russ.).

[4] Doppelbauer J. Command and Control 4.0. IRSE News 2018;246. P.134 – 135.

[5] Okhotnikov A.L. [Types of machine vision systems used in railway transportation]. Nauka i tekhnologii zheleznykh dorog 2020;4,4(16). P.77 – 87. (in Russ.)

[6] Flammini F., De Donato L., Fantechi A., Vittorini V. A Vision of Intelligent Train Control. In: Reliability, Safety, and Security of Railway Systems. Modelling, Analysis, Verification, and Certification. Springer. P.192 – 208.

[7] Ozerov A.V., Olshansky A.M. Safety model construction for

a complex automatic transportation system. Dependability 2021;21(2). P. 31 – 37.
[8] Rozenberg, E.N., Ozerov A.V. Train command and control for commuter and urban lines. Journal of Information Technology and Applications. – 2022. – Vol. 12, No. 1. – P. 5-13.
[9] Tagiew R., Buder T., Tilly R., Hofmann K., Klotz C. Data set for autonomous driving as basis for GoA3+. Eurailpress, ETR 2021;9. P. 10 – 14.
[10] GOST R 8.879-2014. Calibration techniques of measuring instruments. (accessed 09.03.2023). Available at: https://docs.cntd.ru/document/1200118303

Received: September 29, 2023
Accepted: November 18, 2023

About the authors

Alexey Ozerov is the Head of International Department – Head of Intellectual Property Management Centre of JSC NIIAS. He has been working with JSC NIIAS for over 16 years in various positions related to research, signalling business unit and international cooperation. He is finishing his PhD in traffic management and has authored over 50 papers and 8 patents in the field of advanced railway signalling and traffic management.

Andrei Okhotnikov is the Deputy Head of Information Technology Division – Head of Strategic Development Department of JSC NIIAS specializing in the innovative and strategic development, business process management, import substitution industrialization. He is the author of JSC NIIAS corporate strategy and innovation and digitalization programs along with JSC Russian Railways short-term and mid-term strategy for science and technology. He has published over 54 journal and 7 conference proceeding papers and a monograph, as well as authored 16 patents

For citation

Alexey Ozerov, Andrey Okhotnikov, Computer Vision as Part of an Advanced Train Control System, *JITA – Journal of Information Technology and Applications, Banja Luka*, Pan-Europien University APEIRON, Banja Luka, Republika Srpska, Bosna i Hercegovina, JITA 13(2023) 2:99-103, (UDC: 656.073.436:004.42), (DOI: 10.7251/JIT2302099O, Volume 13, Number 2, Banja Luka, December (57-120), ISSN 2232-9625 (print), ISSN 2233-0194 (online), UDC 004

Cybersecurity Standards of Intellectual Transport Systems

Alexey Ozerov

Research and Design Institute for Information Technology, Signalling and Telecommunications on Railway Transport (NIIAS, Moscow, Russia, a.ozerov@vniias.ru

Contribution to the State of the Art

https://doi.org/10.7251/JIT2302104O UDC: 004.056.5:656.222

Abstract: The paper gives an overview of general approaches and existing standards as regards the cybersecurity of automated control systems with the railway transport specifics taken into account. It outlines major directions for the development of guidelines and activities for ensuring the cybersecurity of intellectual control systems.

Keywords: safety/security, functional safety, cybersecurity, risk assessment, system lifecycle, cyber ranges.

The modern railway control/management systems are characterised by a high level of integration and connectivity. On the one hand, that is due to a wide use of computer technology, single data communication buses, digital diagnostics sensors, etc. On the other hand, that is also a basic prerequisite for further development and widespread deployment of intelligent transportation systems.

Given the major trend towards cloud technology, further adoption of intelligent control/management systems in railway transportation means a constantly growing attack surface (primarily, for cyberattacks). Due to that fact, it is required to reconsider the attitude to ensuring cybersecurity of control/management systems not only at the stage of operation, but at the design stage as well. Of increasing importance are industry-specific recommendations, guidelines, and standards that examine the principles of designing secure control/management systems holistically while taking into account the principles of functional safety and the possible mechanisms of ensuring cybersecurity as part of a single balanced approach.

Meanwhile, working out an all-purpose approach in this area is not at all a trivial task. The lifecycle of railway signalling systems is anywhere from 15 to 30 or 50 years, while the functional safety principles of such systems remain unchanged since the era of relay technology. Meanwhile, the cyber integration of modern systems is moving forward and the cyber threat landscape is constantly changing requiring prompt reaction and improvement of defence mechanisms.

The experts do not have a single interpretation of the concepts of “information security” and “cybersecurity” as regards information management systems and their logical association. Thus, some experts believe that information security is a component of cybersecurity, while others insist on the opposite, claiming that cybersecurity is part of information security. That causes the differences in the approaches to ensuring cybersecurity of control/management systems. In one case, they insist on developing special methods of protection aimed at eliminating wrong-side failures, while in others, they claim that the conventional information security methods suffice and do not require taking into account the specificity of railway control/management systems [1].

Additionally, we must also point out the difference in the interpretation of the above concepts as regards non-safety-related systems (generally referred to as information communication technologies, ICT) and critical systems (the so-called supervisory control and data acquisition, SCADA). If, in the case of ICT, the classic "confidentiality – integrity – availability" triad is shifted towards confidentiality, in the case of SCADA, it is shifted towards availability (see Fig. 1) [2].

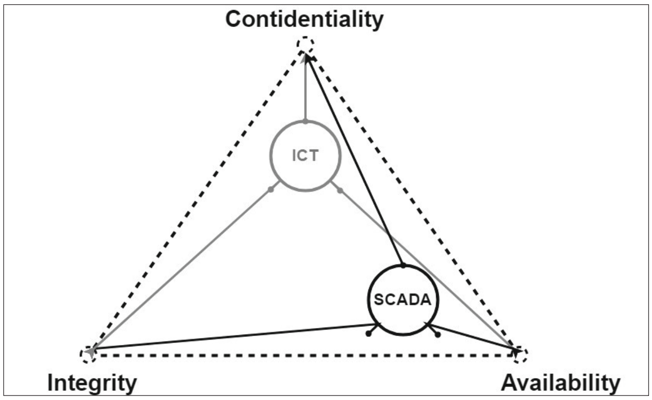


Fig. 1. *Information/cybersecurity triad*

Unlike in the case of ICT, the primary SCADA cybersecurity threats are wrong-side failures that may be caused by both cyberattacks and exploitation of undocumented features in a system's software and components. Naturally, they can also be caused by hardware and software failures and faults in the system's operation, operator errors, and input of erroneous data [3].

As it is known, the designers of vital railway systems conventionally follow the "safety above all" paradigm, meaning that each system component (and the entire system) are to comply with a certain Safety Integrity Level (SIL). In order to achieve the required SIL, certain design rules and test methods are to be implemented that guarantee that the system will continue fulfilling the appropriate safety requirements in the case of a random failure. However, functional safety standards that are used as guidelines for railway system design do not take matters of cybersecurity into consideration, but merely mention that a cybersecurity mechanism is to be developed in accordance with the recommendations of the standards that deal with general-purpose network device security. The primary standard IEC 61508 [4] that describes the requirements for the functional safety of electrical and electronic devices and the CENELEC EN 50159 [5] standard that describes the requirements for data communication within critical railway systems only mention that the possibility of intentional actions of people is to be taken into consideration and refer to the ISA/IEC 62443 [6] standard.

Due to that various international organisations are developing recommendations and guidelines that attempt consolidating functional safety requirements for railway signalling systems and cybersecurity requirements. Thus, in 2015, the International Union of Railways (UIC) initiated the ARGUS project that brought forth guidelines for the cybersecurity of railway systems [7] that extrapolate the risk evaluation principles and assurance of information security of the ISO/IEC 27000 series of standards to the railway signalling and communication systems. The Guidelines for Cyber Security in Railway has actually become the first international document developed with extensive participation of experts in not only information security, but railway signalling as well.

Several projects of the Shift2Rail European initiative also attempted a comprehensive consideration of the matters of cybersecurity of railway control/management systems. Out of those, the following should be noted:

- the 4SECURail project that developed formal methods for ensuring security in a railway environment and recommended creating "computer security incident response teams" (CSIRT) for the railways [8];
- the CYRail project that published various guidelines for improving the security of railway systems, including recommendations for designing cyber-attack resilient systems (secure by design) [9].

Of note is the OCORA initiative (Open CCS Onboard Reference Architecture) that has developed guidelines for a cyber-secure reference onboard train control and protection systems architecture that is largely based on the CYRail recommendations (thorough evaluation of threats and risks, threat model construction, system partitioning, embedded cyber security and monitoring mechanisms) [10].

Of special interest is the EU-funded CLUG project that is dedicated to a more specific task, i.e., the development of a secure onboard train control and protection unit architecture featuring a GNSS-based positioning system taking into account cybersecurity among other things. The project participants are developing requirements for the onboard unit based on the risk evaluation method and the four safety categories according to ISA/IEC 62443. The following threats are taken into consideration: data diddling, spoofing, distortion of measured data supplied by sensors, damage to digital track map databases, output data falsification, denial of service [11].

The existence of a wide class of threats and the variety of ways of dealing with them – in terms of the principles of ensuring functional safety, physical protection of devices and information security – indicates not only the absence of a specialised railway standard, but the complexity of the matter. The authors of [12] conclude that the conventional approach, whereas the matters of cybersecurity are considered only as an addition to functional safety and solved only through methods of information protection, is to be abandoned. An integrated approach is required that would involve the development of the system's digital infrastructure with built-in cybersecurity mechanisms.

Probably, when it has become a new standard, the CENELEC prTS 50701 Railway applications – Cybersecurity technical specification will contribute to the development of an integrated approach [13]. This pre-standard is based on the ISA/IEC 62443 standard and is a specialised solution for the railway industry, including rolling stock, signalling and infrastructure.

The key provision of the prTS 50701 draft standard is the principle of in-depth defence built upon a multi-level security system. PrTS 50701 defines a concept of security levels that largely resembles the approach based on the safety integrity levels (SIL), yet differs from it in several details. In particular, it states that the security level is the measure of confidence that a zone of the system architecture, conduit, communication channel or a component thereof is free from vulnerabilities and functions as intended. PrTS 50701 defines architectural design constraints for railway technology based on the concept of zoning. PrTS 50701 specifies that zoning involves measures for functionality encapsulation for the purpose of keeping a particular service alive in case of an incident in another zone while isolating it by closing the gateways to the affected zone.

According to [14], the basic ISA/IEC 62443 standard is the optimal industry standard in cybersecurity, and in combination with prTS 50701 provides all the required guidelines for ensuring cybersecurity of railway systems.

Nonetheless, given the growing relevance of cybersecurity in the context of modern control/management systems, not only the conventional SIL-based design approach, but the entire lifecycle concept of critical railway control/management systems that is usually depicted with the V model must be reconsidered. The initial cybersecurity risk assessment of a system under development is to be

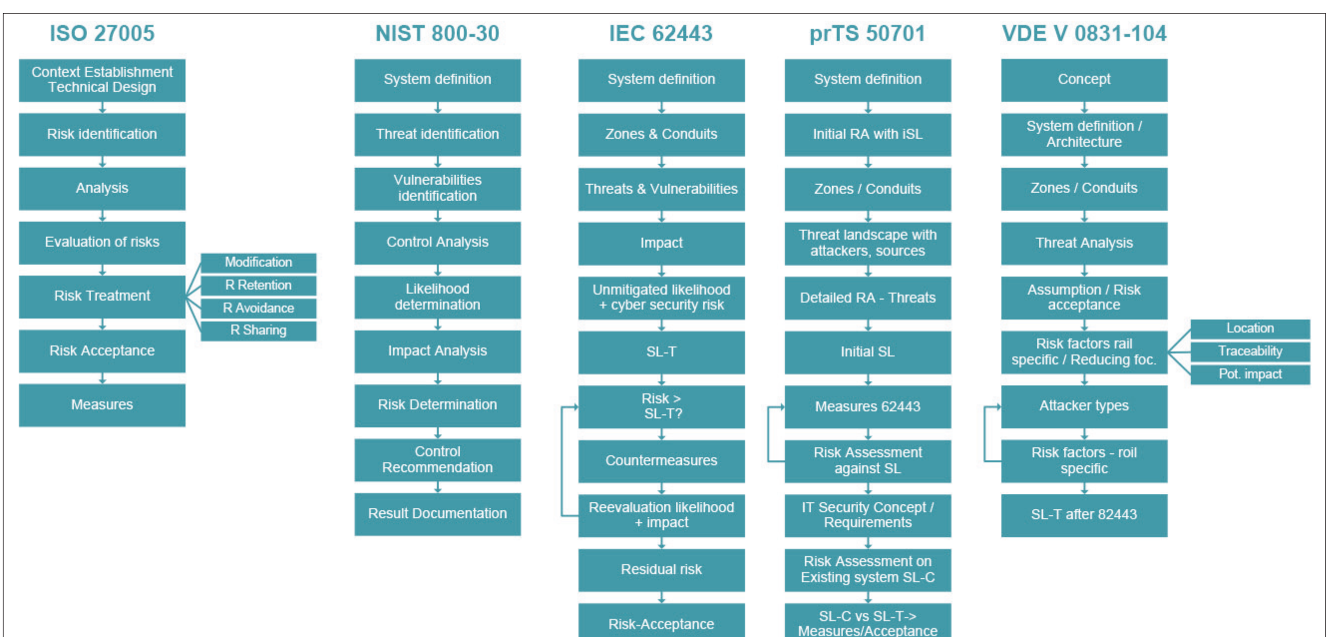


Fig. 2. *Risk evaluation models at system development stages defined in standards*

conducted at the very early stage of concept and requirement definition. Fig. 2 shows the approaches of various standards to the evaluation of risks at various stages of vital control/management system design.

Selecting the most optimal system development process requires conducting the appropriate evaluation procedure. The key evaluation criteria are as follows:

- compliance with the operation processes employed in railway transportation;
- compliance with industry standards and requirements of the certification and regulatory agencies;
- usability;
- efficiency;
- level of detail defined by the standard;
- lack of excessive complexity.

According to IEC 62443 and prTS 50701 the process of risk evaluation is to include the following stages:

1) description of the examined system;

2) pre-zoning principle based on preliminary risk evaluation;

3) definition of basic threat types;

4) assessment of motivation, knowledge, and resources of attackers;

5) definition of specific types of threats, including those on the railway company's register;

6) classification of threats according to the basic requirements;

7) definition of the initial level of security for each threat in accordance with the basic requirements;

8) input of preliminary value zones defined in the basic documents into data vectors;

9) calculation of the security levels for preliminary zones after the definition of the maximum vector values;

10) definition of final security levels using correction coefficients (maximum value 1);

11) performance of cybersecurity measures;

12) verification of whether the measures are applicable to the concept of preliminary zoning, provided that they comply with the respective requirements. If the measures are not applicable, the concept is to be reconsidered;

13) the performance of items 11 and 12 is to be repeated until all system settings have been performed.

All of the stages of the cybersecurity solution development processes are to be coordinated with the respective system lifecycle stages performed based on the requirements of CENELEC standards. That enables verification and validation, especially as regards obtaining representative results that can be conveniently used as output data in the course of the process. Fig. 3 shows an example of the V model of a railway signalling system's lifecycle that integrates cybersecurity measures that was developed

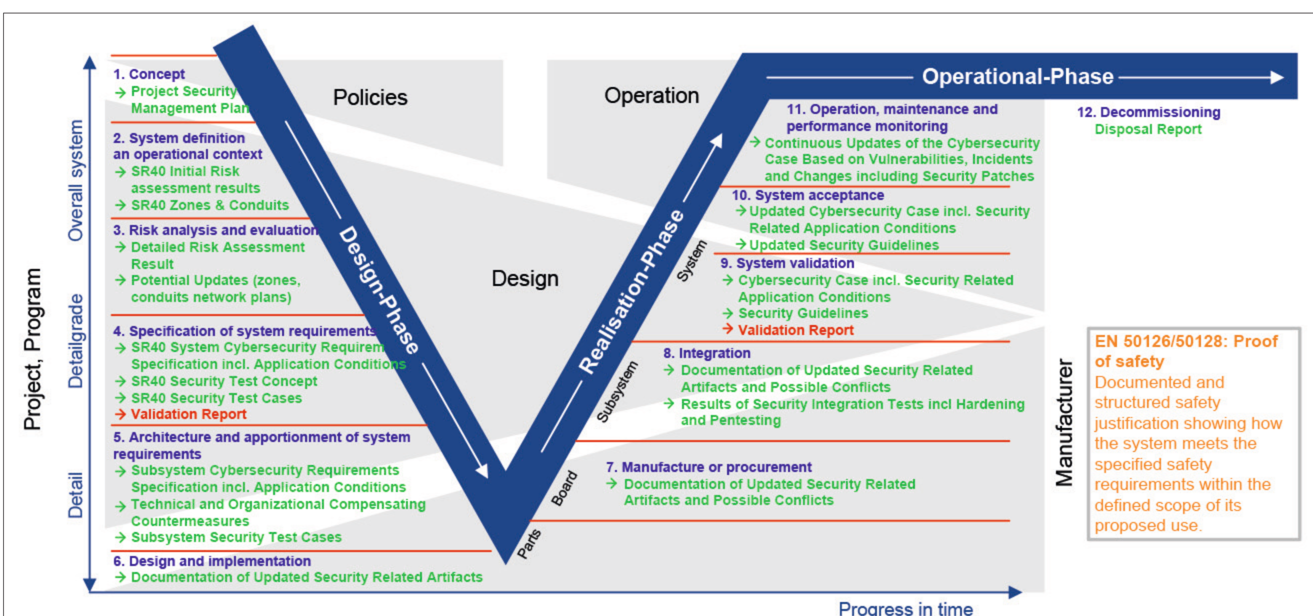


***Fig. 3.** An example of the V model that shows the correlation between the CENELEC standard requirements and assurance of cybersecurity*

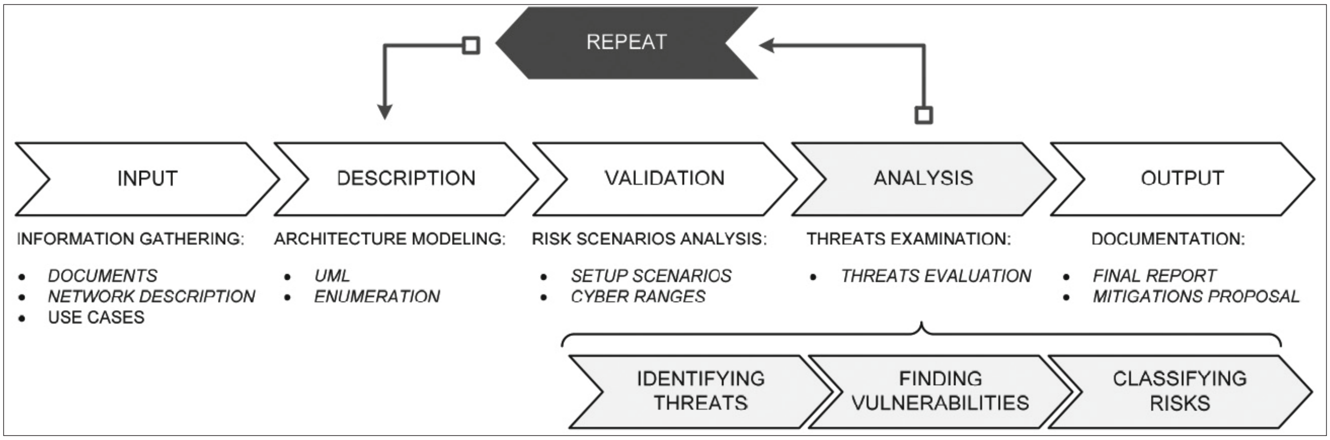


Fig. 4. *Control/management system cybersecurity risk evaluation process*

as part of the Smartrail 4.0 railway innovation program of Switzerland.

Thus, cybersecurity risks are to be evaluated at all system lifecycle stages, and at the stage of verification and validation is to become an integral part of integrated safety assessment that includes the assessment of its cyber resilience subject to the constructed model of cyber threats. The overall risk evaluation process according to those standards is shown in Fig. 4 where the primary analysis procedure and its main stages are shown in grey.

We must note the ever growing popularity of the idea of cyber ranges that involves conducting the required tests within certain virtual boundaries and ensures isolation from operational devices. Cyber ranges enable the performance of tests required by the safety analysis through a rapid simulation of the required scenarios. For instance, the European CONCORDIA consortium is actively working on creating cyber ranges [15].

Cyber ranges may be physical or completely virtual, whereas cyber range scenario components use a virtualisation solution for the purpose of emulating physical assets, as well as hybrid, whereas solutions are employed that are based on a combination of hardware, virtualised, and simulated elements. As the process of virtual scenario definition is quite demanding, it is obvious that most efforts are to be concentrated in its automation with the use of various software solutions. A most important tool for virtual scenario definition is gamification that has been used for a long time in simulation and cyber security risk evaluation.

Today, one of the most pressing problems is the integration of the existing tools for testing system security into digital twins. Another unsolved problem is meeting the computational requirements of the precision simulation environments. Indeed, if the final goal consists in emulating an intelligent control/management system in its entirety, it is obvious that the required computational resources may prove to be above the current technical capabilities. A wide use of artificial intelligence as part of cyber security risk evaluation using cyber ranges can also be restricted by limited computing capabilities.

References

[1] Ozerov A.V. Cybersecurity of Railway Command and Control Systems. Journal of Information Technology and Applications 2019;9(2):53-59. DOI 10.7251/JIT1902053O.

[2] Soderi S., Masti D., Lun Yu.Z. Railway cyber-security in the era of interconnected systems: a survey. IEEE; 2022. (accessed 14.03.2023). Available at: https://arxiv.org/pdf/2207.13412.pdf.

[3] Shubinsky I.B., Makarov B.A. [A little about cyber security]. Information, Communications, Informatics 2014;8:15-18. (in Russ.)

[4] IEC 61508:2010. Functional safety of electrical/electronic/programmable electronic safety-related systems. Switzerland: IEC; 2010.

[5] CENELEC EN 50126:2018. Railway applications – The Specification and Demonstration of Reliability, Availability, Maintainability and Safety (RAMS). Belgium: CENELEC; 2018.

[6] ISA/IEC 62443:2009. Security for Industrial Automation and Control Systems. USA: ISA; 2009.

[7] Guidelines for Cyber Security in Railway. France: UIC; 2018.

[8] 4SecuRail. EU; 2023. (accessed 07.03.2023). Available at: https://www.4securail.eu/.

[9] CYRail. EU; 2023. (accessed 14.03.2023). Available at: https://cyrail.eu/IMG/pdf/final_recommendations_cyrail.pdf.

[10] OCORA-TWS06-020, Version: 1.00. EU: RCA; 2021.

[11] The Clug Project. EU; 2023. (accessed 10.03.2023). Available at: http://www.clugproject.eu/en/news/establishing-security-requirements-gnss-based-train-localisation-

board-unit-tlobu.
[12] CENELEC CLC/TS 50701:2021. Railway applications – Cybersecurity. Technical Specification. Belgium: CENELEC; 2021.
[13] Bearfield G., Van Gulijk C., Parkinson S., Thomas R.J. Transformation of Cyber Security/Safety Assurance. World Congress on Railway Research; 2022.
[14] Parkinson H.J., Basher D.R., Bamford G. Railway cyber security and TS50701. 2022. (accessed 10.03.2023). Available at: https://www.researchgate.net/publication/361006662_Railway_cyber_security_and_TS507.
[15] CONCORDIA. EU; 2023. (accessed 09.03.2023). Available at: https://www.concordia-h2020.eu/news/concordia-releases-an-open-source-cyber-range-platform/.

Received: September 29, 2023
Accepted: November 13, 2023

ABOUT THE AUTHORS

Alexey Ozerov is the Head of International Department – Head of Intellectual Property Management Centre of JSC NIIAS. He has been working with JSC NIIAS for over 16 years in various positions related to research, signalling business unit and international cooperation. He is finishing his PhD in traffic management and has authored over 50 papers and 8 patents in the field of advanced railway signalling and traffic management.

FOR CITATION

Alexey Ozerov, Cybersecurity Standards of Intellectual Transport Systems, *JITA – Journal of Information Technology and Applications, Banja Luka*, Pan-Europien University APEIRON, Banja Luka, Republika Srpska, Bosna i Hercegovina, JITA 13(2023) 2:104-109, (UDC: 004.056.5:656.222), (DOI: 10.7251/JIT2302104O, Volume 13, Number 2, Banja Luka, December (57-120), ISSN 2232-9625 (print), ISSN 2233-0194 (online), UDC 004

Train Control Systems for High Speed Rails

Alexey Ozerov, Elena Denchik

Research and Design Institute for Information Technology, Signalling and Telecommunications on Railway Transport (NIIAS), Moscow, Russia, a.ozerov@vniias.ru, e.denchik@vniias.ru

Contribution to the State of the Art

https://doi.org/10.7251/JIT2302110O UDC: 629.4:621.791

Abstract: The article provides an overview of train control and protection systems used on high-speed railways in given European and Asia-Pacific region countries. Particular attention is paid to currently operated and future means for the transmission of safety-related information to the trains.

Keywords: HSR; Train control systems; Automatic train protection; Cab-signalling; ERTMS; LZB; TVM; BACC; ATC; CTCS.

High-speed rail (HSR) has developed rapidly worldwide in recent years. Over the past 5 years alone, their length has increased by more than a third from 44 thousand km to around 59 thousand km. China has put into operation more than 40 thousand km which was the greatest contribution to this expansion. The HSR operating experience shows that high-speed passenger transportation is a very popular service. According to the International Union of Railways, about 2 billion passengers travel by HSR every year [1], and the number of the passengers is expected to increase.

According to the international classification, the lines newly built to handle speeds above 250 km/h or upgraded conventional lines operating at speeds of more than 200 km/h are considered as HSR [2]. Each country individually determines the maximum speed, which currently does not exceed 350 km/h. The global evidence shows that there has been no regular passenger service with speeds above 350 km/h by now; however, individual test runs have confirmed the possibility of this service.

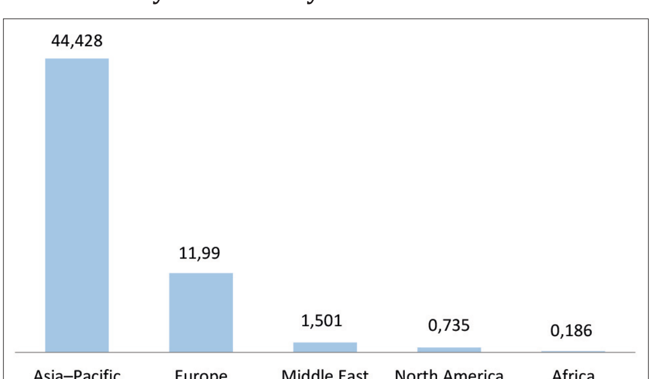


Fig. 1. *Length of the high-speed network in operation by regions (km/h)*

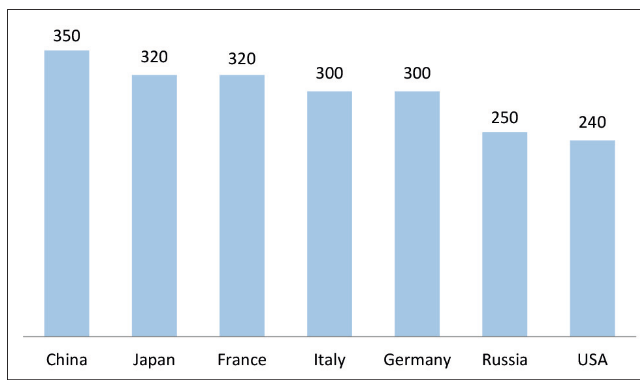


Fig. 2. *Maximum speed of high-speed rail network by country (km/h)*

Increased travel speeds require higher safety level and upgrading of conventional signalling systems. Since the driver is not able to perceive the aspect of trackside signals when running at high speeds, train protection on the HSR is ensured by train separation systems operating without trackside signals.

Despite the communications-based train control systems are widespread, the majority of countries with large HSR network still use track circuits to transmit the information and monitor the occupancy of the track and the integrity of trains.

For example, the TVM train control system deployed on French HSR is based on track circuits. A line equipped with this system is divided into blocks that are 1500 to 2000 m long. Based on information received from the trackside equipment, the onboard computer continuously calculates the braking curve for each block depending on the length, weight and braking capabilities of the train. If a train enters the occupied block, its speed is limited to 30 km/h, and if speed reaches 35 km/h, the train is emergency-braked. The TVM system is backed up by an intermittent cab-signalling system in some areas.

A similar approach is applied on HRS in Japan, where the ATC system is implemented. This system sends audio frequency signals to the track circuits, ensuring the transmission of information about speed limits for each track section to the locomotive. After receiving these signals, the current speed of the train is compared with the maximum permissible speed for the section, and if it exceeds, the train is emergency-stopped. As opposed to the French TVM system, the length of the block is about 3000 m. One block comprises two track circuits. An improved system with digital codes (DS-ATC) is being deployed on newly constructed HSR sections.

As for Italy, lines designed for speeds up to 200 km/h are equipped with the national BACC system based on coded track circuits and cab-signalling system that displays the aspects of the trackside signals. The system makes it possible to continuously monitor the train speed and calculate the braking curve. In BACC system, a block of the open line consists of 4-5 track circuits that are on average 1350 m long. HSR designed for speeds up to 300 km/h are equipped with signal-free ERTMS level 2 that operates without overlaying with other systems. Only trains equipped with the ERTMS operate on such lines.

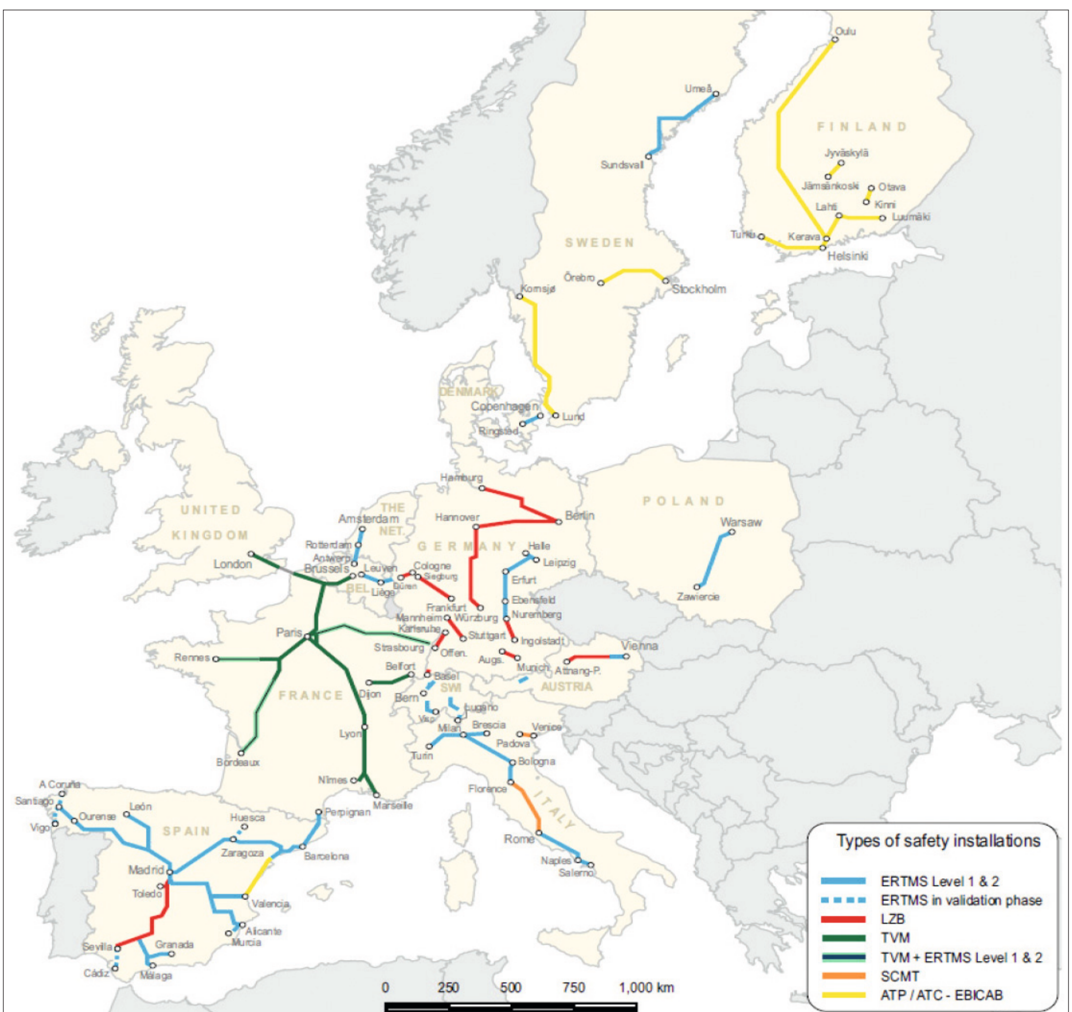


Fig. 3. *Types of European train control systems*

Cable loop is the least used means for continuous transmission of signal aspects to the train, since, compared to track circuits, the loop is quite damageable and its installation and maintenance costs are higher. Cable loops are used mainly in Germany, Austria and Spain (LZB system) [3].

The LZB system is a computer-aided continuous cab-signalling system for HSR with speeds up to 300 km/h. It is overlaid onto the national signalling system. Train movements on the section are controlled by LZB control centre. It stores data about the section and receives the information about vacant blocks and the switch positions coming from interlocking, as well as the data about current train position and braking capabilities coming from the trains. Based on this data, the distance to a point ahead where the speed is to be changed is calculated upon which the information about maximum permissible speed on the section, the distance to an obstacle, etc. are transmitted to the train via the loop. The LZB cable loops are crossed every 100 m, which allows train position and speed to be determined by counting the phase changes by means of onboard equipment as the train passes over the crossings. Track occupancy/vacancy is monitored by interlocking systems with the aid of track circuits or axle counters. The LZB system is also backed up by intermittent cab-signalling.

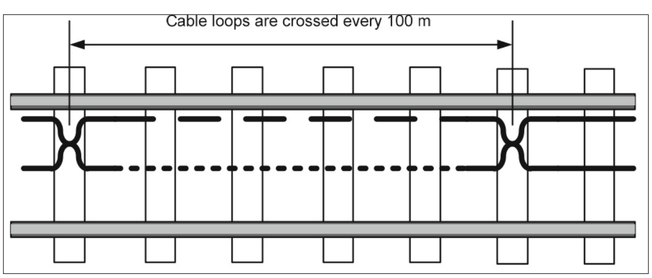


Fig. 4. *LZB cable loop*

In order to ensure interoperability within the European Union, a communication-based ETCS/ERTMS was developed. There are three ETCS/ERTMS levels. The ETCS level 2 is the most applicable system for HSR in Europe, since ETCS level 1 is considered to be unreliable for speeds above 160 km/h. Level 2 implies that train movements are controlled via radio communication (GSM-R standard). Positioning of the train is based on balises, while the track section occupation status is detected with the help of track circuits or axle counters. Level 3 combines the functions of the previous level and onboard train integrity control. This level is under development and is not yet widespread on main railway lines.

The main component of the ETCS/ERTMS is the radio block center (RBC) that controls all vehicles in controlled area and issues movement authorities via GSM-R channels, taking into account the current train situation, permanent and temporary speed restrictions, track profile and braking capabilities. At the same time, the trains transmit the information about their current position and speed to the RBC via a radio channel.

ETCS/ERTMS level 2 and 3 implies using the national onboard protection unit in addition to the European Vital Computer (EVC) in order to ensure interoperability with the national signalling trackside equipment [4].

The ERTMS level 2 is currently being rolled out on HSR not only in Europe, but also in other regions around the world. Based on the technologies used in this system, the Chinese train control system (CTCS) was designed. Similar to the ETCS/ERTMS, there are three levels of CTCS application.

The lines designed for speeds of 200-250 km/h are equipped with CTCS-2, where track circuits are used to control the section occupancy status and transmit information to the train which is similar to TVM system. The CTCS-3 is used for lines which allow speeds above 250 km/h. The main means for transmitting the information to the train is a GSM-R digital radio channel. CTCS levels 2 and 3 include redundant systems, for example, track circuits and active balises are used as a redundant system to CTCS-3.

Another level of the CTCS (CTCS-4) is under development and is considered as a promising one for a new generation system. It involves such features as moving blocks, an integrated navigation module based on the data from the BeiDou system and a digital map for high-precision positioning, as well as the new types of wireless communications (LTE-R and 5G) for safety-related information exchange between the train and the RBC [5].

As regards to Russian HSR it is planned to use the Russian Train Control System (RTCS). The RTCS is designed as a hybrid control system and includes a signal-free train separation system (cab-signalling system) for open lines, an IXL for stations, RBC and a digital radio communication system.

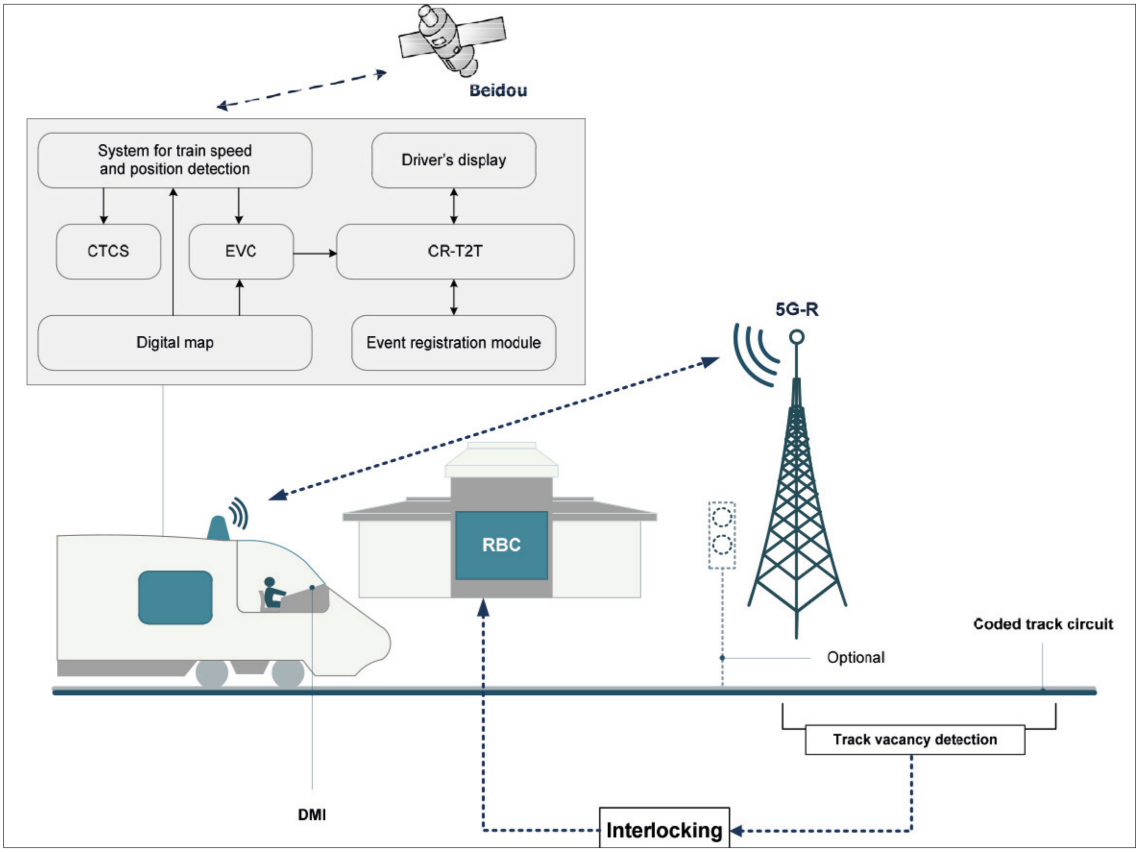


Fig. 5. *CTCS-4 architecture*

RTCS is a dual channel system and enables the regulation of train movements using data received by the train from both conventional block systems via track circuits (ALSN and ALS-EN codes), and the RBC via a radio channel (permitted speed or stopping point).

An important difference between RTCS and ETCS/ERTMS is that the Russian solution uses a single onboard protection unit, which simultaneously communicates with track circuit equipment and the RBC. By comparing the information received via the radio channel with the information received via the track circuit, the onboard equipment builds a braking curve. This approach creates an additional control loop and allows for the implementation of a multi-level protection concept.

If there is no information transmitted to the train via the radio channel, the train does not stop. In this case, the train operates using conventional train control system (automatic cab-signalling). After establishing a stable radio signal, the train automatically continues to be controlled by communication-based train control system along with conventional one.

The train position is detected based on GNSS data and onboard digital maps that are the main source of information about infrastructure facilities when making decisions related to safe train operation.

In order to increase the reliability of the RTCS operation, a new extended audio frequency track circuit (750 m) was designed. This decision is due to the lack of time for the locomotive operating at high speeds to correctly receive information from a standard audio frequency track circuit.

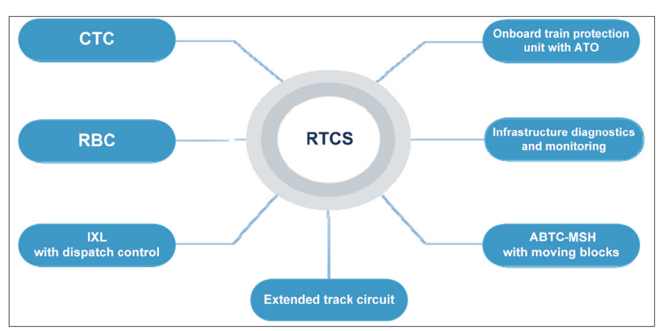


Fig. 6. *RTCS subsystem composition*

It should also be noted that the RTCS includes all the components necessary to implement the moving block concept and the ATO.

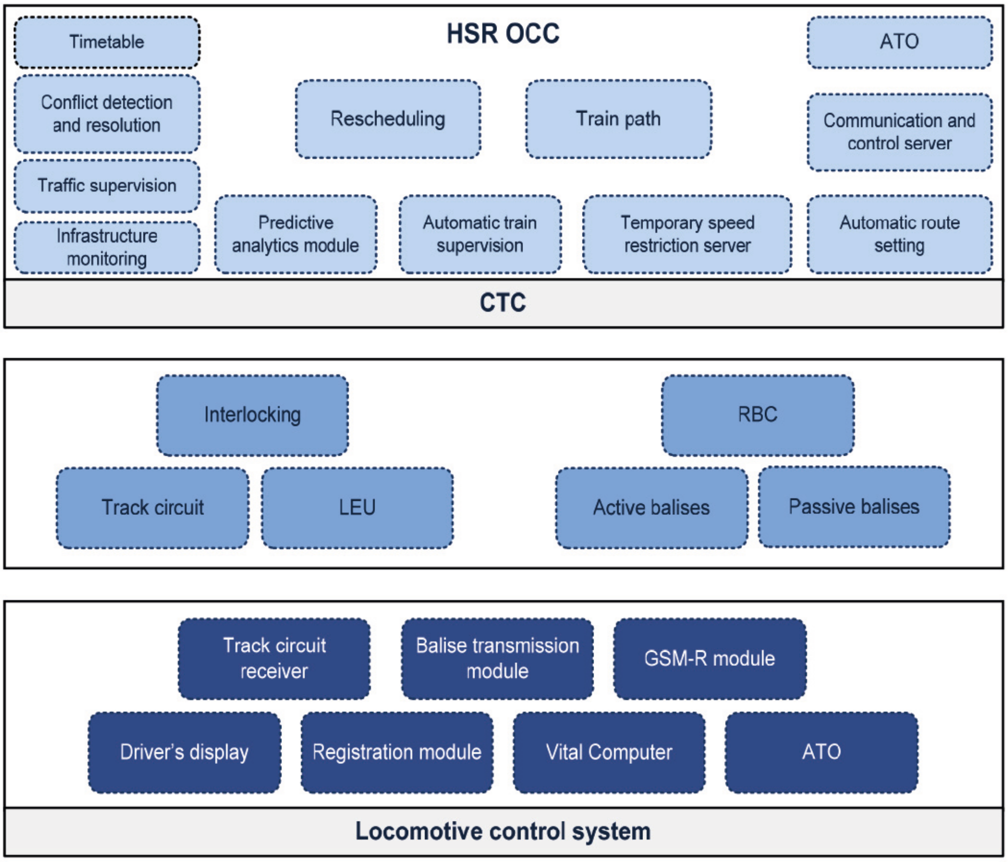


Fig. 7. *Traffic management system for HSR*

The signalling system is an element of the integrated traffic management system for HSR implying that the train traffic on HSR is controlled from the operations control center (OCC). The OCC has the full range of tools to regulate train movements on HSR. In particular, it ensures automatic route setting, real-time supervision, conflict detection and resolution, rescheduling, transmission of updated timetable and information about speed restrictions to the onboard ATO module. The main components of the integrated traffic management system for HSR are shown in Fig.7.

This review shows that modern train control and protection systems for HSR are characterized by individual adaptation of conventional signalling systems in terms of equipment related to interlocking, automatic blocking, cab-signalling, communication. Redundancy of the signalling system components is the basis for achieving high safety level. Therefore the most common train control system for HSR in the world is the one with double control configuration which uses radio communication and a track circuit along with, in some cases, additional redundancy components such as active balises. Dual standard approach additionally provides interoperability with mainlines.

REFERENCES:

[1] Táuler, Á. High-Speed Rail 2022 Atlas / Á. Táuler, S. Martín, M. Benito. – 4th Edition. – France: International Union of Railways (UIC), 2022. – p. 204.

[2] High-speed around the world. Available at https://uic.org/IMG/pdf/uic-high-speed-around-the_world.pdf. Accessed 23.10.2023.

[3] Theeg, G. Railway Signalling and Interlocking / G. Theeg, S. Vlasenko (Eds.). – 3rd Edition. – GmbH: PMC Media House, 2020. – 553 p.

[4] Ozerov A. [European train separation systems]. [Automation, communications, informatics]. 2019. Iss. 6, pp.14-15. (in Russ.)

[5] Ozerov A. [Global trends in the development of train control systems]. [Railway Science and Technology]. 2022, V. 6, Iss. 4(24), pp. 10-14. (in Russ.).

Received: September 1, 2023
Accepted: November 21, 2023

About the authors

Alexey Ozerov is the Head of International Department – Head of Intellectual Property Management Centre of JSC NIIAS. He has been working with JSC NIIAS for over 16 years in various positions related to research, signalling business unit and international cooperation. He is finishing his PhD in traffic management and has authored over 50 papers and 8 patents in the field of advanced railway signalling and traffic management.

Elena Denchik is a Project Manager of International Department of JSC NIIAS. She graduated from National Research Nuclear University MEPhI (Moscow Engineering Physics Institute). She conducts multi-method research on complex technical systems in various industries. Her areas of interest include the analysis of complex technical systems effectiveness and factors determining its' competitiveness. She has 11 years' experience in the space sector and 5 years' experience in the railway sector.

For citation

Alexey Ozerov, Elena Denchik, Train Control Systems for High Speed Rails, *JITA – Journal of Information Technology and Applications, Banja Luka*, Pan-Europien University APEIRON, Banja Luka, Republika Srpska, Bosna i Hercegovina, JITA 13(2023) 2:110-115, (UDC: 629.4:621.791), (DOI: 10.7251/JIT2302110O, Volume 13, Number 2, Banja Luka, December (57-120), ISSN 2232-9625 (print), ISSN 2233-0194 (online), UDC 004

Instructions for Authors

The *Journal of Information Technology and Application (JITA)* publishes quality, original papers that contribute to the methodology of IT research as well as good examples of practical applications.

Authors are advised that adherence to the Instructions to Authors will help speed up the refereeing and production stages for most papers.

- Language and presentation
- Length of submissions
- Submission
- Contact details/biographies
- Title of the paper
- Abstract and keywords
- Figures and tables
- Sections
- Footnotes
- Special characters
- Spelling
- References
- Proofs
- PDF offprint
- Copyright and permissions
- Final material
- Correspondence
- Publication ethics

Language and presentation

Manuscripts should be written in English. All authors should obtain assistance in the editing of their papers for correct spelling and use of English grammar. Manuscripts should have double spacing, with ample margins and pages should be numbered consecutively. The Editors reserve the right to make changes that may clarify or condense papers where this is considered desirable.

Length of submissions

Length of submissions Papers should not normally exceed 15 Journal pages (about 10 000 words). However, in certain circumstances (e.g., review papers) longer papers will be published.

Submission

Manuscripts must be submitted through the JITA online submission system.

Please read the instructions carefully before submitting your manuscript and ensure the main article files do not contain any author identifiable information.

Although PDF is acceptable for initial submission original source (i.e. MS Word) files will be required for typesetting etc.

Contact details/biographies

A separate file containing the names and addresses of the authors, and the name and full contact details (full postal address, telephone and e-mail) of the author to whom correspondence is to be directed should be uploaded at the time of submission (you should select Contact details/Biographies as the file type). This file is not shown to reviewers. This file should also contain short biographies for each author (75 words maximum each) which will appear at the end of their paper.

The authors' names and addresses must not appear in the body of the manuscript, to preserve anonymity. Manuscripts containing author details of any kind will be returned for correction.

Title of the paper

The title of the paper should not be longer than 16 words.

Abstract and keywords

The first page of the manuscript should contain a summary of not more than 200 words. This should be self-contained and understandable by the general reader outside the context of the full paper. You should also add 3 to 6 keywords.

Figures and tables

Figures which contain only textual rather than diagrammatic information should be designated Tables. Figures and tables should be numbered consecutively as they appear in the text. All figures and tables should have a caption.

Sections

Sections and subsections should be clearly differentiated but should not be numbered.

Footnotes

Papers must be written without the use of footnotes.

Special characters

Mathematical expressions and Greek or other symbols should be written clearly with ample spacing. Any unusual characters should be indicated on a separate sheet.

Spelling

Spelling must be consistent with the Concise Oxford Dictionary.

References

References in the text are indicated by the number in square brackets. If a referenced paper has three or more authors the reference should always appear as the first author followed by et al. References are listed alphabetically. All document types, both printed and electronic, are in the same list. References to the same author are listed chronologically, with the oldest on top. Journal titles should not be abbreviated.

- Journal

[1] Avramović Z.Ž. (1995). Method for evaluating the strength of retarding steps on a marshalling yard hump. *European Journal of Operational Research*, 85(1), 504–514.

- Book

[2] Walsham G. (1993). *Interpreting Information Systems in Organizations*. Wiley, Chichester.

- Contributed volume

[3] Huberman A.M. and Miles M.B. (1994). Data Management and analysis methods. In *Handbook of Qualitative Research* (Denzin NK and Linkoln YS, Eds), pp 428-444, Sage, Thousand Oaks, California.

- Conference Paper

[4] Баранов Л.А. (2017). Принципы построения и алгоритмы интеллектуальных автоматических систем управления движения поездов, функционируемых в рамках городских транспортных систем. In G. Radić & Z.Ž. Avramović (Eds.), *Proceedings of a IX International Scientific Conference "Information Technology for e–Education"*, (pp.9-18). Pan-European University APEIRON, Banjaluka, 29–30.9.2017. Republic of Serpska, B&H

- Unpublished reports/theses

[5] Nandhakumar J.J. (1993). The practice of executive information systems development: and in-depth case study. *PhD Thesis*, Department of Engineering, University of Cambridge.

Proofs

Proofs of papers will be sent to authors for checking. Alterations to diagrams should be avoided where possible. It will not be possible to accept major textual changes at this stage. Proofs must be returned to the publishers within 48 hours of receipt by fax, first-class post, airmail or courier. Failure to return the proof will result in the paper being delayed.

PDF offprint

Corresponding authors will receive a PDF of their article. This PDF offprint is provided for personal use. It is the responsibility of the corresponding author to pass the PDF offprint onto co-authors (if relevant) and ensure that they are aware of the conditions pertaining to its use.

The PDF must not be placed on a publicly-available website for general viewing, or otherwise distributed without seeking our permission, as this would contravene our copyright policy and potentially damage the journal's circulation. Please visit http://www.jita-au.com to see our latest copyright policy.

Copyright and permissions

The copyright of all material published in the Journal is held by Pan-European University APEIRON. The author must complete and return the copyright form enclosed with the proofs.

Authors may submit papers which have been published elsewhere in a foreign language, provided permission has been obtained from the original publisher before submission.

Authors wishing to use material previously published in JITA should consult the publisher.

Final material

All final material must be submitted electronically in its original application format (MS Word is preferred). The file must correspond exactly to the final version of the manuscript.

Correspondence

Business correspondence and enquiries relating to advertising, subscriptions, back numbers or reprints should be addressed to the relevant person at:

Pan-European University APEIRON
Journal JITA
Pere Krece 13, P.O.Box 51
78102 Banja Luka
Bisnia and Hercegovina / RS
E-mail: jita@apeiron-edu.eu

Publication ethics

We take an active interest in issues and developments relating to publication ethics, such as plagiarism, falsification of data, fabrication of results and other areas of ethical misconduct. Please note that submitted manuscripts may be subject to checks using the corresponding service, in order to detect instances of overlapping and similar text.

JITA

Journal of Information Technology and Applications
Pan-European University APEIRON Banja Luka
www.jita-au.com
jita@apeiron-edu.eu

PUBLISHER: **Pan-European University APEIRON**, Banja Luka
College of Information Technology Banja Luka, Republic of Srpska, B&H
www.apeiron-uni.eu
Darko Uremović, Person Responsible for the Publisher
Aleksandra Vidović, PhD, Editor of University Publications

ISSN 2232-9625
9 772232 962005