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E. K. MANAFOV

Department of Power Engineering and Automation, National Aviation Academy, Mardakan Avenue 30, Baku, Azerbaijan, AZ 1045, tel. +994 55 7417939, email: emanafov@naa.edu.az, ORCID 0000-0001-5697-577X

Department of Transport Engineering and Control Technologies, Azerbaijan Technical University, G. Javid Avenue 25, Baku, Azerbaijan, AZ 1073

DIGITAL IMPLEMENTATION OF THE THEORY OF OPERATIONAL RELIABILITY OF RAILWAY STATIONS

Purpose. This study aims to establish a theoretical relation between the classical theory of operational reliability of railway stations and the modern concept of a digital railway station, as well as to develop a methodological model for the digital implementation of this theory within the context of transportation process management digitalization. The work purposes to substantiate the fact that the digital railway station does not represent an alternative concept, but rather a logical and technological development of the classical theory of operational reliability. **Methodology.** The study used methods of system and logical-methodological analysis, probabilistic understanding of operational reliability, validation of the operational states of transport systems, as well as elements of queuing theory, simulation modeling, and data-driven analysis. The theoretical necessities of the classical theory of operational reliability are compared with the functional skills of digital twins and intelligent control systems. To describe the digital application of the theory, a multilayer representation of the station state is proposed, including the physical, technological, graphical, and management levels. **Results.** It is demonstrated that the operational reliability of a railway station can be formalized as a probabilistic function of its operational state over time. A methodological model for the digital implementation of operational reliability theory is proposed, based on the formation of a station state vector, predicting the probabilities of operational failures for each layer, and their aggregate valuation. An algorithm for digital reliability valuation has been established, enabling the transition from a retrospective normative-analytical approach to dynamic and predictive operational risk management. Integrated operational reliability indicators are introduced, allowing a quantitative assessment of station stability in a digital environment. **Scientific novelty.** The scientific novelty of this work dishonesties in the formalization of the theoretical linking between the classical theory of operational reliability of railway stations and the concept of a digital railway station. For the first time, operational reliability is taken as a probabilistic function of the digital station's state, dependent on a combination of physical, technological, scheduling, and management factors. A multilayer model is proposed that enlarges the classical classification of operational failures by incorporating an algorithmic control component. **Practical value.** The results obtained can be used in developing digital twins of railway stations, designing decision support systems, evaluating the effectiveness of digitalization measures, and training specialists in railway station operations management.

Keywords: operational reliability, railway station, digital twin, artificial intelligence, transportation process management, throughput.

Introduction

Modern rail transport is entering a phase of enhanced digitalization, with an increasing share of automated traffic control, planning, and dispatching functions, as well as the application of digital signaling and communication systems (e.g., ETCS, ATO, and advanced communication standards). Experience with digital programs at major operators demonstrates that digitalization is viewed as a key tool for improving throughput and the quality of the transportation process, including schedule stability and network manageability.

At the station level, digitalization manifests itself in a transition from «local operational» management based on rules and personnel experience to management based on real-world operational data: station automated control system logs, signaling device telemetry, infrastructure and rolling stock condition monitoring, digital models, and predictions. This transformation leads to an increase in the difficulty of station processes for three reasons. First, structural complexity increases: the station becomes a cyber-physical system, in which the physical infrastructure is closely linked to digital control and monitoring circuits. Secondly, dynamic complexity increases: process stability is determined not only by infrastructure and technology, but also by the present state of flows, the propagation of delays, and the control system's reply to disturbances. Thirdly, information complexity increases: the quality of operation depends on the completeness, reliability, and timeliness of data, as well as the precision of its processing algorithms.

In this environment, station operational reliability obtains the status of a systemic, integral indicator, reflecting the station's ability to maintain the required level of transport service in the presence of random disturbances, changing operating modes, and limited resources. Unlike the barely technical «failure-free» nature of individual devices, operational reliability is directly linked to the manageability of the transportation process and the economic consequences of delays.

Furthermore, the development of digital twins and intelligent control systems enhances the practical significance of this issue. Digital solutions are claimed to improve predictability and efficiency; however, their effectiveness must be theoretically evaluated through indicators of reliability and quality of the transportation process. Research in the field of AI-assisted digital twins for the railway sector highlights the role of artificial intelligence (AI) as a key «amplifier» of the digital twin, particularly in predictive maintenance and decision support tasks [1, 2, 3, 4, 5].

Thus, the significance of this study lies in the need to relate the classical theory of operational reliability of railway stations to modern digital concepts, ensuring the continuity of the conceptual framework and facilitating a rigorous assessment of the effects of digitalization.

It should be noted that the creation of the theory of operational reliability of railway stations as an independent scientific field dates back to the late 20th century and is not unintentional. Before this period, the operating conditions of railway stations were characterized by a relatively stable flow structure, reasonable traffic intensity, and the predominance of local technological solutions, which made it possible to solve reliability problems within the framework of specific disciplines - the theory of throughput, standardization, and technical reliability of devices.

A significant rise in traffic volumes, a more complex train flow structure, increased demands for schedule stability, and the increasing interconnection of rail network elements led to station failures manifesting themselves not only as technical failures but also as systemic disruptions to transport functions. Under these conditions, an objective need arose for a theory that reflects stations as holistic transport systems with limited resources, operating in a probabilistic environment. It was at this stage that a theory of station operational reliability, brief the technical, technological, and organizational aspects of operation, became possible and in demand. A complete theory of station operational reliability was presented by P.S. Gruntov in his 1986 monograph, «Operational Reliability of Stations.» This work posed problems and proposed solutions, which are still used by academic schools to study station operational reliability in the post-Soviet space. Gruntov's key methodological influence is a shift in focus from «element reliability» to the reliability of the transport function. Within this approach, a station is viewed as a system of limited resources, operating under the effect of incoming flows and process regulations. Consequently, operational failure is determined not only by a technical failure but also by conditions under which the system cannot provide the required level of service: overloaded yards, exponential queue growth, schedule disruptions, failure to meet the formation plan, augmented downtime, and missed delivery deadlines.

The concept of «operational failure» is the central relation between the theory and the digital railway station. The digital station is focused on incessant monitoring and forecasting of conditions that lead to disruptions: increased track occupancy, increased operation times, reduced availability of technical equipment, and changes in the flow structure. In classical theory, these conditions were considered primarily analytically and retrospectively, whereas the digital environment makes them observable and predictable.

Consequently, the theory delivers the correct «functional framework» for digitalization: the digital station does not remove classical criteria (technological failure, schedule disruption, overload), but rather provides tools for measuring and managing them at a new level – through data, predictive models, and digital twins.

At the same time, the operating conditions of railway stations today differ significantly from those in which the classical creeds of operational reliability theory were formulated. Modern operations are characterized by highly variable flows, severe schedule stability requirements, deteriorating operational reserves, and the active implementation of automated and intelligent control systems.

In classical theory, operational reliability was typically evaluated based on standard parameters, averaged characteristics, and retrospective analysis. In the context of digitalization, this approach is inadequate, as a significant portion of operational failures are generated dynamically, influenced by the current state of flows, infrastructure, and management decisions.

This condition does not reduce the value of classical theory, but it points to the need for its development and rethinking toward greater measurability, predictability, and adaptability, which is made possible by the use of digital data, digital twins, and intelligent control algorithms.

Purpose

The purpose of this study is to create a theoretical relation between the classical theory of operational reliability of railway stations and the concept of a digital railway station as a cyber-physical system driven by data and intelligent algorithms. To achieve this goal, the article addresses the following objectives:

1. To analyze key theoretical concepts, including the interpretation of a station as a transport system, the meaning of operational failure, the relationship between reliability and throughput/processing capacity, and the stability of the transportation process.

2. To define the spirit of a digital railway station, based on modern concepts of the digitalization of railway infrastructure, the implementation of digital control rings, and the use of digital twins and AI services.

3. To compare the basic concepts of «operational failure,» «station status,» «throughput reserves,» and «schedule stability» with digital objects of observation (data), digital models (twins), and forecast indicators.

4. Demonstrate the continuity and development of the theory, validating that the digital station represents a data-driven implementation of the classical concept of operational reliability, and also expands it through measurability, forecasting, and the inclusion of an algorithmic control component [6].

5. Formulate methodological conclusions for the building of digital operational reliability management systems, including the structure of indicators and principles of data integration, a digital twin, and AI models.

Theory of operational reliability of railway stations

In the theory of operational reliability, a railway station is viewed not as a collection of technical devices, but as a transportation system designed to achieve a specific function within the transportation process. This approach fundamentally distinguishes operational reliability from the classical reliability of technical systems, where the object of analysis is the operability of a separate element or unit.

In this context, a station is a system of limited resources, including:

– track development (receiving, dispatching, and sorting railway tracks);

– throats and hump devices;

– freight and passenger handling areas;

– locomotive and shunting equipment;

– technical and information control systems.

The functioning of a station is determined by the interaction of these resources with incoming and outgoing train and wagon flows, as well as the established processing technology. Consequently, the state of the station at any given time is characterized by the degree of utilization of its throughput and processing capacity, and not just the serviceability of its individual elements.

This conceptualization of the station as a transport system is key to the following transition to a digital model: it is this systemic approach that allows us to describe the station through a vector of states observed and measured by digital infrastructure [7].

The theory introduces the concept of operational reliability as the ability of a transport system to perform its envisioned functions under operating conditions without disrupting the transportation process. A crucial methodological step is to abandon the narrow understanding of failure as a technical malfunction. In an operational sense, a station failure can occur with a fully functional infrastructure if:

– the handling capacity of the yards is surpassed;

– train handling technology is disrupted;

– capacity reserves are exhausted;

– there is a disruption to the schedule;

– wagon and train downtime increases beyond permissible limits.

Thus, an operational failure is defined as a condition in which the station is powerless to provide the required level of transport service, regardless of the cause. This principle is important for a digital railway station, as digital systems are designed to identify and predict such conditions, rather than diagnose equipment failures [8].

To analyze operational reliability, the theory proposes a classification of failures that replicates the multifaceted nature of station operation. The classical interpretation differentiates the following main groups:

1. Technical failures related to malfunctions of tracks, switches, signaling devices, rolling stock, and other technical equipment.

2. Technological failures resulting from violations of established train and wagon handling

technology, failure to obey operating time standards, and indecorous shunting operations.

3. Organizational failures caused by unsuccessful planning, management errors, and resource distribution.

4. Information failures related to a lack, distortion, or delay of information necessary for management decision-making.

This classification is fundamentally important in that it spreads station reliability beyond its technical condition and emphasizes the role of control, information, and organization. It is this aspect that makes the theory theoretically compatible with digital control systems, where information and algorithmic components become dominant [9].

In a digital environment, each of the listed failure types can be formalized through data and indicators, allowing for a transition from a qualitative description to a quantitative assessment of the risks of operational failures.

Another key element of the theory is the idea of an economically optimal level of operational reliability. The author emphasizes that improving station reliability is related to additional costs, including:

– capital investments in track infrastructure development;

– acquisition and modernization of technical equipment;

– augmented operating costs;

– augmented technology complexity.

At the same time, low reliability leads to economic losses in the form of wagon downtime, schedule delays, penalties, and reduced service quality. Consequently, the task of operational reliability management is formulated as a compromise between the costs of improving reliability and the losses from its inadequate level. This approach has a direct postponement on the digital railway station, where reliability optimization can be implemented using digital twins, predictive models, and optimization algorithms. It is important to note that in classical theory, the optimal level of reliability is determined on the basis of analytical calculations and simulation modeling using standard parameters. The digital station allows for a transition to adaptive optimization, where the economically optimal level of reliability is recalculated in real time, taking into account actual data and forecasts [10].

The concept of a digital railway station

A modern digital railway station is a cyber-physical system in which physical infrastructure and rolling stock are integrated with digital monitoring, analysis, and control tools. Unlike the traditional concept of a station as a group of technical and technological elements, a digital station operates within a single information and control system that safeguards the continuous collection, processing, and use of real-world operational data.

The physical coating of a digital station includes tracks, switches, chute systems, hump devices, locomotives and wagons, as well as signaling and power supply systems. The digital layer is formed by automated station control systems, technical condition sensors, telemetry, video surveillance, and communications equipment, as well as computing platforms for data analysis.

The key feature of a digital station is that its condition ceases to be a hidden or assessed value and becomes directly observable. Parameters such as track load, yard occupancy, traffic intensity, operation duration, and schedule deviations can be measured and analyzed in real time. This situation fundamentally changes the approach to operational reliability management, transferring it from a reactive mode to a predictive and proactive one [6, 7, 11].

The operation of a digital railway station is based on a continuous data flow reflecting both the physical condition of facilities and the progress of technological processes. Data sources include:

– Logs from automated station control systems;

– Telemetry from infrastructure devices and rolling stock;

– Data on actual train movements and shunting operations;

– Results from diagnostic and measurement systems;

– Data on the actions of dispatch and operational personnel.

In a digital environment, data ceases to be a supplementary analysis tool and becomes a primary management resource. It forms the basis for digital pictures of the current station state, identifies deviations from standard operating conditions, and assesses the risks of operational failures.

An important element of a digital station is the presence of closed digital control circles, including data collection, analysis, forecasting, and the generation of recommendations or control actions. Such loops enable adaptive control, in which technological and organizational decisions are attuned based on current and expected station operating conditions [6, 7, 12, 20].

The central element of the digital railway station concept is the digital twin, a virtual model of the station coordinated with the actual operational facility. The digital twin syndicates the structural model of the infrastructure, a description of technological processes, and real-time data, enabling the simulation and prediction of station behavior in various operational situations (Table 1). In the context of operational reliability, the digital twin performs the following functions:

– forming an integrated view of the current station state;

– modeling the consequences of failures and overloads;

– assessing throughput and processing capacity reserves;

– analyzing flow and technology change scenarios;

– forecasting the likelihood of schedule disruptions and augmented downtime.

Table 1

Digital twin tools for a railway station in the context of operational reliability

№	Functional Task of the Digital Twin	Software Tool	Type of Model	Input Data → Output Indicators	Reliability Layer
1	Simulation of station processes	Any Logic	Discrete-event, agent-based	Train arrivals, consists, operation durations, resources → Queues, track occupancy, and idle times	Technological (P_t)
2	Marshalling yard hump simulation	Any Logic / Simio	Discrete-event	Traffic intensities consist of structure → Throughput, saturation	Technological (P_t)
3	Train movement simulation	Open Track	Dynamic, graph-based	Timetable, infrastructure, operational constraints → Delays, timetable stability	Graph-based (P_g)
4	Capacity planning	Rail Sys	Analytical + simulation	Station layout, timetable → Capacity margins	Graph-based (P_g)
5	Digital twin of infrastructure	Bentley Open Rail	Object-oriented	Track condition, switch defects → Failure probabilities	Physical (P_f)
6	Predictive maintenance	Siemens Railigent X	ML/ diagnostics	Telemetry, fault logs → Equipment failure risk	Physical (P_f)
7	Queue and flow modelling	Any Logic / FlexSim	Queueing theory	Arrival and service intensity → The probability of saturation	Technological (P_t)
8	Network-level stability analysis	Python + Network X	Graph, stochastic	Network topology, delays → Cascading effects	Graph-based (P_g)
9	Delay prediction	Python (LSTM, GNN)	Machine learning (ML)	Historical train movement data → $P(\Delta t > \Delta t_{max})$	Graph-based (P_g)
10	Station overload prediction	Python (XG Boost)	ML classification	Track occupancy, queues, resources → $P(\rho \geq 1)$	Technological (P_t)
11	Management decision analysis	Any Logic + DSS	Scenario optimisation	Decision logs, constraints → Decision effectiveness	Managerial (P_u)
12	Dispatcher support	DSS / AI assistant	Rule-based + ML	Real-time KPIs → Recommendations	Managerial (P_u)
13	Integration of models	Azure Digital Twins	Integration platform	Multilayer data → Unified state X(t)	Integral
14	Scenario analysis	Any Logic + Digital Twin	What-if simulation	Alternative decisions → $R(t, \Delta T\|u)$	Integral
15	Calculation of reliability indicators	Python / MATLAB	Analytical	P_f, P_t, P_g, P_u → DRI, CR, GSI, ARI	Integral

It should be emphasized that a digital twin is not a separate replacement for operational reliability theory, but rather its instrumental implementation. It is exactly the theoretical principles regarding the role of flows, resource limitations, and the systemic nature of failures that define the semantic and functional limits of a station's digital twin. In the practical implementation of a digital twin for a railway station, it is sensible to use a combined approach, in which simulation models of station processes (e.g., based on Any Logic) are supplemented by specialized tools for analyzing train schedules (Open Track, Rail Sys) and platforms for monitoring the physical condition of the infrastructure. This architecture allows the implementation of a multi-layer operational reliability model consistent with the theory and allows the calculation of operational failure likelihoods across the physical, technological, scheduling, and management layers [13].

AI plays a key role in the development of a digital railway station, enabling the transition from evocative data analysis to interpretation and forecasting. Machine learning (ML) methods are used to identify patterns in large sets of operational data that cannot be detected by traditional analytical methods.

The main applications of AI at a digital station include:

– predicting technical failures and infrastructure degradation;

– identifying critical yard and siding loading conditions;

– predicting train delays and schedule stability;

– analyzing the effectiveness of technological and management decisions;

– supporting decision-making by dispatch personnel (Table 2).

Table 2

AI algorithms and control procedures for a digital railway station

№	Management procedure	Operational task	AI Algorithms	Input Data → Output of AI Model	Link to reliability
1	Infrastructure diagnostics	Early detection of degradation	Random Forest, XG Boost, CNN	Telemetry, defect logs, vibration data → P (failure)	Physical (P_f)
2	Predictive failure forecasting	Predictive maintenance	Survival models, LSTM	Historical failures, load data → P (failure ≤ ΔT)	Physical (P_f)
3	Track occupancy monitoring	Prevention of station overload	Logistic Regression, XG Boost	Track occupancy, queue length, arrival forecasts → $P(\rho \geq 1)$	Technological (P_t)
4	Congestion prediction	Early warning of saturation	LSTM, Temporal CNN	Time series of station load → Station mode	Technological (P_t)
5	Delay prediction	Timetable stability forecast	LSTM, GNN	Train movement history, timetable → $P(\Delta t > \Delta t_{max})$	Graph/timetable (P_g)
6	Analysis of cascade effects	Propagation of delays	Graph Neural Networks	Network topology, delay propagation data →Pockets of instability	Graph/timetable (P_g)
7	Train dispatching sequence	Minimizing delays	Reinforcement Learning	Real-time station state → Optimal dispatching action	Managerial (P_u)
8	Shunting and resource planning	Reduction of idle time and conflicts	RL, Genetic Algorithms	Queues, resources → Optimal shunting plan	Managerial (P_u)
9	Dispatcher decision evaluation	Quality assessment of decisions	Supervised ML	Dispatcher logs, outcomes → Risk of suboptimal decision	Managerial (P_u)
10	“What-if” scenario analysis	Forecasting the effects of decisions	Bayesian Networks	System state + hypotheses → Probability distribution of outcomes	Integral
11	Multi-objective optimisation	Cost–risk trade-off	Multi-objective optimisation, GA	Risk indicators, costs → Pareto-optimal decisions	Integral
12	Anomaly detection	Identification of unexpected behaviour	Autoencoders, Isolation Forest	Real-time operational streams → Anomaly score/alerts	All layers
13	Decision support	Human–AI collaboration	Rule-based, XAI	Real-time KPIs → Action recommendations with explanations	Managerial (P_u)
14	Adaptive threshold learning	Adjustment to changing conditions	Online learning	Operational history → Updated reliability thresholds	All layers

In terms of operational reliability, AI enables a shift from assessing actual failures to measuring their probability, which fundamentally expands management capabilities.

Thus, AI is no longer an independent goal of digitalization, but a means of refining the manageability and reliability of the transport process. AI algorithms in the digital twin of a railway station are primarily used to predict operational failures, assess risks, and support decision-making. ML methods allow quantitative assessment of the probabilities of overloads, failures, and schedule disruptions, while strengthening learning and scenario analysis methods are applied within the digital twin to select management solutions while maintaining regulatory and technological constraints. This approach does not deny operational reliability theory, but rather ensures its practical implementation in the context of digitalization [4, 14, 15, 21, 22].

A comparison of the digital railway station concept with operational reliability theory demonstrates their deep methodological compatibility. The digital station is focused on measuring, predicting, and managing the same characteristics that theoretically describe operational reliability: resource utilization, technology stability, capacity reserves, and the probability of disruption to the transportation process.

Unlike the classical approach, where reliability is evaluated primarily retrospectively, the digital station allows operational reliability to be viewed as a dynamic and predictable value, changing over time and dependent on the current state of the system. This circumstance creates the preconditions for a new stage in the development of the theory, a transition from a normative-analytical to a data-driven interpretation of operational reliability.

These provisions provide the foundation for further analysis of the theoretical relationship between classical operational reliability theory and the digital railway station.

Theoretical relationship between operational reliability theory and the digital rail station concept

In operational reliability theory, a rail station is essentially viewed as a system capable of various operational states determined by resource utilization, traffic intensity, and compliance with technology. Although these states are not always openly defined in the classical formulation, they are logically present in the analysis of peak congestion periods, capacity reserves, and delay probability.

These states can be interpreted as:

– normal operating mode;

– increased load mode;

– saturation mode;

– overloaded or faulty state.

In classical theory, these states are described analytically, through average indicators and probabilistic estimates obtained based on standard parameters. The digital rail station recalls this concept but translates it into an observable and measurable form. Station states are recorded in real time based on track occupancy data, operation durations, schedule deviations, and the technical condition of the infrastructure. Thus, the digital station practically embodies the same idea underlying the theory: a station as a system of states with limited resources and probabilistic transitions between operating modes [2, 7].

One of the central tenets of the theory is the probabilistic interpretation of operational reliability. Station reliability is defined as the probability that, under given operating conditions, the transportation process will be carried out without disruption to technology and schedule.

In the digital railway station, this concept is directly formalized. Operational reliability can be represented as the probability of maintaining a satisfactory system state over a given time horizon:

$$R(t, \Delta T)=P\{\text{ the station performs its transport function within the interval } [t, t+\Delta T]\}$$

Unlike classical theory, where this probability is projected based on analytical models and historical statistics, a digital station allows for its dynamic calculation using current operating data and predictive models. This ensures the direct development of the theory's original probabilistic concept without changing its semantic content [8].

The classification of failures proposed by the theory includes technical, technological, organizational, and informational failures. This classification reflects the multi-level nature of station operation and fundamentally distinguishes operational reliability from purely technical reliability. A digital railway station not only preserves this classification but also translates it into measurable form. Each type of failure is associated with specific data sources and indicators:

– technical failures – with diagnostics and telemetry;

– technological – with operation logs;

– organizational – with analysis of management decisions and resource allocation;

– informational – wth the quality and timeliness of data.

Additionally, the digital environment generates algorithmic failures associated with the improper operation of automated systems and decision-making models. These failures logically spread the organizational category of theory but reproduce the specifics of digital control. Consequently, a digital station expands the classification of failures without troubling its theoretical foundation.

In theory, the throughput and processing capacity of a station are considered key factors in operational reliability. They determine the limits of a system's stable operation and the likelihood of overloads.

In the classical interpretation, these characteristics are typically static or slightly variable quantities determined by the track structure and technology. A digital railway station transforms these parameters into a dynamic state, dependent on current load, the technical condition of components, the composition of flows, and management decisions.

Thus, a digital station does not change the concepts of throughput and processing capacity, but rather transforms them into time functions, enhancing the practical applicability of operational reliability theory.

The theory emphasizes that operational reliability should not be maximized totally, but rather maintained at an economically optimal level, determined by the balance between costs and losses from disruptions to the transportation process. The digital railway station provides tools for the practical implementation of this principle. The use of digital twins, predictive models, and optimization algorithms allows for the valuation of the consequences of management decisions and infrastructure changes in terms of both reliability and economic indicators. Thus, the classical problem of economic reliability optimization receives an algorithmic extension that fully corresponds to the original formulation of the theory.

Analysis shows that there is no gap between operational reliability theory and the concept of the digital railway station, but rather a clear theoretical continuity. The theory's key creeds:

– a systemic interpretation of the station;

– a probabilistic understanding of reliability;

– a multifactorial classification of failures;

– the relationship of reliability with flows, technology, and economics is fully preserved in the digital paradigm, but is given new means of implementation.

The digital railway station, therefore, represents not an alternative to classical theory, but its data-driven and algorithmic development, allowing the original ideas to be implemented in the context of a modern information and technological environment [15-19].

Methodology and methodological model for digital ımplementation of operational reliability theory

The digital implementation of operational reliability theory is based on representing a railway station as a dynamic system of states, operating under the effect of traffic flows, infrastructure constraints, and management decisions. Unlike the classical analytical approach, the digital model is oriented toward the use of real-world operational data and predictive methods. Within the proposed methodology, operational reliability is considered as a probabilistic function of the station's state, changing over time and contingent on current and predicted operating parameters.

1. Formalization of the Digital Station State. The state of a railway station at time t is represented as a vector:

$$X(t)=[X_f(t), X_t(t), X_g(t), X_u(t)] \quad (1)$$

where: $X_f(t)$ – is the infrastructure and rolling stock status; $X_t(t)$ – is the state of technological processes; $X_g(t)$ – is the schedule fulfillment status; $X_u(t)$ - is the control system state (organizational and algorithmic).

Each component of the vector $X(t)$ is determined based on digital station data and can take values from a finite or continuous set of states reflecting operational modes (normal, saturation, overload).

2. Operational Reliability as a Probability Function. According to theory, the operational reliability of a station is defined as the probability of performing the transport function without operational failure. In the digital model, this value is formalized as follows:

$$(t, \Delta T)=P(X(\tau)\in Q_{per}, \ \forall\tau\in[t, t+\Delta T] \quad (2)$$

where Q_{per} – is the range of permissible operational states of the station.

Thus, reliability is interpreted as the probability that, over a given forecast horizon ΔT, the system will not enter the operational failure region [7].

3. Assessing the Probabilities of Operational Failures. For each state layer of the station, the probability of an operational failure is entered:

$$P_{k\ fail}(t,\Delta T)=P\left(X_k(t+\Delta T)\in Q_{k\ cr} /\ X_k(t)\right), \\ k\in\{f,t,g,u\} \quad (3)$$

where $Q_{k\ cr}$ – is the set of critical states for the corresponding layer.

These probabilities are estimated using:

– Infrastructure failure prediction models (for X_f);

– Load mode and process disruption classification models (for X_t);

– Delay and schedule stability prediction models (for X_g);

– Management and algorithmic decision analysis models (for X_u).

4. Aggregation of Operational Reliability. The integrated operational reliability of a station is defined as an aggregated function of the reliabilities of individual layers:

$$R(t, \Delta T)=A(1-P_{f\ fail}, 1-P_{t\ fail}, 1-P_{g\ fail}, 1-P_{u\ fail}) \quad (4)$$

where $A(\cdot)$ is an aggregation function reflecting the structure of the relationships between layers.

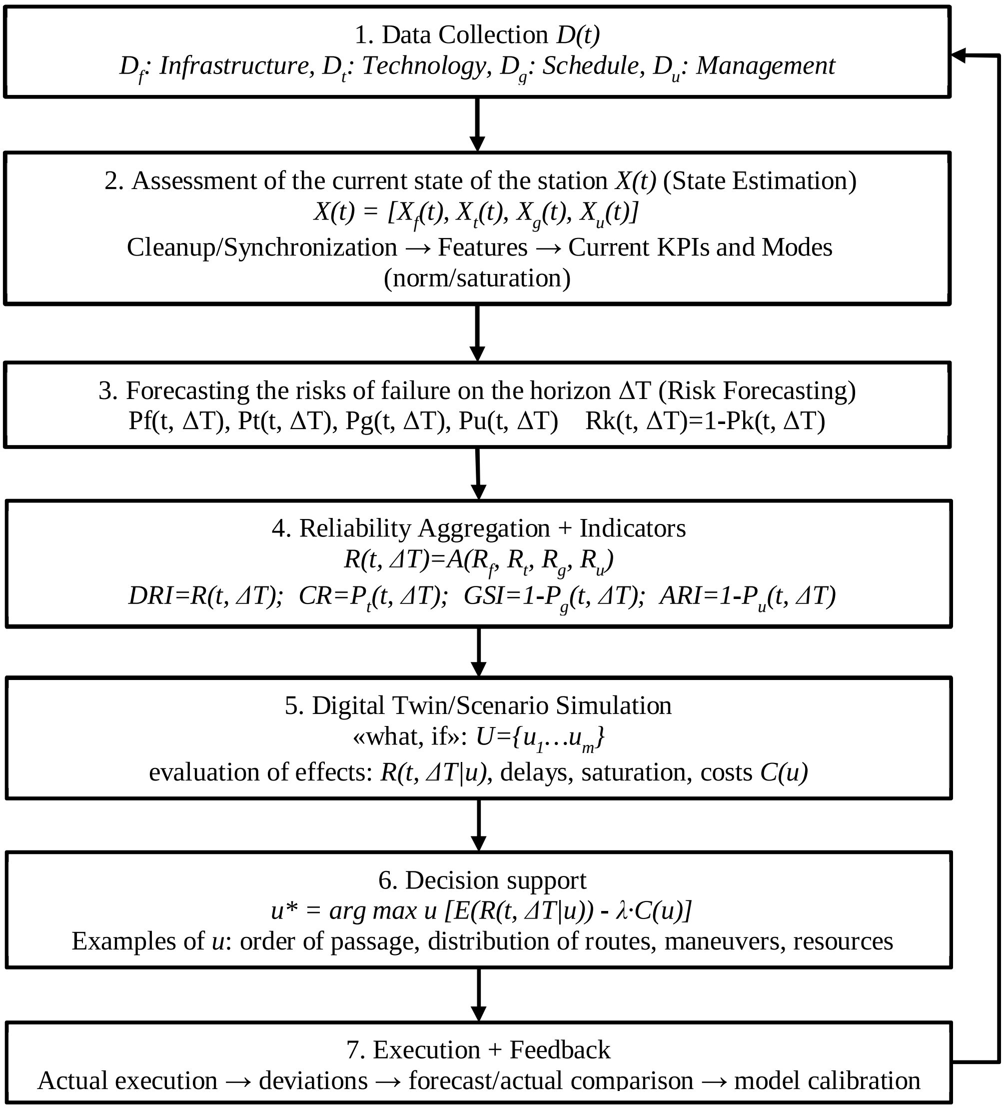

Fig. 1. Closed-loop digital control system for the operational reliability of a railway station

In practical applications, aggregation of the operational reliability of a digital railway station can be performed in various ways, depending on the system structure and the purpose of the analysis. The multiplicative form is appropriate for sequential process chains, where the failure of any layer leads to the failure of the transport function. Weighted aggregation allows for the consideration of the varying importance of factors and is used in decision support systems. Bayesian reliability networks are used to model the cause-and-effect relationships between physical, technological, and management failures and provide scenario analysis of operational risks.

5. Digital Station Operational Reliability Indicators. Based on the aggregated model, the following indicators are introduced:

1. Dynamic Reliability Index: $DRI\ (t) = R\ (t, \Delta T)$

2. Congestion Risk: $CR\ (t) = P_{t\ fail}\ (t, \Delta T)$

3. Graph Stability Index: $GSI\ (t) = 1 - P_{g\ fail}\ (t, \Delta T)$

4. Algorithmic Reliability Index: $ARI\ (t) = 1 - P_{u\ fail}(t, \Delta T)$

These indicators provide a quantitative interpretation of classical theoretical concepts in digital form [9].

6. Algorithm for the Digital Assessment of Operational Reliability. The process of assessing and managing operational reliability is implemented using the following algorithm:

1. Collecting data on the state of infrastructure, technology, schedule, and management.

2. Generating the current state vector $X(t)$.

3. Predicting the probabilities of operational failures for each layer.

4. Aggregating reliability and calculating integral indicators.

5. Assessing management decision scenarios.

6. Selecting the solution that ensures maximum expected reliability at acceptable costs (Fig. 1).

Formally, the optimal control solution $u*$ is defined as:

$$u^* = arg \max_{u \in U} \left[E\big(R(t + \Delta T|u)\big) - \lambda C(u)\right] \quad (5)$$

where *C(u)* - is the solution cost, and λ is the tradeoff coefficient between reliability and costs.

The proposed methodological model:

– maintains the interpretation of operational failure as a disruption of the transport function;

– relies on a systemic representation of the station;

– utilizes a probabilistic interpretation of reliability;

– implements the principle of economically optimal reliability.

Therefore, the digital model does not replace theory, but rather implements it in a formalized, algorithmic, and data-driven form.

Scientific novelty and practical significance

The analysis shows that the classical theory of operational reliability of railway stations has not lost its significance in the context of digitalization; on the contrary, it obtains new content and practical significance. Viewing a station as a transport system with limited resources, operating under the influence of flows and management decisions, is fully consistent with the modern interpretation of a station as a cyber-physical object. The key result of the study is the justification that the digital railway station concept is not an alternative, but a logical and technological development of operational reliability theory. All the basic elements of the theory - the systemic representation of the station, the probabilistic interpretation of reliability, the multifactorial nature of failures, and economic optimization - are retained in the digital paradigm, but they are given new means of implementation.

Unlike the classical approach, the digital station allows for:

– making station operational states observable in real time;

– moving from retrospective reliability assessment to forecasting;

– formalizing previously qualitative categories (organizational and informational failures);

– incorporating algorithmic control factors into reliability analysis.

It should be especially noted that the implementation of AI does not change the essence of operational reliability, but just expands the tools for its assessment and management. This is basically important from a methodological perspective, as it avoids the replacement of engineering or Information Technology terminology for theoretical concepts.

Unlike studies primarily focused on:

– the reliability of individual infrastructure elements (predictive maintenance);

– capacity and delay valuations independent of reliability theory;

– digital twins as engineering or visualization tools;

– the proposed approach considers the digital railway station within the framework of a holistic theory of operational reliability. This allows us to link the technical, technological, managerial, and economic aspects of station operation in a single formalized model.

Thus, the work fills a methodological gap between:

– classical transport theory,

– modern digital and intelligent solutions, which often remain unexplored in the existing literature. The scientific novelty of this work lies in the following:

1. A theoretical connection between the classical theory of operational reliability of railway stations and the concept of a digital railway station is established and formalized.

2. It is shown that the digital railway station is a data-driven implementation of operational reliability theory, rather than a new, independent concept, ensuring the continuity of the conceptual framework.

3. Operational reliability is formalized as a probabilistic function of the digital station's state, dependent on physical, technological, graphical, and management layers.

4. A multi-layered operational reliability model is proposed, allowing for the consideration of technical, technological, organizational, and algorithmic factors within a single structure.

5. A methodological model and algorithm for digital reliability assessment are developed, enabling the transition from normative-analytical calculations to predictive management.

6. The classification of operational failures has been expanded by introducing algorithmic failures as a logical continuation of organizational disruptions in the digital environment.

The practical significance of the results lies in their potential use:

– in the development and implementation of digital twins of railway stations;

– in decision support systems for dispatch and operations personnel;

– in the design of next-generation station automated control systems;

– for assessing the effectiveness of digitalization measures;

– in the training and professional development of specialists in station operation management.

The proposed model can be adapted to various station types without changing its theoretical basis.

Conclusion

This article examines the problem of correlating the classical theory of operational reliability of railway stations with modern concepts of digitalization of rail transport. It is shown that the theory of operational reliability has a high degree of methodological maturity and conceptually meets the requirements of digital transport systems. It is established that a digital railway station represents the practical implementation and development of this theory, ensuring:

– measurability of operational conditions;

– orecasting the risks of operational failures;

– integration of technical, technological, and management factors;

– implementation of the principle of economically optimal reliability in algorithmic form.

The proposed multilayer model and algorithm for digital assessment of operational reliability provide the basis for the transition from normative management to intelligent management of railway station operations. The obtained results can serve as a theoretical basis for further research in the field of digital transport systems and the practical implementation of the digital railway station concept.

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Е. К. МАНАФОВ

ЦИФРОВА РЕАЛІЗАЦІЯ ТЕОРІЇ ЕКСПЛУАТАЦІЙНОЇ НАДІЙНОСТІ ЗАЛІЗНИЧНИХ СТАНЦІЙ

Мета. Метою цього дослідження є встановлення теоретичного зв'язку між класичною теорією експлуатаційної надійності залізничних станцій та сучасною концепцією цифрової залізничної станції, а також розробка методологічної моделі цифрової реалізації цієї теорії в контексті цифровізації управління транспортними процесами. Метою роботи є обґрунтування того факту, що цифрова залізнична станція не є альтернативною концепцією, а радше логічним та технологічним розвитком класичної теорії експлуатаційної надійності. **Методологія.** У дослідженні використовувалися методи системного та логіко-методологічного аналізу, ймовірнісного розуміння експлуатаційної надійності, валідації експлуатаційних станів транспортних систем, а також елементи теорії масового обслуговування, імітаційного моделювання та аналізу на основі даних. Теоретичні потреби класичної теорії експлуатаційної надійності порівнюються з функціональними можливостями цифрових двійників та інтелектуальних систем управління. Для опису цифрового застосування теорії запропоновано багатошарове представлення стану станції, що включає фізичний, технологічний, графічний та управлінський рівні. **Результати.** Показано, що експлуатаційну надійність залізничної станції можна формалізувати як ймовірнісну функцію її експлуатаційного стану з плином часу. Запропоновано методологічну модель цифрової реалізації теорії експлуатаційної надійності, що базується на формуванні вектора стану станції, прогнозуванні ймовірностей експлуатаційних відмов для кожного шару та їх сукупній оцінці. Розроблено алгоритм цифрової оцінки надійності, що дозволяє перейти від ретроспективного нормативно-аналітичного підходу до динамічного та прогнозного управління операційними ризиками. Введено інтегровані показники експлуатаційної надійності, що дозволяють кількісно оцінити стійкість станції в цифровому середовищі. **Наукова новизна.** Наукова новизна цієї роботи полягає у формалізації теоретичного зв'язку між класичною теорією експлуатаційної надійності залізничних станцій та концепцією цифрової залізничної станції. Вперше експлуатаційна надійність розглядається як ймовірнісна функція стану цифрової станції, що залежить від комбінації фізичних, технологічних, диспетчерських та управлінських факторів. Запропоновано багатошарову модель, яка розширює класичну класифікацію експлуатаційних відмов шляхом включення алгоритмічного компонента керування. **Практична цінність.** Отримані результати можуть бути використані при розробці цифрових двійників залізничних станцій, проектуванні систем підтримки рішень, оцінці ефективності заходів цифровізації та навчанні фахівців з управління операціями залізничних станцій.

Ключові слова: експлуатаційна надійність, залізнична станція, цифровий двійник, штучний інтелект, управління транспортним процесом, пропускна здатність.