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MECHATRONIC SYSTEM FOR BULLDOZER'S INTELLECTUAL CONTROL

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ABSTRACT

Improvement of quality, decrease of terms and cost of construction are inseparably linked with problems of effective use of bulldozer equipment. The most important problem of control tractions modes of the bulldozer is the fullest use of traction opportunities of the machine at the expense of management of work tool. Automatic maintenance of the maximum traction power or resistance preset value on work tool is complicated by a large number of the random factors operating on the bulldozer. In this regard the system of automatic control has to possess possibility of self-adjustment. In this paper with applying of analytical simulation method and neural network technologies, been decomposed model bulldozers workflow as mechatronic system realized. Models of the sub-processes are included into the general structure of bulldozer's workflow simulation model. They are intended to be used to study bulldozer's separate units applying analytic dependences of between their workflow parameters and to simulate bulldozer's workflow in general. Technique of identification and modeling of bulldozer's workflow based on neural networking technologies is described.

***Index Terms*:** Robotics and mechatronics, Automation and control, Bulldozer, Neural network technologies.

1. INTRODUCTION

On the basis of bulldozer's workflow dynamics modeling and analyses described in a variety of works, we have concluded that the models to describe kinematics and dynamics of its working equipment, hydraulic and transmission features tend to be analytical formulas derived from well-known laws of physics and from information on bulldozer's structure and mechanisms [1](Krapivin et al., 2010). If some parameters of the workflow are unknown or constantly changing, the models are either statistical tables or empiric dependences summarizing experimental data. The models depict interaction of end-effectors, engines and environment as well as statistic features of bulldozer's complex units.

Application of regulators based on classical control theory is difficult due to the frequent changes in workflow conditions. Thus, it is necessary to develop adapted control systems to eliminate the difficulties described. The system includes both the bulldozer's dynamics modeling and bulldozer's workflow control method to take into consideration the complex non-linear dependencies between workflow parameters and incomplete information on its working conditions changes [2-5, 6] (Bulgakow et al., 2011-2014, Cheng et al., 2012).

2. SIMULATION MODEL OF BULLDOZER WORKING PROCESS

2.1 General Structure of Bulldozer Working Process Model

The main goals for analytic simulation modeling of bulldozer workflow are:
- Bulldozer simulation as a controlled object to realize bulldozer's workflow parameters for using them at workflow neural network identification;
- Efficient traction modes parameters definition to be supported by the control system;

Simulation tasks:
- To single out the main sub-systems in bulldozer's structure and interrelations between the sub-systems;
- To develop analytic and simulation models for workflow elements and to include them into the general structure of the model.

General structure of the workflow model for automated bulldozers is developed (Fig. 1). The structure meets the goals of workflow control. When moving soil by the bulldozer, it is necessary to utilize bulldozer's traction capacity in full keeping the nominal traction value N; when surfacing, the altitudes of the right and left side of the blade $y = \left(y_n; y_l\right)$ are to correspond the design marks. The key element at the scheme (Figure 1.) shows the choice for the first or the second operational mode.

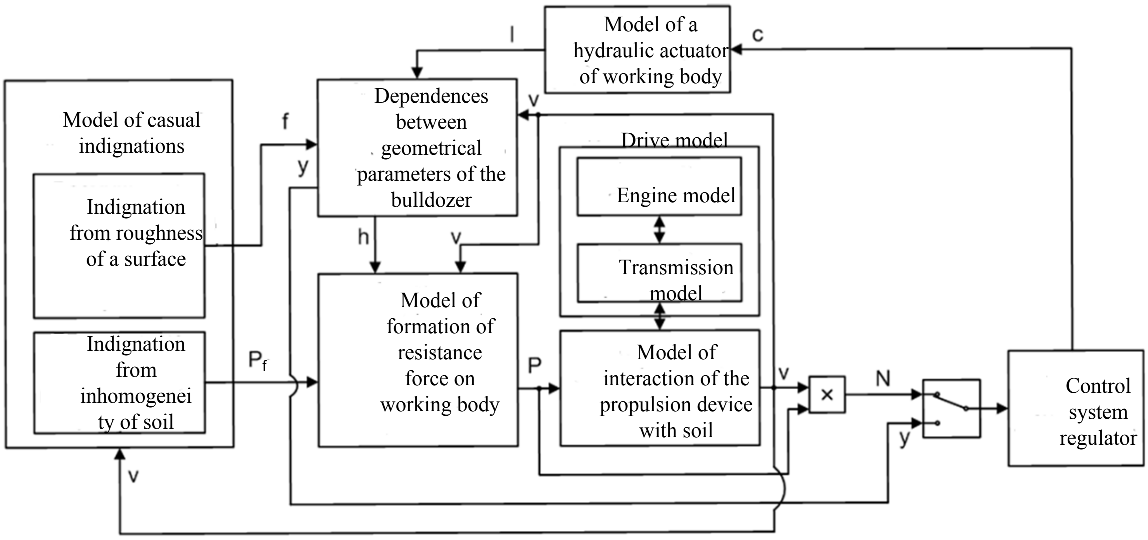

Figure 1. General Structure of Bulldozer Working Process Model

2.2 Formation of casual resistance force on working blade

At developing the models, we use mathematical apparatus of the random processes theory, transfer functions, table interpolation, numerical solution of algebraic equations and ordinary differential equations in the Cauchy form. Random changes in the coordinates of untreated soil surface f, as well as normalized fluctuations in the resistance forces on the working organ P_f, caused by the heterogeneity of the soil are highlighted among the disturbing effects on the working organ of the bulldozer from soil conditions. Disturbance f cause unwanted vertical movement of the working organ that affects both the y coordinates and the change in the digging depth h. Dependence of the blade position and dig depth from disturbances f reflects the intricate relationship between the geometric parameters of the bulldozer in space. Loading conditions on the working organ are due to random variation in the dig depth and heterogeneity of soil properties. Soil digging process with bulldozer working organ is studied on the base of the finite element model of the soil mass, a mathematical model of random forces of resistance on the working organ P being developed. The actual bulldozer velocity v depends on the strength P and the properties of the mover, transmission and the power unit. In its turn, disturbance parameters, movement of the working organ and the formation of stress depend on the velocity v. Bulldozer drive model and mover interaction with the soil include engine model, mechanical and hydro mechanical transmission, as well as slipping. Control system regulator depending on the objectives, control algorithm and the incoming data from the bulldozer as a control object produces electrical signals c to the electro- hydraulic distributors being part of the working organ hydro drive. Lifting or burying the blade is done to control either the pulling power N, or the blade coordinates y. The following describes the models of the bulldozer workflow elements. A formation model of the random forces of resistance on the working organ being developed as follows[1]:

$$P=P_{tr}(1+P_f); \qquad (1)$$

where P_{tr} – is the trend of resistance forces depending on the dig depth h; P_f – are the normalized random fluctuations caused by the heterogeneity of the soil (Figure 2).

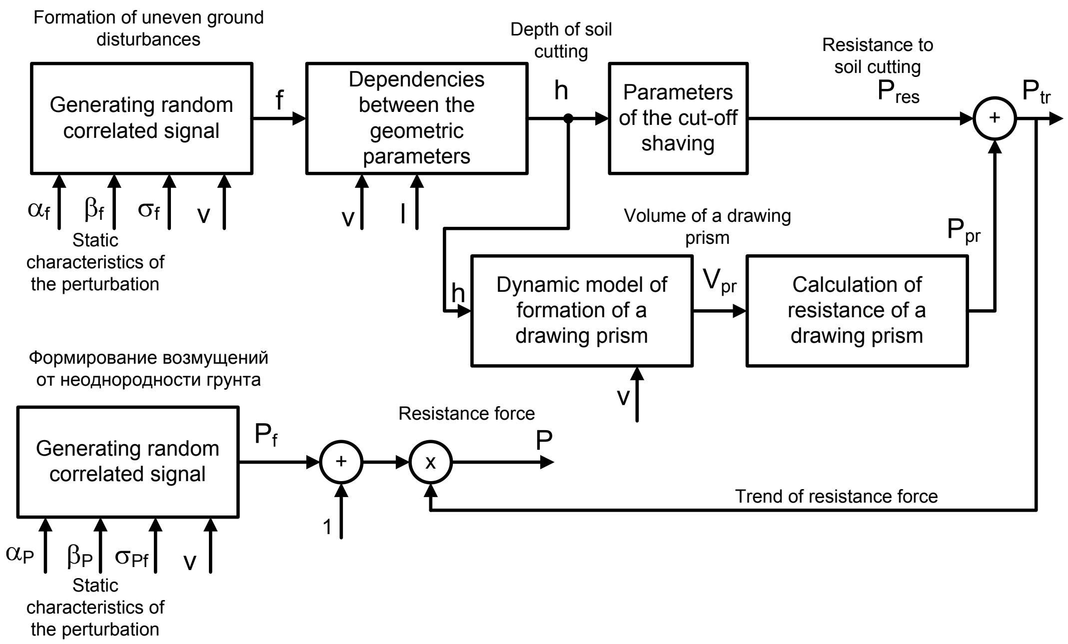

Figure 2. Formation of casual resistance force on working blade.

3. SIMULATION MODEL IS IMPLEMENTED IN MATLAB / SIMULINK

The developed models for bulldozer workflow elements are to be used for separate bulldozer units study with the help of analytical dependences between workflow parameters as well as for bulldozer general workflow simulation.

Elements models of bulldozer workflows being developed are intended both for the research of individual bulldozer units using analytical relationships between the parameters of the workflows and simulation of bulldozer workflows in general.

When constructing a discrete simulation model, the following assumptions are taken:

- the linear motion of the machine is investigated;
- the design is considered to be rigid;
- backlash and friction between the elements of the working equipment are not considered;
- the elastic- damping properties of movers are not considered;
- the dynamic characteristics of a diesel engine with fuel regulator and hydro mechanical transmission torque converter are replaced with static ;
- coordinates of the treated soil surface are completely determined by the coordinates of the cutting edge of working organ ;
- engine power selection to the drive of the working organ and auxiliaries are neglected;
- rate of motion of hydraulic cylinders rods for lifting and burial of the working organ is identical and does not depend on the applied load ;
- mover rolling resistance is constant.

A simulation model is implemented in MATLAB / Simulink (Figure 3).

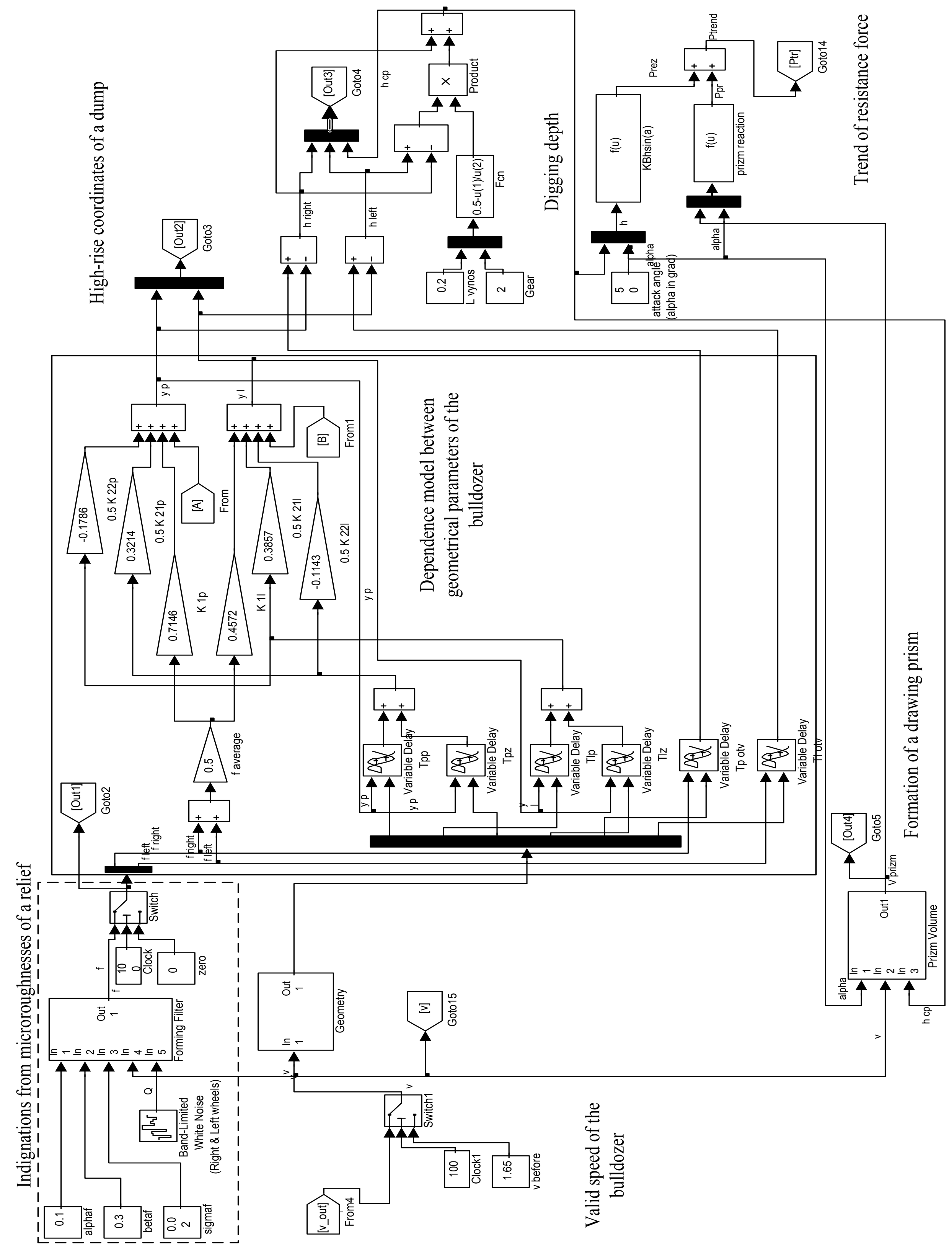

Figure 3. Simulation Model for Bulldozer Workflow.

4. NEURAL NETWORK MODEL OF BULLDOZER WORKFLOW

The Autoregressive model structure with external inputs (Figure 4) is a dynamic two-layer recurrent neural network. It is found from the autocorrelation signal functions that the autocorrelation coefficient is greater than 0.8 in the time interval 0.1 sec. for speed $v(t)$ of 0.5 sec. for digging depth $h(t)$ and 0.2 sec for the resistance force $P(t)$. Length of delay lines TDL taking into account the sampling frequency of 10 Hz are up to 1, 5 and 2 accordingly (Figure 4).

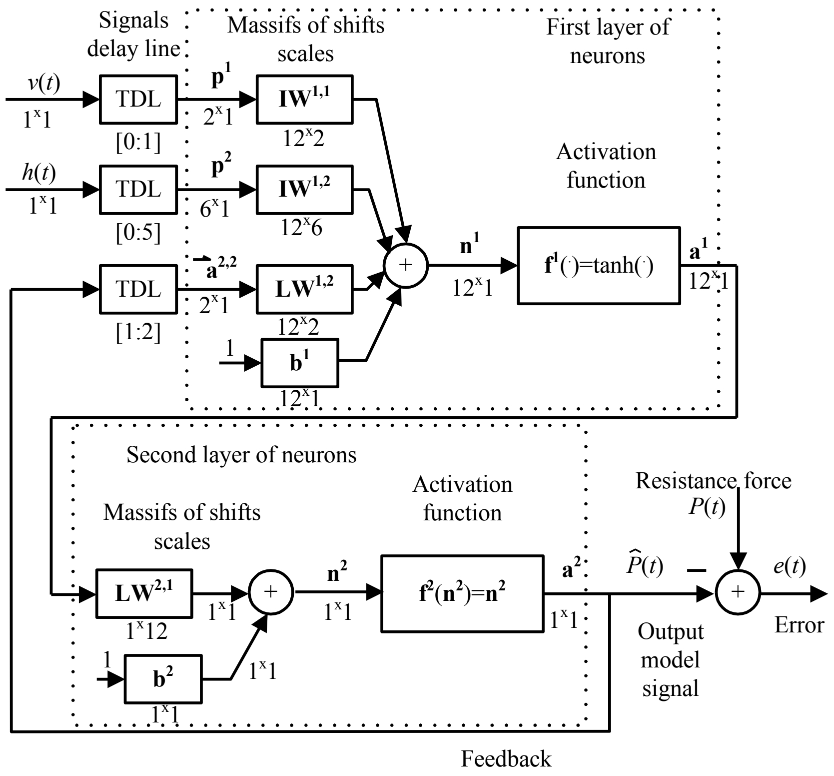

Figure 4. Neural network model for bulldozer's bogie workflow.

The author propose the bulldozer workflow neural network model adaptive learning algorithm based on the recurrent least square method (exponential forgetfullness method) and on the algorithm of Forward Perturbation or dynamic back propagation[4,5].

In the process of learning the neural network accumulates information on workflow dynamics, new tendencies of process development prevail on the earlier ones at that[7-9]. Degree of importance for the previously learned information is considered with forgetfullness parameter λ. Network optimal learning criterion gradient comprises frequent derived learning errors based on neural network model adjusted parameters:

$$\nabla F=\frac{\partial F}{\partial \mathbf{X}}=\left[\frac{\partial F}{\partial \mathbf{b}^1};\frac{\partial F}{\partial \mathbf{b}^2};\frac{\partial F}{\partial \mathbf{IW}^{1,1}};\frac{\partial F}{\partial \mathbf{IW}^{1,2}};\frac{\partial F}{\partial \mathbf{LW}^{1,2}};\frac{\partial F}{\partial \mathbf{LW}^{2,1}}\right]=$$

$$=-\nabla \mathbf{a}^2=-\frac{\partial \mathbf{a}^2}{\partial \mathbf{X}}=-\left[\frac{\partial \mathbf{a}^2}{\partial \mathbf{b}^1};\frac{\partial \mathbf{a}^2}{\partial \mathbf{b}^2};\frac{\partial \mathbf{a}^2}{\partial \mathbf{IW}^{1,1}};\frac{\partial \mathbf{a}^2}{\partial \mathbf{IW}^{1,2}};\frac{\partial \mathbf{a}^2}{\partial \mathbf{LW}^{1,2}};\frac{\partial \mathbf{a}^2}{\partial \mathbf{LW}^{2,1}}\right]; \quad (2)$$

Software algorithm of adaptive learning for neural network model of bulldozer workflow has been designed and implemented. The weight vector and bias network $\mathbf{X}(t)$ are adjusted in accordance with the recursive expressions at each time step:

$$\mathbf{X}(t)=\mathbf{X}(t-\Delta t)+\mathbf{P}(t-\Delta t)\nabla F(t)e(t); \quad (3)$$

Covariance matrix of the vector $\mathbf{X}(t)$ of neural network parameters used in the algorithm:

$$\mathbf{P}(t)=\mathbf{P}(t-\Delta t)-\frac{\mathbf{P}(t-\Delta t)\nabla F(t)}{\left(\lambda+[\nabla F(t)]^T\times\mathbf{P}(t-\Delta t)\nabla F(t)\right)}[\nabla F(t)]^T\times\mathbf{P}(t-\Delta t)/\lambda; \quad (4)$$

5. CONCLUSIONS AND RESULTS

Adaptive neural network model of digging allows you to simulate and predict the dependence of the resistance strain of gauge bogie displacement depending on the dig depth and trolley speed in dynamics. The accuracy of the prediction $P()$ being estimated, the average relative error after learning the network is 4.5 %.

A neural network model of bulldozer workflow has been developed, allowing modeling the dependence of pulling power from the blade penetration.

Input model signal, used for training, simulation and verification is presented in Figure 5. Adaptive learning for the model is stopped at time $t = 9{,}5$ sec. Receiving at this moment a neural network model parameter values, modeled digging resistance force and speed of the machine (Figure 6, 7) are accomplished, as well as the forecast for another 0.5 seconds is developed.

Figure 8 shows the output of neural network models- pulling power of the bulldozer. In modeling and prediction of the neural network output is close to the experimental data only in the time interval of 7-10 sec. This is due to a change in unmeasurable chip thickness, as well as the rapidly changing conditions of the mover clutch with the ground. Therefore, the parameters of the adaptive neural network model must be adjusted in real time. The accuracy of prediction of pulling power $N()$ has been estimated; the average relative error being 14.7 % on an interval from 7 to 10 s.

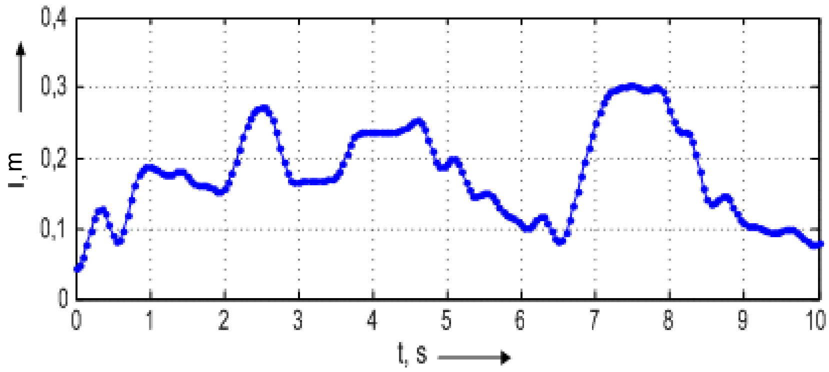

Figure 5. Deepening Dozer Blade.

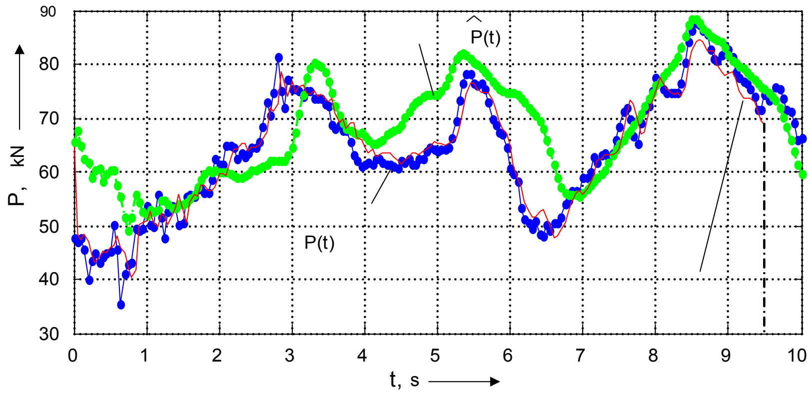

Figure 6. Digging Resistance Force Simulation.

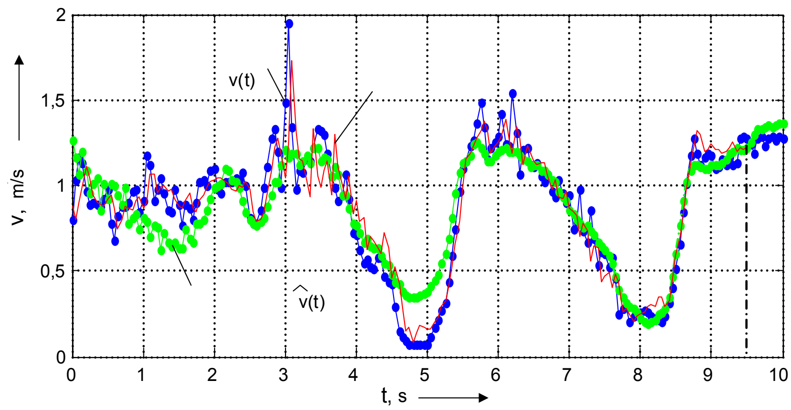

Figure 7. Bulldozer Current Velocity Simulation.

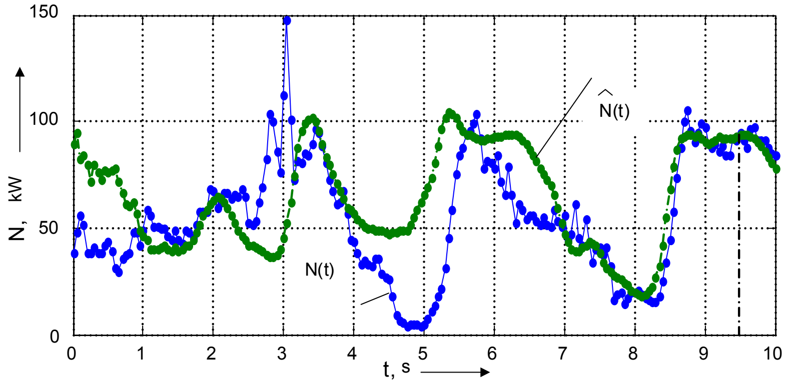

Figure 8. Bulldozer Pulling Power Simulation.

Identification Technique of bulldozer workflows and models obtained on its basis, are designed for use in the development of adaptive systems of automatic workflow management of bulldozer.

The development methodology of the adaptive control systems of bulldozer workflows is based on the application of neural network technology. For the formation of the control actions influencing the bulldozer, particularly electrical signals actuating control valves of hydraulic cylinders lifting and lowering the working organ, the structure and algorithms of adaptive neural network controller have been designed.

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