Neurocontrolled Car Speed System

Markiyan Nakonechnyi, Orest Ivakhiv, Dariusz Świsulski

Abstract:
The features of the synthesis of neural controllers for the car speed control system are considered in this article. The task of synthesis is to determine the weight coefficients of neural networks that provide the implementation of proportional and proportional-integral-derivative control laws. The synthesis of controllers is based on an approach that uses a reversed model of the standard. A model of the car speed control system with the use of permitting subsystems has been developed, with the help of the synthesized controller that is connected under certain specified conditions. With the iterative programming and mathematical modeling environment in MATLAB, and using the Simulink package, a structural scheme for controlling the speed of the car was constructed and simulated using synthesized neural controllers.

Keywords: *neural controller, PID-algorithm of control, dynamic object, neural networks, electric car, speed control*

1. Introduction

In recent human activities, different computerized devices and systems have been widely incorporated in various fields, especially in the automotive and avionics industries [1-12].

These possibilities come up during the design, simulation, and testing processes [13-16] as well as in the ordinary exploitation period of a concrete product [17-23]. Controllers that use neural network systems achieve an effective speed control in both electric and traditional cars [24-30].

2. Mathematical Model of the Car Movement

The task of any automatic control system's creation is to supplement the managed object with external links that would allow processes to proceed according to certain predefined criteria. The choice of these criteria is primarily determined by the fact that the purpose of the automatic control system is to ensure the output of the controlled object at any point in time. The controlled value is as close as possible to the specified.

For the most part, automatic control systems consist of non-linear elements that are covered by complex feedbacks. The operation of such systems in the real world is affected by a variety of noises, interferences, and other disturbing factors, which significantly limit the use of modern and classical control theory in the construction of controllers [31-36]. In recent decades, management strategies have used theories based on the idea of a system linearization, which does not fully reflect its physical properties. In some cases, even when the dependencies between the inputs and outputs of the system are accurately reproduced, their use cannot provide adequate control of the system. Therefore, artificial neural networks are increasingly used in synthesizing control algorithms. This method considers object features that the network must reproduce, and its training is conducted based on the input and output data that characterizes the processes that run in the object [37, 38]. In general, the neural controller is implemented into the automatic control system (Fig. 1).

The main attention here is focused on the possibility of choosing the proper controller type. Meanwhile, the creation of the controller architecture itself is out of the scope of this research because this task has already been described in detail [37].

Let us assume that the architecture of the neural controller is known and while training, it is only necessary to determine its weighting factors. In this case, the neural controller complements the nonlinear object so that when submitting any valid sequence r_k, the formed system is as close as possible to the standard (ideally $y_{rk} = y_k$). Since one needs to know the input and output signals to train a neural network, then a neural controller can be trained if the following are known:

1. setting signal at the input of the neural controller (sequence r_k);
2. feedback signal of the output object (sequence y_k);
3. the object's input and the corresponding sequence y_k, which is taken from its output. Using the model of the inverted reference, based on the sequence y_k, it is possible to obtain an input sequence of the reference r_k, which, when fed to the controller input of the system, will cause its reaction u_k.
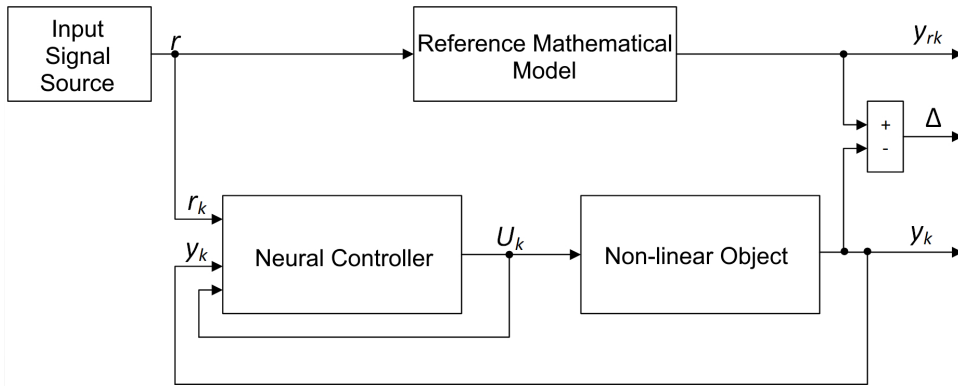
Fig. 1. Automatic control system with neural controller implementation
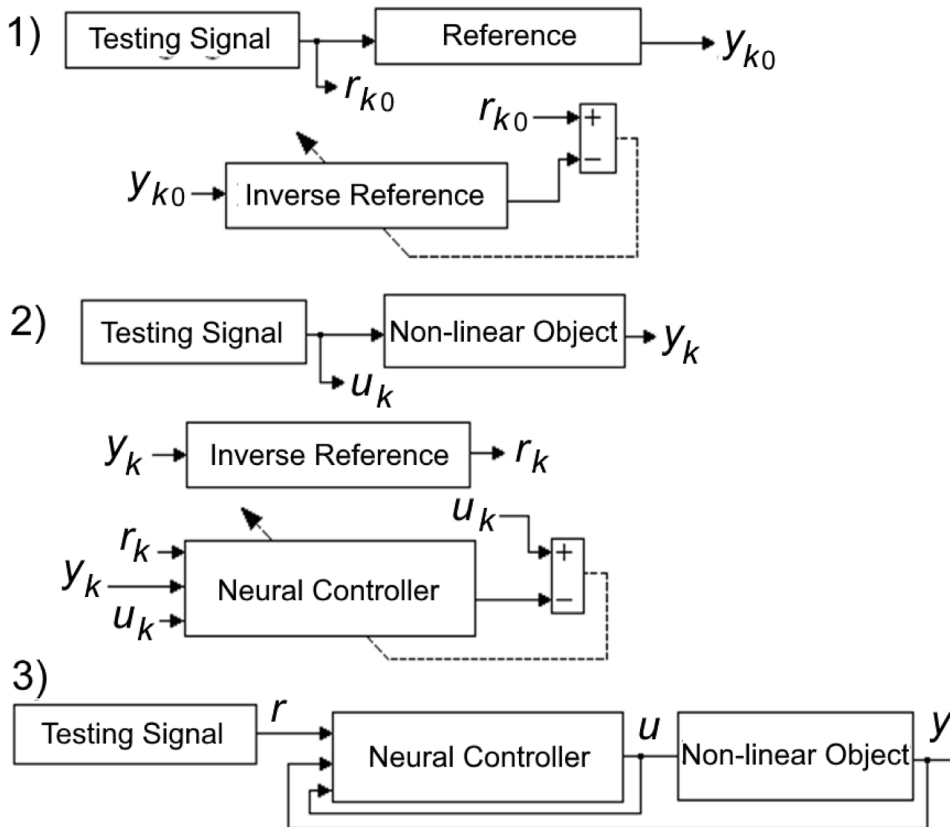

Fig. 2. The general scheme of the neural controller training, using the neural model of the inverted reference

When the reference is simple, this training scheme has several significant advantages. The process of building a model of the inverted reference is much simpler than the process of building a model of the inverted object. There are two ways to convert the reference in the classical sense: the first is to solve reference equation relative to the input variable, and the second is to construct a model inversion using SIMULINK [39, 40]. One of the most effective ways to reverse a reference is to build a neural network-based inverted model (Fig. 2).

Let us consider using a neural network controller to control the speed of a car [39]. For example, let us look at the car movement on an inclined plane surface (Fig. 3). Let us consider the main external forces applied to the car, i.e., the thrust force of the engine F_e (or in the case of its negative value, the braking force) transmitted through the wheels; the aerodynamic force due to the wind action F_w,; and the projection of gravity on the longitudinal axis of the car F_h.

The equation of a car's motion under Newton's second law can be written as follows:

$$m\ddot{x} = F_e - F_w - F_h, \tag{1}$$

where m is the mass of the car, x is the displacement, and F_e is the magnitude of the force for which the maximum and minimum values are given, i.e., the maximum thrust of the engine and the maximum braking force, respectively.
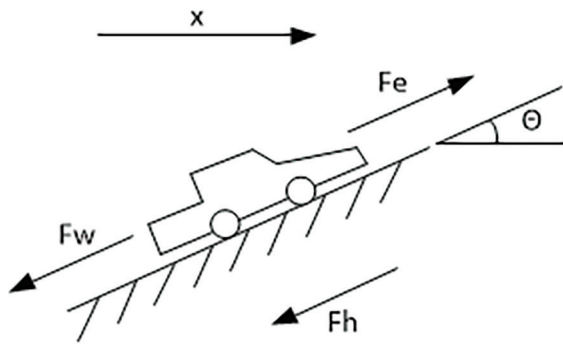
Fig. 3. Car position on an inclined plane surface

There are accepted limits of thrust change and car weight [39]:

$$-2000 \leq F_e \leq 2000 \quad \text{and} \quad m = 1000 \text{ kg}. \quad (2)$$

The aerodynamic force is directly proportional to the drag coefficient C_D, the frontal area of the car A and the speed pressure P, which is determined as follows:

$$P = \frac{\rho V^2}{2}, \quad (3)$$

where ρ is the air density, and V is the speed, which includes speed of the car and the speed of the wind V_w.

Suppose that there is given a value of a relation as follows [39]:

$$\frac{C_D A \rho}{2} = 0,001, \quad (4)$$

and the wind speed is described by the following expression [39]:

$$V_w = 20\sin(0.01t). \quad (5)$$

Thus, the aerodynamic force is determined by the following equation:

$$F_w = 0.001(\dot{x} + 20\sin(0,01t))^2. \quad (6)$$

Since the considered surface of the road is not horizontal, the angle between the longitudinal axis of the car and the horizontal plane surface is given by the following equation [39]:

$$\theta = 0.0093 \sin(0.0001\,x). \quad (7)$$

The equation of the projected gravity force is written in the following form:

$$F_h = 30\sin(0.0001x). \quad (8)$$

As can be seen from equations (1)-(8), the car speed simulation system cannot be represented by a linear differential equation or a transfer function. The nonlinearity of the model eliminates the possibility of using classical methods of controller synthesis [35, 36]. That is why the synthesis of controllers is carried out using artificial neural network technology [38]. To ensure a high performance using the principle of a variable structure [39], the implementation is carried out by a permitting subsystem. While operating a car movement speed control system, the use of any controller is necessary to fulfill the following requirements:

1. ensuring that the car reaches set speed value without over-adjusting;
2. providing the specified system performance.

The dynamics of the processes that occur in the speed control system of the car depend on both the type and parameters of the selected controller and the given car of a nonlinear model. As such, it is necessary to determine the effectiveness of the process control system in a nonlinear object in the implementation of various control laws [41]. That means that the proportional (P) and proportional-integral-derivative (PID) controllers, based on neural networks, follow their testing in the speed control system model.

This type of prepared model of the car speed control system, using P and PID controllers based on neural networks, is presented below (Fig. 4). The proper results of such a system simulation, namely the advantages of a control system using a PID controller (Fig. 5b), compared to a system based on a P controller (Fig. 5a), are shown in Figure 5.

The advantages of the PID controller in comparison with P controller are the shorter transition time and the practical identity of settled and adjustable quantities behavior in the transition mode. It should also be noted that the weight coefficients of the PID and P controllers, obtained in the neural network training course, ensure the absence of oscillations of the original value in both transient and steady-state modes. Thus, based on the simulation results, it can be concluded that to provide a predetermined performance of the car speed control system using P and PID controllers, it is advisable to switch on the PID controller on the first stage of the control process, and the P controller should be used when the difference between the given and real speeds reaches a small value.

Today, to solve such problems, variable structure systems are used [39]. To provide the necessary parameters of the control process, when reaching the difference between the reference and the output values of the setpoint, the switching of individual functional units is envisaged. In such systems, monitoring of the adjustable value is carried out during the operation of the system and when it reaches a certain value, the corresponding control algorithm is switched on by way of logical blocks. The switching procedure is possible due to the modular structure of the system, which can be used as a subsystem in the composition of more complex systems. These systems are used in robotic complexes, and in transport, as well as in controlling the operation of electric motors and
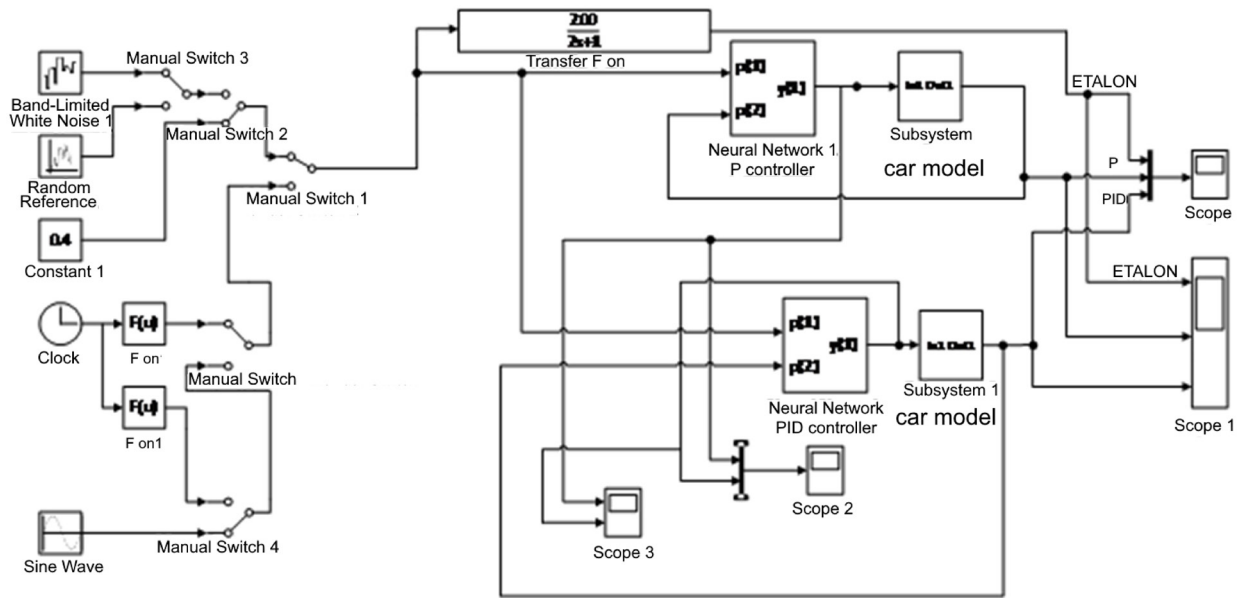
Fig. 4. Model of the car speed control system using P controller and PID controller based on neural networks
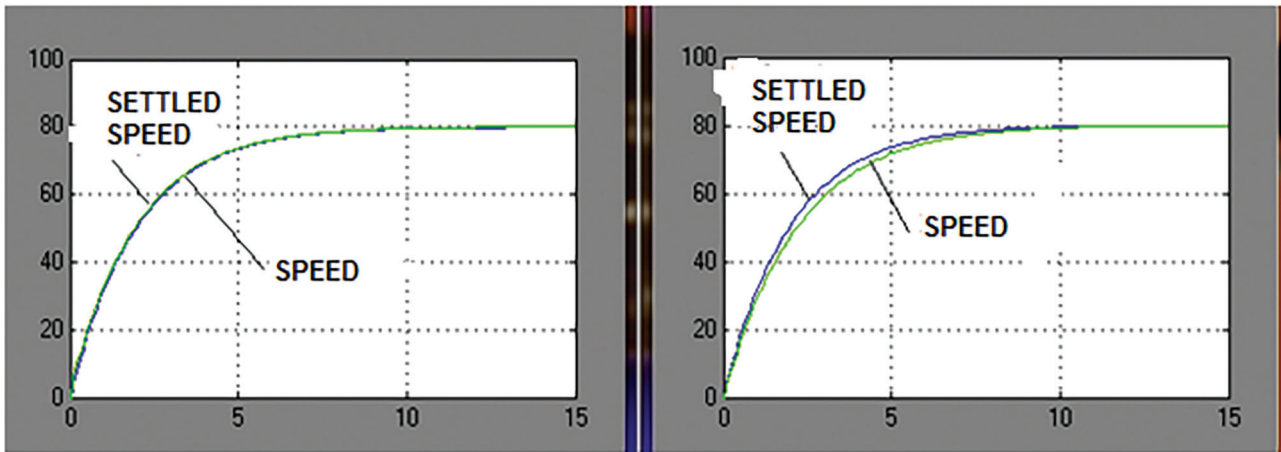

Fig. 5. Results of system modeling using neural PID controller (a) and P controller (b)

generators. In such cases, considering the features of the object, the model of one object can be replaced with the model of any other object.

Let us consider the features needed to create a system with a variable structure to control the speed of the car [39]. There is a constructed model of the car speed control system at the application of the principle of variable structure (Fig. 6).

The model consists of a speed setting unit, a car model, controllers made based on neural networks, a subsystem of choice of operating modes of controllers and output units (oscilloscopes and display). The system model uses the mode selection subsystem (Fig. 7).

The inputs of the subsystem are given a known and real value for the speed and their difference is determined, which is simultaneously fed to the inputs of the unit of calculation of the module and the differentiator. The resulting module value is fed to one of the inputs of the relational operator "<=", the second input of which is connected to the output of block *C1*. The output of the differentiator via the module calculator is fed to the first input of relational operator "<=", the second input of which is connected to the output of block *C2*.

The operation of the mode selection subsystem is as follows. If the absolute value of the speed error is greater than the threshold value set in block *C1* and the rate of change of the error signal is greater than the threshold value set in block *C2*, then the PID controller is used. The PID controller cycle continues until the difference between the set and real speeds reaches the value set in block *C1,* and the rate of change of the error signal is less than the value set in block *C2*. In all other cases, the P controller is used. Without any grounds for justification, the established limits and thresholds were used only to demonstrate the operation of the system with variable structure.
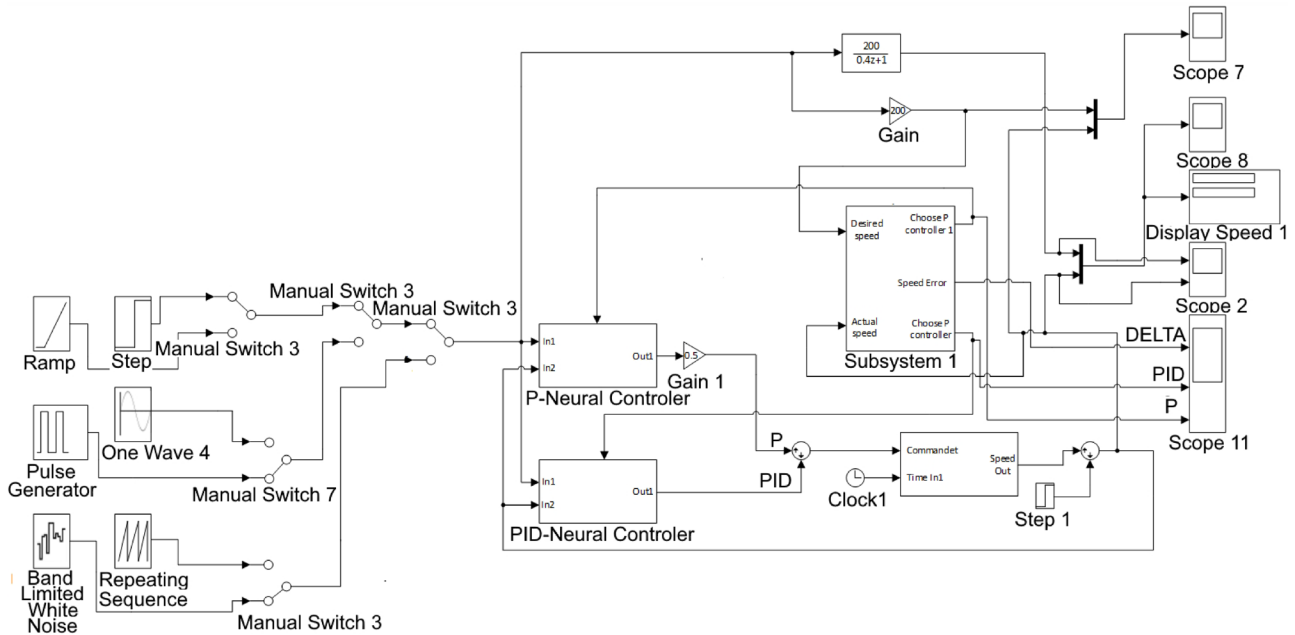
Fig. 6. Model of the car speed control system using the principle of variable structure
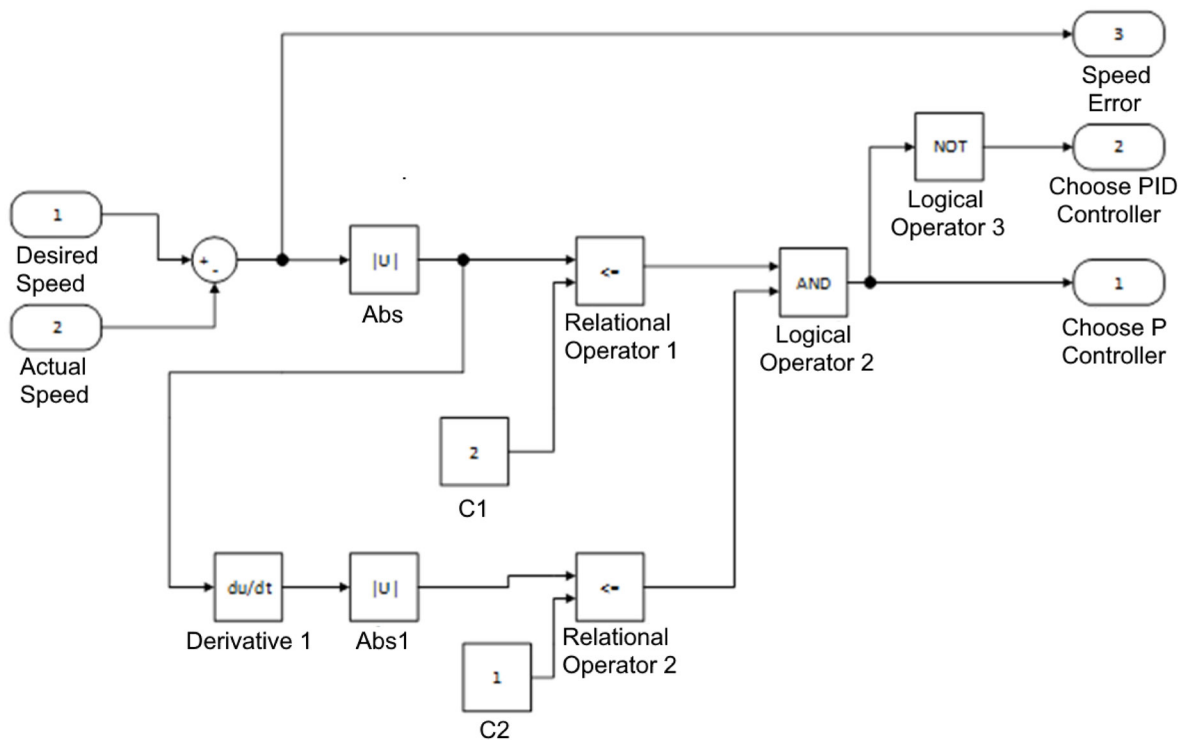

Fig. 7. The controller operation mode choosing subsystem

Relational operators "<=" determine the activation of a controller as follows:

PID controller, if

$$C1 < \left| X_{set} - X_{real} \right|$$
$$C2 < \frac{d}{dt} \left| X_{set} - X_{real} \right| \qquad (9)$$

P controller, if

$$C1 > \left| X_{set} - X_{real} \right|$$
$$C2 > \frac{d}{dt} \left| X_{set} - X_{real} \right| \qquad (10)$$

The result of model operation with such mode selection subsystem when using synthesized neuro-controllers is shown in Fig. 8, and the graphs of the resolution signals of PID (b) and P (c) controller sub-systems are shown in Fig. 9.

The created mode selection subsystem accelerates the speed setting and provides the required statistic error value (Fig. 9a). Therefore, the synthesis of con-trollers based on artificial networks and the use of criteria for switching on and switching controllers are

17

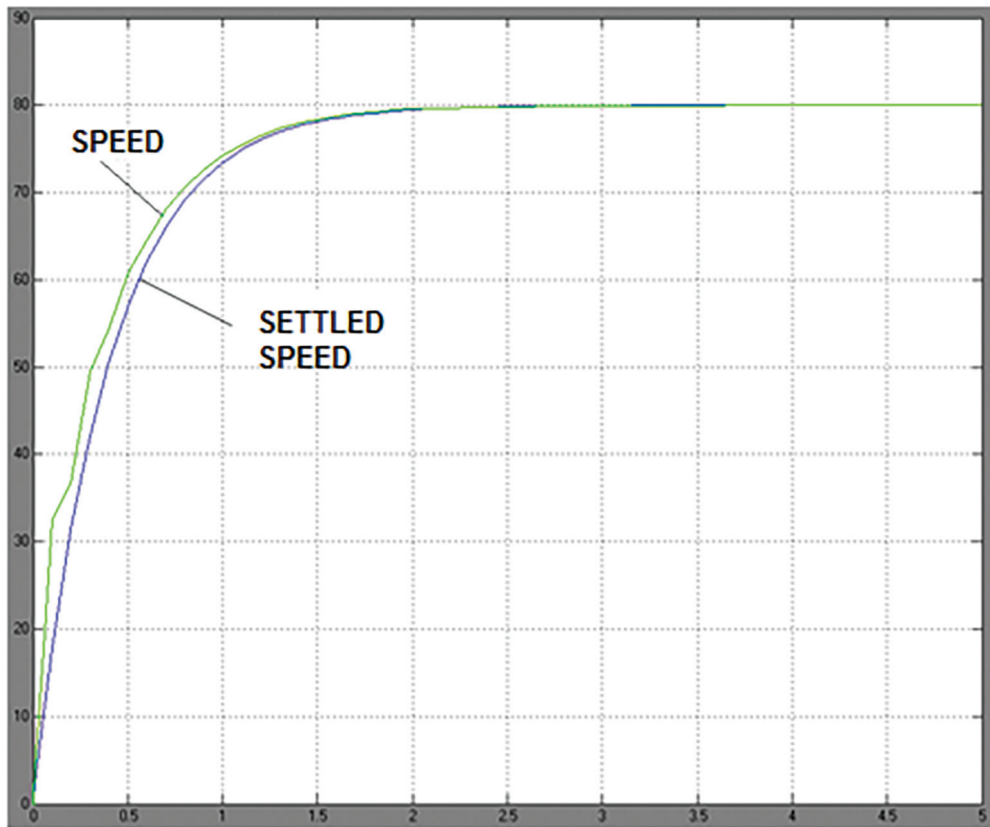**Fig. 8.** Operational diagram of the car speed control system with the mode selection subsystem using synthesized neurocontrollers
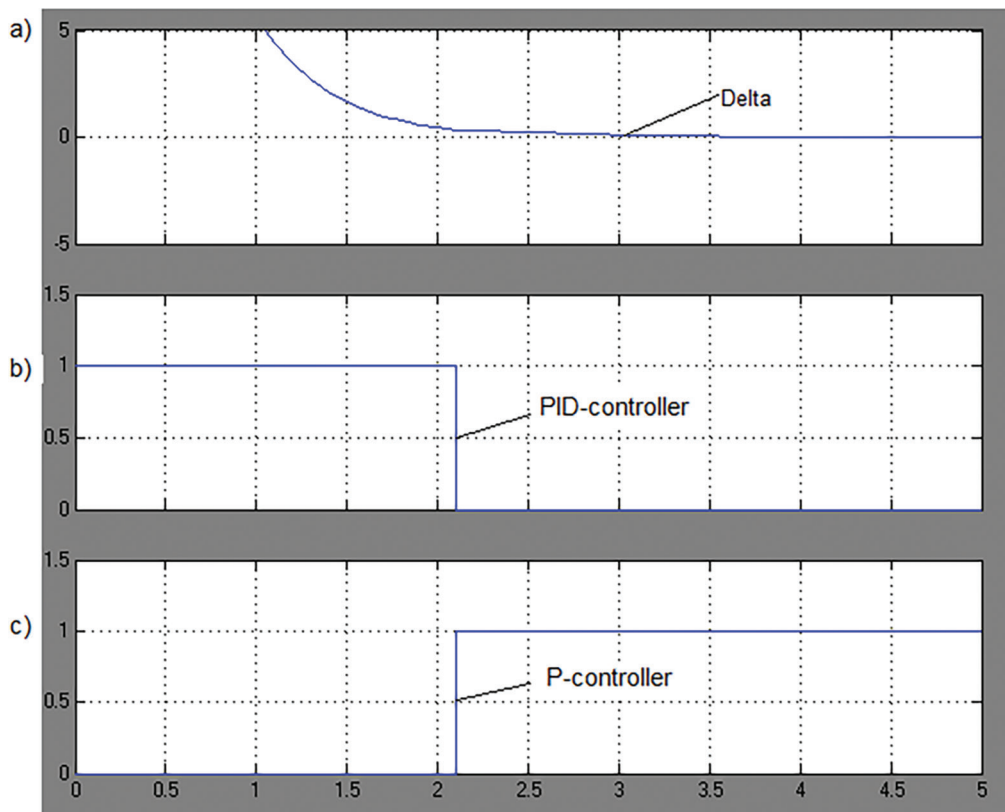

Fig. 9. Graphs of error (a), switch permissions of PID controller (b) and P controller (c) subsystem signals

effective. It is advisable to use this type of subsystem in the model of the car speed control system using the principle of variable structure.

3. Conclusion

We have investigated a system with a variable structure that can be used to control the speed of a car described by a nonlinear differential equation using the SIMULINK environment.

The structure of the system uses both proportional and proportional–integral-derivative controllers made based on neural networks. In the simulation process, the available difference between the reference and the output values of the setpoint can be achieved (for example, the speed of the car as well as the car acceleration).

To provide the necessary parameters of the control process by means of permitting subsystems, its separate functional units are switched. This model can be used not only in the transport application, but also in several other areas especially in robotic complexes, as well as in the control of the operation of electric motors and generators. In those cases, the model of the car may be replaced by the model of any other object.

The switching procedure is possible due to the modular structure of the control system, which can be used as a subsystem in the composition of more complex systems.

AUTHORS

Markiyan Nakonechnyi – Computerized Automatic Systems Department, Computer Technology, Automation and Metrology Institute, Lviv Polytechnic National University, 12 Bandera str., Lviv 79013, Ukraine, markian.v.nakonechnyi@lpnu.ua.

Orest Ivakhiv* – Intelligent Mechatronics and Robotics Department, Computer Technology, Automation and Metrology Institute, Lviv Polytechnic National University, 3 kn. Romana str., Lviv 79008, Ukraine, orest.v.ivakhiv@lpnu.ua.

Dariusz Świsulski – Faculty of Electrical and Control Engineering, Gdańsk University of Technology, Gdańsk 80-233, Poland, dariusz.swisulski@pg.edu.pl.

*Corresponding author

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19

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