Application of Artificial Intelligence Methods for the Prediction of Hazardous Failures

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Contribution to the State of the Art

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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.

<u>Stage 1.</u> 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.

<u>Stage 2.</u> 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

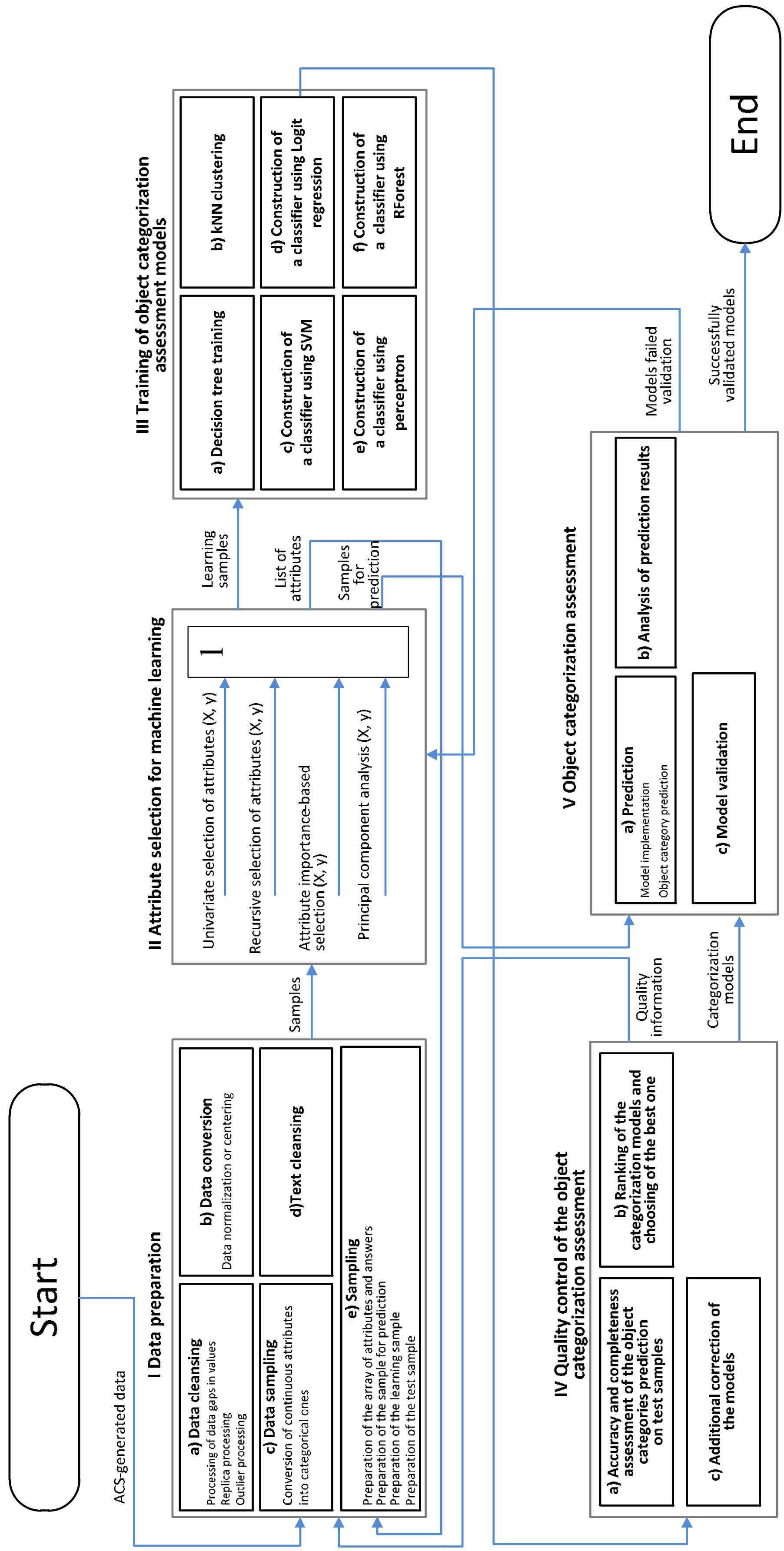

Fig. 1. Diagram of a conceptual mathematical dynamic model for predicting failures

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.

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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

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