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DEVELOPING ADAPTIVE AUTOMATIC CONTROL SYSTEMS FOR RAILWAY OPERATIONS USING NEURAL NETWORK MODELS

Summary. *This article reviews current methods for the automatic control of railway operations, focusing on adaptive algorithms and neural network models. It examines how train motion is modeled mathematically, how adaptive control systems are structured, and how neural networks can be used to estimate uncertainties in dynamic processes. Approaches to designing neural network control algorithms are discussed alongside published studies that report improved control accuracy and lower energy consumption. The article also identifies the main limitations of neural network technologies and outlines prospects for integrating them into existing railway signaling and automation systems.*

Key words: *railway transport, railway operations, automatic control, adaptive control systems, neural networks, mathematical modeling, neural network algorithms, train operation optimization, energy efficiency, railway safety.*

Introduction. Improving automatic control systems for railway operations is an important way to increase the efficiency, reliability, and safety of rail transport. Changing operating conditions, external disturbances, and complex process dynamics limit the capabilities of conventional control methods, which rely on mathematical models with predefined parameters.

One promising solution is to use adaptive systems built on neural network models. Such models can capture nonlinear relationships, predict the state of controlled objects, and adjust control inputs as operating conditions change. At the same time, the use of neural networks raises issues of stability, control accuracy, and compliance with safety requirements.

There is therefore a need for adaptive automatic control systems for railway operations that improve control accuracy and efficiency under uncertainty and changing operating parameters.

Objective. This study aims to substantiate approaches to developing a neural-network-based adaptive automatic control system for railway operations that improves control accuracy, energy efficiency, and control stability under changing operating conditions.

Materials and Methods. The study draws on international scientific publications and technical documents on the automatic control of railway transport, mathematical modeling of train motion, and the application of neural network technologies.

The methods used were comparative analysis, systematization of scientific data, mathematical modeling, and analysis of adaptive control algorithms. The effectiveness of the approaches considered was assessed on the basis of numerical simulation results reported in published studies.

Results. Automatic control of railway operations spans several interrelated functional levels: maintaining safe headways between trains, regulating speed and traction and braking modes, routing, and real-time timetable adjustment. Each level relies on different control methods, depending on the nature of the controlled object, the availability of information about its state, and the applicable operational constraints.

In European railway practice, automatic train protection is based on ETCS (European Train Control System), which is part of ERTMS (European Rail Traffic Management System). Its core functions are supervising movement

authorities, determining the permitted speed profile, and intervening automatically when the set limits are exceeded. Unlike automatic train operation systems, ETCS is not designed to optimize traction and braking; its main task is to ensure safe movement within the authorized limits. This distinction is set out in Commission Implementing Regulation (EU) 2023/1695 [2].

In ETCS Level 1, information is transmitted to the train at specific points along the track via Eurobalise transponders. The onboard equipment uses these data to continuously supervise compliance with speed restrictions. Level 2 adds continuous radio communication between the train and a Radio Block Centre, which issues movement authorities and receives train position reports. Technical materials published by UNIFE also describe Level 2 variants with fixed and moving blocks, which differ in how the safe distance between trains is determined [3].

Figure 1 shows the basic organization of information transmission in ETCS Levels 1 and 2.

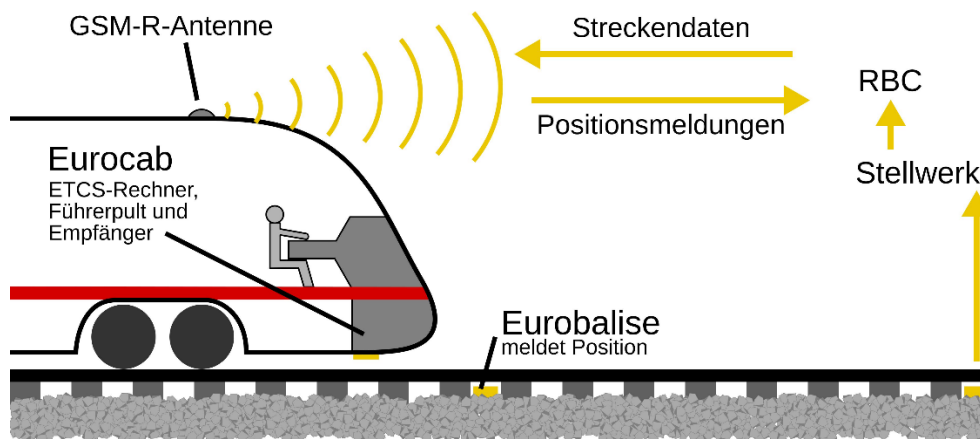


Fig. 1. Basic organization of information transmission in ETCS Levels 1 and 2 [6]

The next functional level is Automatic Train Operation (ATO). Unlike ETCS, ATO generates train control commands, including acceleration, speed holding, and braking. When ATO and ETCS are used together, ATO drives the

train within the limits supervised by the safety system. Materials presented by the European Union Agency for Railways describe the ATO over ETCS architecture, which involves interaction between the traffic management system, trackside and onboard ATO equipment, the Radio Block Centre, and the traction and braking actuators [8].

Speed regulation relies on methods of classical control theory, including proportional–integral–derivative (PID) control. A PID controller computes the control input from the current error, the accumulated error, and the rate of change of the error. The approach is practical because it can be implemented at relatively low computational cost. Control quality, however, depends on the choice of gains and on the train’s dynamics. Wang and Ou studied adaptive train control that combines sliding mode and PID control [9].

More complex problems, which require meeting speed restrictions and arrival times while minimizing energy consumption, are solved with optimal control methods. In their review, Zhu, Lu, and Li identify three lines of research on energy-efficient operation of high-speed trains: driving strategy optimization, timetable optimization, and integrated optimization of both. These studies take into account traction equipment characteristics, track profile, speed limits, and running time. The authors view optimization algorithms as a way to reconcile operational and energy requirements, not as a substitute for safety systems [11].

Mathematical programming methods play a major role when multiple trains are controlled. Real-time rescheduling problems may involve changing the train sequence, arrival and departure times, and track assignments, as well as maintaining passenger connections (Table 1).

Table 1

Comparison of control methods for railway operations

Method or system	Application area	Main limitation
ETCS	Supervision of movement authorities and speed restrictions	Does not by itself address optimal train driving

ATO	Automation of acceleration, running, and braking	Algorithm depends on input data and predefined constraints
PID control	Speed holding and control of dynamic parameters	Controller gains must be tuned
Optimal and predictive control	Generation of driving strategies subject to constraints	Computational cost and dependence on model accuracy
Mathematical programming	Timetable rescheduling and allocation of infrastructure resources	Computational complexity grows with the number of trains and constraints
Neural network methods	State prediction, identification, and control support	Require high-quality data and verification of generalization ability and safety

Source: compiled from Regulation (EU) 2023/1695, the studies by Zhu et al. and Tang et al., and a review of train rescheduling methods

Neural network models are a promising direction in the automation of railway operations. According to Tang et al., the largest shares of studies on artificial intelligence in railway transport concern maintenance and equipment diagnostics (58%) and traffic planning and management (24%) [8].

Neural network methods can reveal complex relationships in operational data, predict the condition of technical assets, and improve control algorithms. Their use, however, requires verification of prediction accuracy, operational stability, and compliance with safety requirements.

Advances in automatic control also depend on the integration of different technical systems. For example, Siemens Mobility materials discuss the combined use of a traffic management system (TMS) and ATO to align the timetable with rolling stock operation.

Mathematical modeling of train motion is based on a description of longitudinal dynamics that accounts for traction and braking forces, train mass, running resistance, and track characteristics. The study “A Robust Model Predictive Control for Virtual Coupling in Train Sets” uses a dynamic model that captures changes in train position and speed, actuator lag, and external

disturbances. This approach makes it possible to examine how the control system behaves when operating parameters change [4].

Radial basis function (RBF) neural networks can be used to account for uncertainties in the dynamic model. Guo et al. applied this method to estimate unknown components of high-speed train dynamics, taking into account interactions between cars and possible actuator faults. The neural network model can approximate complex nonlinear relationships that conventional mathematical models do not fully capture [5].

An adaptive control system architecture may include a data acquisition and processing module, a neural network unit for uncertainty estimation, an adaptive controller, and traction and braking actuators. Together, these components generate control inputs based on the current state of the train. Speed supervision and safety functions, however, must remain with independent protection subsystems.

Figure 2 shows the architecture of interaction between onboard and trackside automatic train control subsystems.

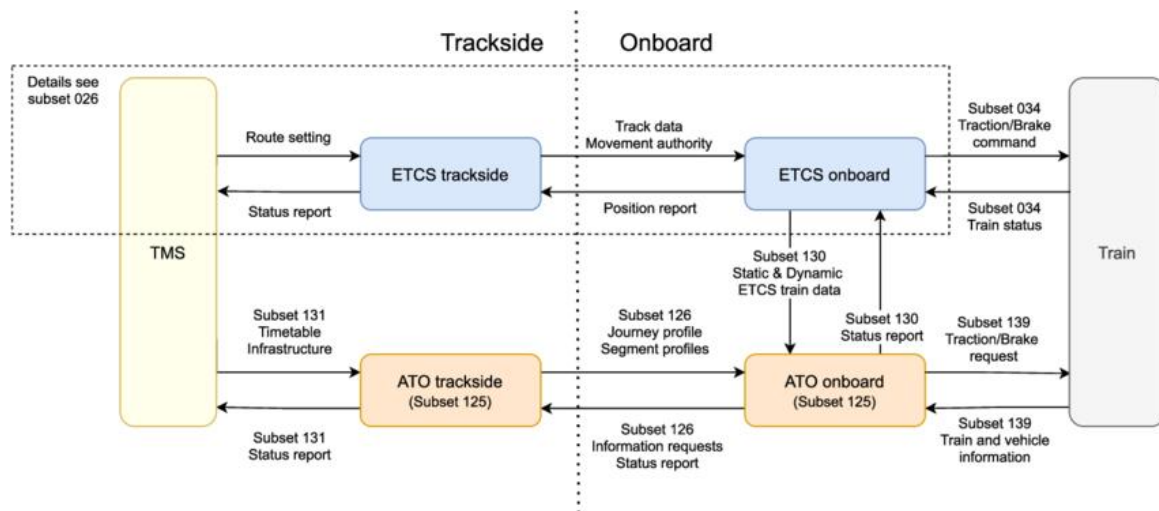


Fig. 2. Architecture of interaction between onboard and trackside automatic train control subsystems [1]

The neural network adaptive control algorithm sequentially processes data on train speed, position, and current running conditions, estimates deviations

from the reference values, and adjusts the control inputs. Guo et al. proposed a method that combines adaptive sliding mode control with an RBF neural network. The neural network compensates for uncertainties arising from changes in plant characteristics [5].

The algorithm estimates the train state, determines the required traction or braking effort, and adapts the controller parameters. The neural network is tuned according to the chosen adaptation law. System stability is established mathematically, which makes it possible to judge whether the algorithm can be applied under changing running conditions.

Guo et al. evaluated this approach on a simulation model of the CRH380B high-speed train. According to their results, compared with model reference adaptive control (MRAC), the proposed algorithm reduced the root-mean-square speed tracking error by 23.4% and the position tracking error by 52%. These results were obtained in numerical simulation and do not characterize the performance of neural network control systems in general [5].

These results indicate that neural network compensation of uncertainties can improve the accuracy of train motion control. Further development of the algorithm must account for traction and braking force limits, measurement errors, and system stability requirements. It is particularly important to verify controller performance under changing running parameters and external disturbances.

Experimental evaluation of neural network control systems for railway operations relies mainly on simulation. Tests analyze timetable adherence, energy consumption, stopping accuracy, and the convergence speed of learning algorithms. To obtain comparable results, the same route characteristics and running conditions are used.

Lu and Liu simulated automatic train operation using an improved deep Q-network (DQN) algorithm. In their experiment, energy consumption decreased by 15.75% relative to actual operation, and the convergence speed of the algorithm increased by approximately 37% [7].

Zhou et al. reported further results from a study of speed optimization for high-speed trains using a neural network model. In some simulation scenarios, the energy consumed in overcoming motion resistance fell by up to 27.85% compared with conventional control strategies [10].

The studies reviewed confirm the potential of neural network methods for optimizing train operation. Differences in the modeled systems and evaluation criteria, however, preclude direct comparison of the reported figures. Assessing the effectiveness of the system under development requires a dedicated computational experiment with identical initial conditions and a baseline control algorithm.

Future research should focus on improving neural network control algorithms, increasing their resistance to external disturbances, and adapting them to different railway operating conditions. Particular attention should be given to validating the proposed solutions on real operational data, conducting field tests, and assessing their compatibility with existing railway signaling and automation systems. Practical deployment of these technologies requires evidence of their reliability and safety, as well as a justification of their economic efficiency.

Conclusions. The analysis shows that the use of neural network models in adaptive automatic control systems can improve control accuracy and optimize train operation. The international studies reviewed indicate that such methods can reduce energy consumption and compensate for uncertainties in dynamic processes. Practical deployment of neural network algorithms, however, requires further verification of control stability, reliability, and safety. A promising direction is the integration of neural network models with conventional controllers and with independent railway safety systems.

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