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APPLICATION OF ARTIFICIAL INTELLIGENCE IN RUSSIA'S RAILWAY NETWORK ASSET MANAGEMENT

Igor Shubinsky[1], Alexei Zamyshlaev[2], Alexander Bochkov[3]

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[1]JSC NIIAS, Doctor of Sci., Professor, Division manager,
Moscow, Russia, igor-shubinsky@yandex.ru
[2]JSC NIIAS, Doctor of Sci., Deputy Director General,
Moscow, Russia, zam0279@gmail.com
[3]JSC NIIAS, Doctor of Sci., Deputy Head of Integrated R&D Unit,
Moscow, Russia, a.bochkov@gmail.com

Abstract

The article presents general information on the system and methodology of asset management and Big Data methods (EKP URRAN) used on Russia's railway network. The relevance of the publication is defined by the requirement of rational management of available resources amidst the stagnation of the global economy. That applies fully to the railway industry, where it is required to ensure an acceptable level of dependability of facilities and processes, while maintaining the traffic safety risks at an acceptable level. The architecture of EKP URRAN is presented. The system's future outlooks are examined, most importantly in terms of application of artificial intelligence in predicting hazardous events in the operation of railway transportation.

Keywords: Big Data, asset management, risk, safety, dependability, artificial intelligence

I. Introduction

Railway networks represent major assets in most countries and their adequate management has always been a concern for owners and operators. That determined the idea of asset management in the railway infrastructure environment that evolved from a number of sources, including the concept of total system support [1]. That is due to the high rate of digitalization creating enormous amounts of data in the day-to-day operations of many industries, including the railways.

The conventional methods of processing such data are unable to meet the current social and industrial performance requirements, which determined the recent emergence and development of an entirely new discipline, the so-called Big Data analytics [2-5]. As the industry support of asset management systems grew, standardization processes led to the development of the ISO 55000 asset management standards [6]. All aspects of the asset lifecycle, from concept development to disposal, are critical to a company's success [7]. The motivation for asset management and the migration to condition-based maintenance provided stimulated the introduction of Big Data analytics in railway asset management.

Russian Railways Network is the largest owner and operator of transportation infrastructure in Russia [8], holding leading positions worldwide along the US and China, including in terms of traffic volume. Infrastructure accounts for over 60 percent of the total cost of fixed assets, while the operating costs of infrastructure amount to around 35 percent of the total costs. As a result, one of the company's key objectives is to optimize the cost of asset maintenance.

Technical assets benefit a company only if they operate reliably and efficiently. The efficiency of an asset is directly related to its performance, level of functionality and especially safety. Thus, dependability, safety, performance, functionality are the main characteristics of a technical asset. They have a critical impact on the value of an asset's lifecycle.

II. URRAN Single Corporate Platform (EKP URRAN)

The basic methodology Russian Railway Network uses to manage dependability, safety and risks to technical assets is the methodology for managing resources, risks, and dependability of railway facilities at lifecycle stages (URRAN) that includes guidance documentation and software for management process automation [9].

URRAN-based asset management includes interdisciplinary approaches that require collaboration between business units and integration of short- and long-term decision-making. An asset is placed at the center of a value-oriented management process and its maintenance is one of the activities performed throughout the life cycle of such asset [8]. EKP URRAN contains five functionally complete virtual technical subsystems. Four subsystems (EKP URRAN Track, EKP URRAN Signaling, EKP URRAN Communications, EKP URRAN Power) automate infrastructure facilities management (track, signaling, telecommunications, and power supply), one subsystem (EKP URRAN Traction) automates rolling stock management (locomotive and multiple units).

The subsystems interact through software interfaces (Fig. 1).

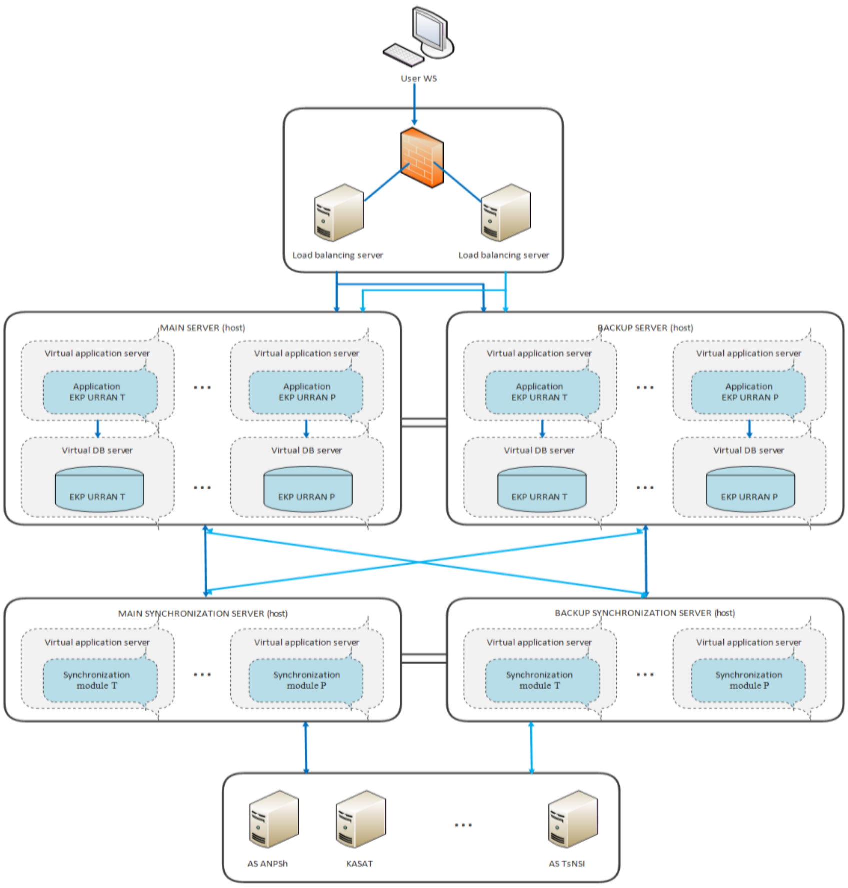

Figure 1. *Overall architecture of EKP URRAN*

There is an urgent need for accurate and reliable prediction of non-measurable system states: hazardous failures, pre-failures, failures, process violations. URRAN-based maintenance management involves processing large amounts of data received from the Russian Railway Network integrated automated systems.

III. METHODS OF DATA SCIENCE AND ARTIFICIAL INTELLIGENCE FOR MANAGING SAFETY, DEPENDABILITY AND RISKS IN RAILWAY TRANSPORTATION

BD analytics slightly change the decision-making method. Instead of choosing the right methods for analysing data, the available data is browsed, and new patterns and correlations are found. That allows making decisions based not only on a common understanding of assets, but also on not yet revealed correlations between different parameters.

3.1. Safety management

The specificity of Data Science application clearly shows in the context of hazardous event prediction in railway transportation. High train traffic and speed, environmental conditions, ageing cause tear and wear of railway infrastructure, primarily the track. Rail defects may cause derailments or crashes. Such accidents are associated with damage to the track, power supply networks, as well as cars and locomotive units with potential exclusion from the inventory rolling stock. Derailed units of rolling stock may also intrude into the operational space of the adjacent track, which may cause a collision with an opposing train with catastrophic consequences. A significant share of undesired events being attributed to the condition of track can be observed worldwide. The analysis of derailments and crashes involving units of freight trains identified that derailments/crashes caused by track defects could occur on track sections rated, for instance, as "good". In this context, the aggregated estimate of a kilometer of track is not sufficient for predicting its condition, and it is required to take into consideration other parameters: number of widenings, realignments, etc. Today's methods of multiple factor data analysis and the machine learning technology that allow including over 50 factors into models enable – based on existing knowledge of measured featured that characterize the condition of track – making conclusions regarding the need for urgent repairs to avoid track failures and derailments and crashes caused by an unsatisfactory condition of track [10]. Machine learning is increasingly popular as means of improving the dependability of railway systems. It also allows minimizing the daily cost of asset maintenance [11]. The machine learning methods can be divided into classical algorithms and deep learning methods that primarily differ in terms of the level of representation.

As of late, the academic community has been making use of the advantages of the deep learning methods for studying rail defects (Fig. 2).

Researchers [12] believe that deep learning may become an element of completely automatic railway monitoring systems. Neural network-based algorithms are employed as the primary tool for detecting structural defects in rails. Examples include the convolution neural networks (CNN) that are a special case of artificial neural networks. However, CNN have a major disadvantage as they are a "black box" and practically cannot be interpreted.

In [13, 14], the authors show the results of a numerical experiment of line categorization based on failure prediction. Thus, on the Kuybyshevskaya Railway, between 2014 and 2019, track superstructure condition statistics were collected. Failures of the following types of railway infrastructure elements were registered: isolated joint, concrete tie, rail line, rail joint, geometrical parameters of the track, etc. Over several years, for each kilometer of track the following parameters were measured monthly: number of widenings, number of deviations, number of realignments, number of sags, traffic speed within the specific kilometer, etc. The classification problem was solved with a wide use of machine learning algorithms: logistic regression, solution trees, random forest, support vectors and nearest neighbor. The experiments showed that the mathematical models of decision tree and random forest are most efficient. They enable acceptable prediction accuracy (over 75%) with the minimal rate of "false alarms" (28%).

3.2. Dependability management

Railway facilities are operated in a variety of natural (temperature, humidity, wind, pressure, number of precipitations, snow, floods, etc.) and technological (track layout, track class, target speed, etc.) conditions. Additionally, different approaches are applied to the operation of different facilities depending on the load factors. Functionally identical facilities may differ significantly in terms of design. All these circumstances mean that functionally identical facilities may fail at different rates, while the failure rate can vary significantly depending on the operating conditions [13, 14].

Out of that follows that the dependability of a facility cannot be assessed based on the total number of its failures in various parts of a railway network. This problem can be solved by introducing a system of coefficients for operating conditions and facility design, i.e., transforming such facility into a sort of a reference. For that purpose, URRAN was provided with technical characteristics and conversion factors enabling conversion into reference infrastructure facilities (track facilities, signaling systems, railway telecommunications, power supply and electrification) and rolling stock reference facilities (locomotives and multiple units). One of the most important aspects of standardization involves key dependability indicators of transportation facilities.

3.3. Risk management

URRAN uses the definitions, approaches to risk classification and safety principles common to International Union of Railways (UIC) member companies. A risk management methodology is employed that includes the stages of risk assessment, processing, monitoring and analysis. An ALARP-based risk matrix is used as one of the key risk management tools. Formulas are used for defining the number of matrix elements depending on the statistics of hazardous event rate and the amount of caused damage. A method has been developed for estimating the integral risk associated with the operation of a set of various types of facilities and a risk-oriented criterion of facility life extension.

If the risk of a hazardous state for a facility in its limit state exceeds the permissible level, the facility is removed from operation. Otherwise, the economic feasibility of further operation is assessed. In respect to facilities that fail suddenly or regularly, the functionality is considered (the functionality of a facility is considered in terms of the quantity and quality of functions that define its applicability in various operating conditions). The facility's life cycle cost is estimated, the optimal strategy is selected for planning maintenance and repair. Taking the examples of a line section, a risk-oriented algorithm of facility maintenance management is shown.

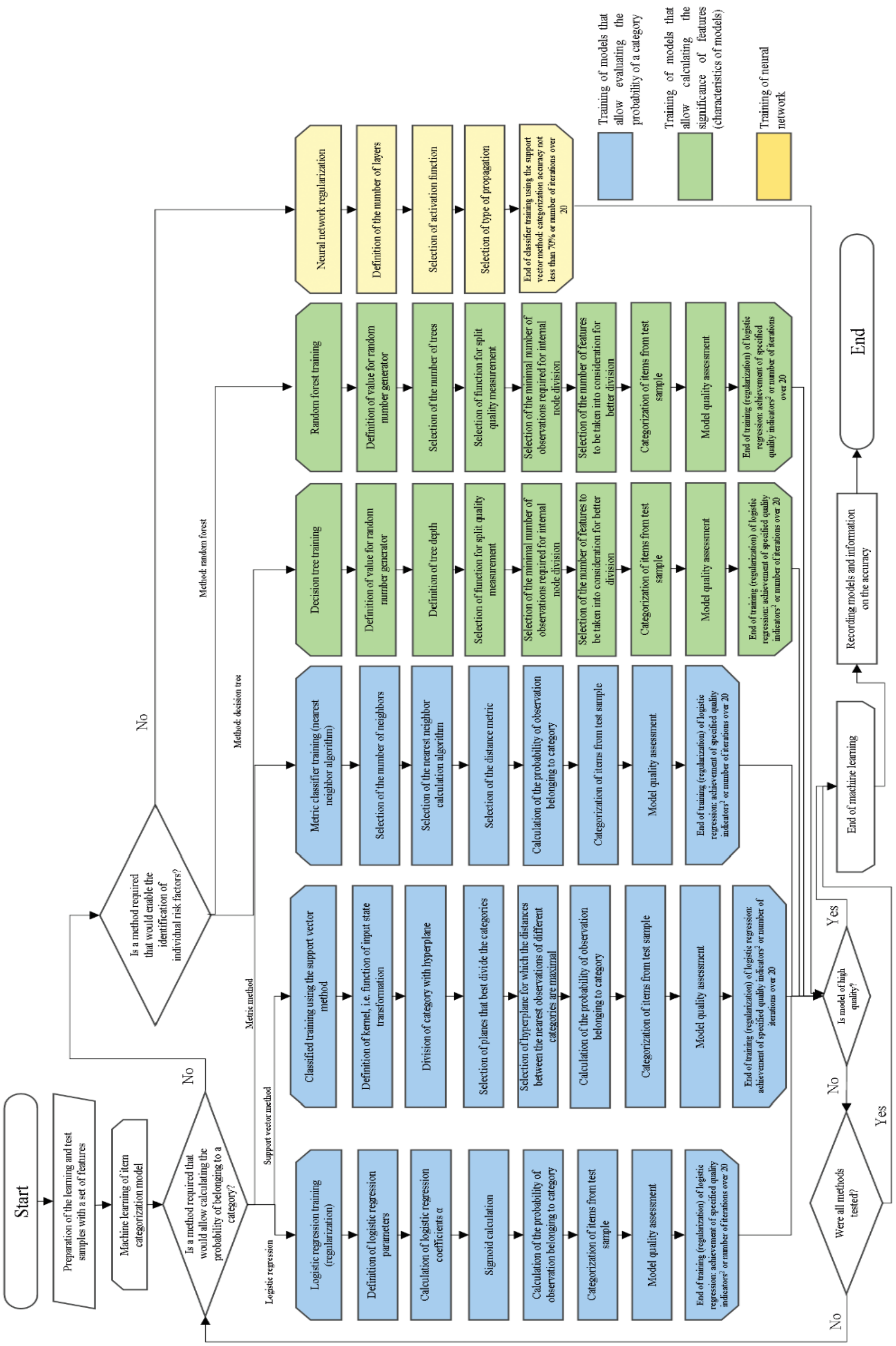

Figure 2. *Algorithm of machine learning application*

IV. FINAL REMARKS

The required levels of safety and dependability of facilities, as well as sufficient performance and functionality with an acceptable life cycle cost, can only be achieved through reasonable, risk-based asset management.

The efficiency of technical asset management is largely defined by the level of artificial intelligence in decision support, including the ability to adapt to the changing conditions of railway facilities maintenance, scope and depth of management using artificial intelligence (in particular, Data Science), evaluation of risks at all levels of management from whole system/facility to a process and, ultimately, a service.

The above tasks have been partially solved and will be further solved as EKP URRAN develops. Whereas the current procedure goes as: facility operation – event (e.g., failure) – reaction (elimination of failure), the now mature Data Science allows migrating towards the innovative asset management process: operation and technical diagnostics – predictive analysis – proactive action. Predictive analysis is an analysis of current and historical events based on mathematical statistics, game theory, etc. for predicting future events. Predictive action is preliminary work aimed at improving the dependability of those facilities where failures, especially hazardous ones, are predicted. Using artificial intelligence, it is planned to predict not only technological but also process-related risks. The large amount of available statistical data on the process violations in railway transportation allows creating for that purpose representative training sets.

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