METHOD OF ACCIDENT PREVENTION USING INTELLIGENT CONTROL SYSTEM FOR RAILWAY TRANSPORT

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Abstract. This paper is devoted to propose method for prevention of train collisions. Nowadays human factor plays a significant role in control of railway system in a whole and a rolling stock in particularly. Some crashes with lethal outcomes happened in Latvia in last three years. Main reason is the driver’s inattention passing the red signal. The task is to prevent such accidents by reducing the human factor. In this paper artificial neural network controller is proposed for motion control of rolling stock and for braking way calculation to stop the train timely and safely before the dangerous point. Mathematical models and algorithm for task solution is proposed. Results of experiment show the possibility to use neural network controller for speed control of DC drive depending on the distance to stop. The results show the possibility of the developed systems to prevent accidents and to avoid different problems by intelligent diagnostic and coordination devices. Neural network may be used to prevent breakdowns and accidents and such kind of controllers may be integrated in working infrastructure for optimal speed control of railway traffic.

Keywords: railway transport, intelligent control, safety.

1. Introduction

The paper is based on authors’ previous scientific work researching the intelligent device systems and its’ application in mechatronic systems. Intelligent devices are controllers, which has interface to work in global network and wireless networks and are programmed to use methods of the artificial intelligence. Intelligent devices have possibility to negotiate with each other and to coordinate their work to get better decision.

2. Problem formulation

There are three main safety levels in transport systems. The first is the safety of mechatronics system of a train. That means, an intelligent diagnostic system for engine states is needed to separate dangerous situations by critical testimonies from sensors from the regular states of the system.

The second level is the safe control of mechatronics system in a rolling stock. One of the primary tasks is an intelligent speed control of a train, using with multi-criteria decision making, taking in account weather factors, state of the way and schedule.

The third safety level includes an intelligent control of the whole transport system. That is why the solution of coordination task between all trains in the system is necessary.

This paper is devoted to propose method for prevention of train collisions. Nowadays human factor plays a significant role in control of railway system in a whole and a rolling stock in particularly. Some crashes with lethal outcomes happened in Latvia in last three years. Main reason is the driver’s inattention passing the red signal. The task is to prevent such accidents by reducing the human factor.

3. Method of solution

Authors propose to solve this task using intelligent devices system for all three safety levels. Method for diagnostics task solution was proposed in author’s previous work [5], based on neural network and clustering, gives possibility to detect and warn about changes in the engine, detect the problem immediately, and to fix it in some cases without human intervention.

In this paper artificial neural network controller is proposed for motion control of rolling stock and for braking way calculation to stop the train timely and safely before the dangerous point. Mathematical models and algorithm for task solution is proposed.
4. Mathematical models of rolling stock

Mathematical model of rolling stock consists of two parts – electromechanical and control. Models are simplified.

A. Mathematical Model of Electromechanical Part of Rolling Stock

Electromechanical part of rolling stock is represented as

- Pantograph
- Electric drive
- Switches
- Braking resistor
- Carriages of rolling stock
- Wheels of motor carriage
- Transmission (gears) from electric drive

Mathematical model of electromechanical part of rolling stock consists of the following variables:

- $U$ – railway contact net voltage;
- $E$ – counter-electromotive force of the drive of the train;
- $I_a$ – armature current of the train;
- $R_a$ – armature resistance of the drive of the train;
- $L_a$ – armature inductance of the drive of the train;
- $I_f$ – field current of the drive of the train;
- $R_f$ – field resistance of the drive of the train;
- $L_f$ – field inductance of the drive of the train;
- $L_{df}$ – mutual field-armature inductance of the drive of the train;
- $K_E$ – voltage constant;
- $K_T$ – torque constant;
- $T_e$ – electrical torque of the drive;
- $T_L$ – torque load;
- $R_b$ – braking resistance;
- $m$ – mass of rolling stock;
- $g$ – gear box ratio;
- $T_e$ – torque from electric drive;
- $F$ – friction force;
- $B$ – mechanical braking force;
- $J$ – inertia of the drive;
- $B_m$ – viscous friction coefficient of the drive;
- $T_b$ – Coulomb friction torque of the drive;
- $\omega_1$ – angular velocity of the motor;
- $\omega_2$ – angular velocity of output shaft of transmission;
- $T_2$ – torque on the output shaft of transmission;
- $P_1$ – power on the input shaft of transmission;
- $P_2$ – power on the output shaft of transmission;
- $r$ – wheel radius;
- $F$ – force on the wheel periphery;
- $v$ – linear velocity on the wheel periphery;
- $t$ – time

Functional dependencies of electromechanical part of are following:

1) $E = K_E \omega$
2) $K_E = L_{df} \cdot I_f$
3) $T_e = K_T \cdot I_a$
4) $K_T = K_E$
5) $T_e \cdot TL < 0$ – motor mode;
6) $T_e \cdot TL > 0$ – generator mode;
7) $\frac{d\omega}{dt} = T_e - \text{sgn}(\omega) \cdot T_L - B_m \cdot \omega - T_f$
8) $\omega_1 = g \cdot \omega_2$
9) $T_2 = g \cdot T_e$
10) $P_1 = \omega_1 \cdot T_1$
11) $P_2 = -\omega_2 \cdot T_2$
12) $v = r \cdot \omega_2$
13) $F = m \frac{dv}{dt}$
14) $T = r \cdot F$

B. Mathematical Model of Control Part Based on Neural Network

Control part of rolling stock is represented as neural network mathematical model:

- Input data set for neural network:
  \[ X = \{ x_1, x_2, \ldots, x_n \} \]
- Set of artificial neural network hidden layers:
  \[ L = \{ l_1, l_2, \ldots, l_k \} \]
- Set of neurons for each $j$-th hidden layer:
  \[ p^j = \{ p_1, p_2, \ldots, p_i \} \]
- Set of neural network outputs:
  \[ Y = \{ y_1, y_2, \ldots, y_m \} \]
- Weights for each input of $i$-th neuron of $j$-th layer:
  \[ W^j = \{ w_{i1}, w_{i2}, \ldots, w_{in}, w_{in} \} \]
- Bias for each $i$-th neuron of $j$-th layer: $b_{i}$
- Input summation function for each $i$-th neuron of $j$-th layer:
  \[ s^j_i = \sum(W^j \cdot X^j) + b_i \]
- Transfer function for all neurons of $j$-th layer: $F^{j}(s^{j})$

5. Algorithm for accident prevention

This part presents the algorithm proposed for task solution. Algorithm of motion control for intelligent agent of electric vehicle has a cyclic structure with following steps:

B. Algorithm of Intelligent Speed Control of Train

Step 1. Detect next checkpoint – chp.
Step 2. Calculate breaking point and breaking time: $brp = chp_{dist} – breaking_{way} (v_{min} \to 0)$; $brt = breaking_{time} (v_{min} \to 0)$. 
Step 3. Calculating rolling way and rolling time:

\[ rw = \text{rolling way} (v \rightarrow v_{\text{min}}) \]
\[ rt = \text{rolling time} (v \rightarrow v_{\text{min}}) \]

Step 4. Evaluating the rolling way:

\[ brp = s + rw \]

Yes – Step 5; No – Step 3.

Step 5. If checkpoint type is a point:

\[ \text{type[chp]} = \text{“X”} \]

Yes – Step 6; No – Step 3.

Step 6. Start negotiations with point agent;
Step 7. Signal = green?
Yes – Step 1; No – acceleration = false.
Step 8. If checkpoint type is station:

\[ \text{type[chp]} = \text{“S”} \]

Yes – Step 9 No – acceleration = false.
Step 9. Start negotiations with station agent.
Step 10. Satisfies directive term

\[ rt + brt \leq t(chp) \]

Yes – acceleration = false; No – Step 3.

C. Algorithm of Communication between Trains and Traffic Lights

Step 1. Getting input data from all jobs and processors about current situation in a zone.
Step 2. Negotiation Set B creating for all trains coming to the point or station.
Step 3. Crossing time set C calculating.
Step 5. CONFLICT ? Yes – New restriction in B, Step 2; No – Step 6.

Step 7. Sending acceptance messages to participants.

6. Computer Experiment

For the computer experiment the model of rolling stock ER-2 and traffic light connected by wireless communication channel (Fig. 1.)

Let us assume, that modeled situation is following:

- Rolling stock consists of 4 carriages with 2 head carriages and 2 motor carriages with 8 identical dc motors.
- Initial velocity of rolling stock \( v_0 = 0 \text{ kmh} \).
- Initial relative position of rolling stock is \( p_0 = 0 \text{ m} \).
- Railroad signal is situated at maximal length of block at relative position \( p_1 = 2 \text{ 600 m} \).
- Red light is on. Green light is off. \( S_{\text{red}} = 1, S_{\text{green}} = 0 \).
- Communication channel between rolling stock and railroad signal contains position, where railroad signal is located \( p_1 \) and status of green light \( S_{\text{green}} \).

Fig. 1. Model of railroad lights

Model of rolling stock (fig. 2.) consists of control part getting input signal from traffic light by antenna, electric part and mechanical part of rolling stock. Schemes are simplified.

Fig. 2. Model of rolling stock
Electrical part of the model (fig. 3.) consists of DC drive with characteristics of 8 DC motors, 1 switch to connect or disconnect electric drive to electric contact network. 2 pairs of switches for acceleration and for braking that changes direction of field current $I_f$. Braking branch contains braking resistance. Output of DC drive is electrical torque which handles mechanical part of rolling stock.

Mechanical part of rolling stock model (fig. 4) gets electrical torque of electric drive as input transmitted to gears of rolling stock and wheels. Mass of rolling stock is 192 000 kg.

Control part of rolling stock (fig. 5) contains two artificial neural network ANN controllers.

ANN controller for braking way calculation is trained to predict estimated distance of rolling stock which will be passed if braking process will begin at current speed. Input of this controller is wireless signal from railroad signal, current relative position of rolling stock and linear speed of rolling stock. Output of this controller is a distance to traffic light and braking way transmitted to motion controller of rolling stock. Cascade-forward back-propagation neural network (fig. 6) is used for braking way calculation. It is trained using Levenberg-Marquardt algorithm.

ANN controller for motion control uses input signals from sensors of mechanical and electrical part of rolling stock – linear speed, field current. It outputs command signals for acceleration and braking.
Fig. 6. Cascade-forward back-propagation neural network for braking way calculation

Fig. 7. Field current dynamics of rolling stock

Fig. 8. Acceleration dynamics of rolling stock

Fig. 9. Linear velocity dynamics of rolling stock

Fig. 10. Relative path length of rolling stock

Figures 7–10 presents dynamics of field current of electric drive and acceleration, velocity and path of rolling stock. As a result of modeling (fig. 11), rolling stock stops at 26.1 m before the stop point.

Fig. 11. Distance to railroad signal after braking
7. Conclusion

Main advantage of using negotiations in intelligent control systems is the possibility to coordinate actions of all participants in transport systems and to realize multi-criteria decision-making in control, diagnostic and scheduling for electric transport.

Results of experiment show the possibility to use neural network controller for speed control of DC drive depending on the distance to stop. The most important is to use the most precise samples for neural network training. Bigger number of samples will provide better precision.

The results show the possibility of the developed systems to prevent accidents and to avoid different problems by intelligent diagnostic and coordination devices. Neural network may be used to prevent accidents and such kind of controllers may be integrated in working infrastructure for optimal speed control of railway traffic.

References