Bulldozer as a mechatronics System with the intelligent Control

Alexej Bulgakov [a] Thomas Bock [b] Georgy Tokmakov [c]

[a] South West State University, Russia
[b] Technical University Munich, Germany
[c] South Russian State Polytechnic University, Russia

E-mail: a.bulgakow@gmx.de, thomas.bock@bri.arch.tu-muenchen.de, tokmakov.tun@gmail.com

Abstract-
Background. Improvement of quality, decrease of terms and cost of construction are inseparably linked with problems of effective use of bulldozer equipment.
Purpose. 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 [1].
Method. In this paper with applying of analytical simulation method and neural network technologies, been decomposed model bulldozers workflow as mechatronic system realized [2,3].
Results & Discussion. For those sub-processes, where is possible analytical modeling based on knowledge on the links between the parameters of the bulldozer, analytical dependences are obtained. Models of these sub-processes included in the overall structure of the simulation model bulldozers workflow and are designed for both individual research bulldozers units using analytical relationships between the parameters of the workflow and simulation bulldozers workflow in general. For another thing are method of identification and modeling bulldozers base workflow based on represented (Fig. 5.).

Keywords-
Robotics and mechatronics, Automation and control, Bulldozer, Neural network technologies.

1 Introduction

Bulldozers equipped with modern navigation and information systems are mobile mechatronic objects, and they can be integrated into general process of intellectual construction. The integration will provide optimal efficiency of the construction cycle and will ensure lean production process.

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. 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.

Having reviewed adaptive and intellectual control methods [4, 5], we propose to create an adaptive control system for technological processes to increase efficiency of bulldozer's control in comparison with traditional control methods.

2 Bulldozer's Workflow Modelling

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 $y=(y_n; y_l)$ 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.

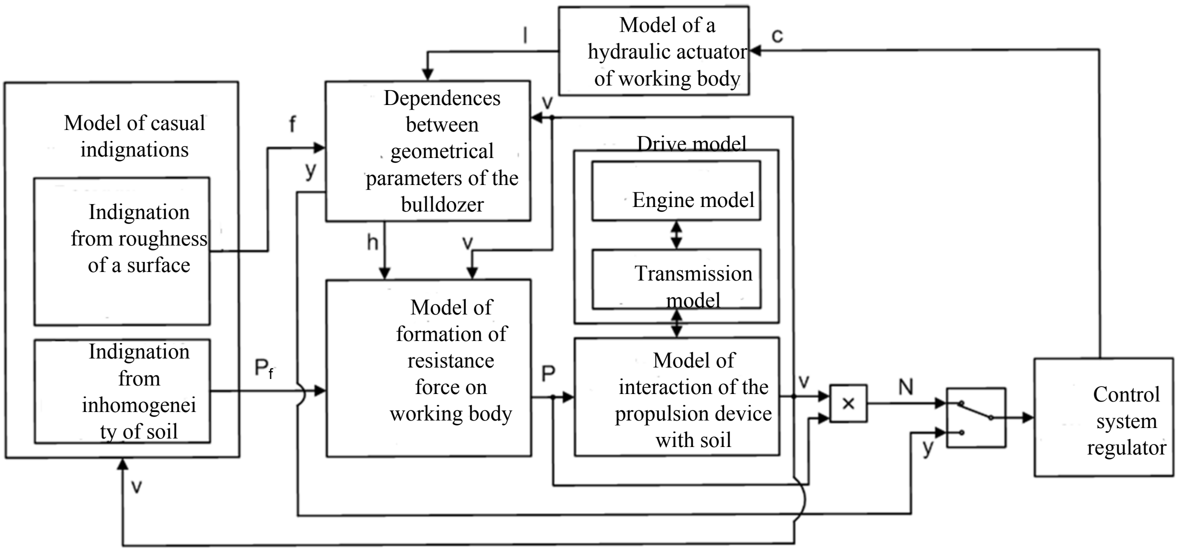

Figure 1. General Structure of Bulldozer Working Process Model.

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[2]:

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

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).

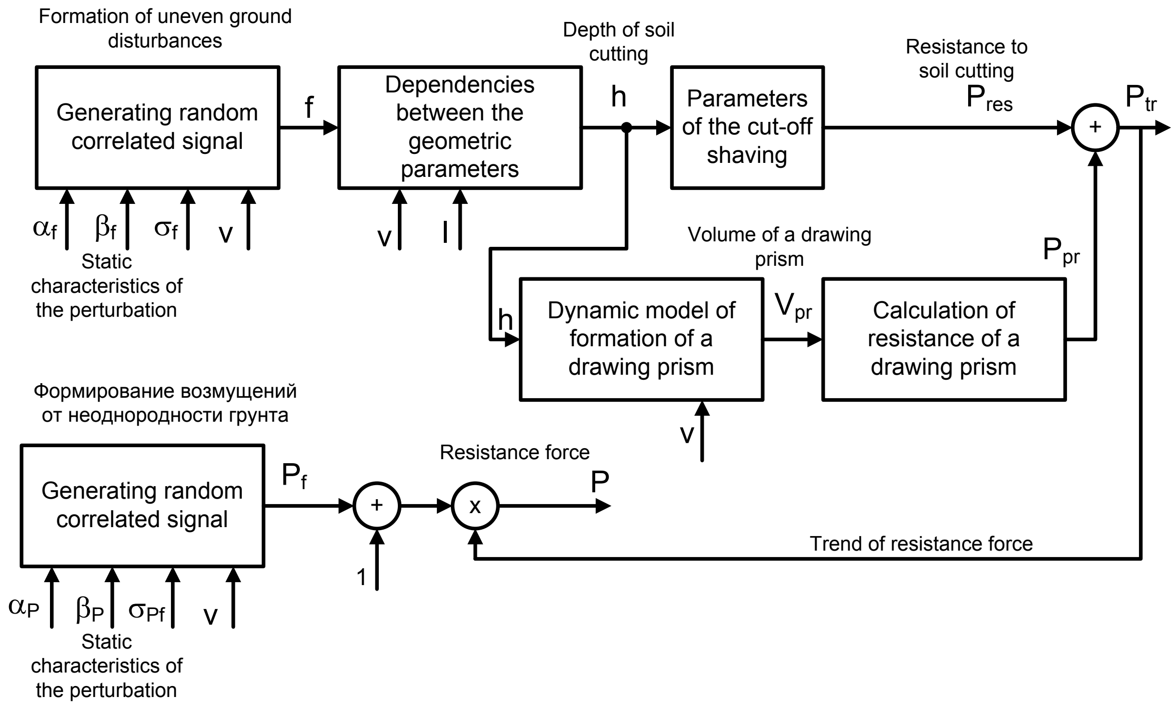

Figure 2. Formation of casual resistance force on working blade.

Auto correlated random signal f is generated based on the specified values of the autocorrelation function α_f, β_f parameters, and the standard deviation of the coordinates σ_f, as well as speed v. Soil cutting depth h associated with f, geometric parameters of the bulldozer, its speed v and extension rods of hydraulic cylinders of the working organ l. Normalized fluctuations P_f dependent on heterogeneity of physical and mechanical properties of the soil are a random signal with a standard deviation σ_{pf} generated by the given parameter values of the autocorrelation function α_P, β_P and depending on the speed of the bulldozer v

Component of the random process P is due to heterogeneity of the soil and equals $P_{tr}P_f$ while the standard deviation of the P_f process equals the coefficient of fluctuations variation $\sigma_{Pf} = \psi_f$. Autocorrelation functions $R_f(l)$ of micro profile f coordinates can be approximated by the expression:

$$R_f(l) = \sigma_f^2 e^{-\alpha|l|} \cos \beta l; \tag{2}$$

Where l – is the waypoint coordinate; σ_f^2 – is the variance of the random process; α, β – are coefficients of the autocorrelation function.

The corresponding expression of the spectral density of disturbance at a bulldozer constant speed:

$$S_f(\omega) = 2\alpha\sigma_f^2 \frac{\alpha^2 + \beta^2 + \omega^2}{\left(\alpha^2 + \beta^2 + \omega^2\right)^2 - 4\beta^2\omega^2}; \tag{3}$$

Generating a random signal f is performed by filtering white noise Q with specially created shaping filter. A discrete transfer function of the shaping filter, corresponding to (3) being generated as follows:

$$W_{ff}\left(z^{-1}\right) = \frac{a_0 + a_1 z^{-1}}{1 + b_1 z^{-1} + b_2 z^{-2}}; \tag{4}$$

Discrete shaping filter for generating random auto correlated signal $f(n)$ is also represented with the recurrence relation:

$$f(n) = a_0 Q(n) + a_1 Q(n-1) - b_1 f(n-1) - b_2 f(n-2); \quad (5)$$

Where n – is the current number of element sequence f or Q; a_0, a_1, b_1, b_2 – are the shaping filter coefficients.

A continuous transfer function of the shaping filter disturbances from the ground conditions being generated as follows:

$$W_{ff}(p) = \sqrt{2\alpha}\sigma_f \frac{p + \sqrt{\alpha^2 + \beta^2}}{(p+\alpha)^2 + \beta^2}; \quad (6)$$

The coefficients of the transfer function (6) are dependent on the speed of the bulldozer. For convenience of the shaping filter implementation in MATLAB, a second order differential equation that relates the white noise $Q(t)$ in the shaping filter input with disturbance $f(t)$ at the output has been obtained:

$$f(t) = \frac{\sqrt{\frac{2\alpha}{v^3}}\sigma_f \frac{dQ(t)}{dt} + \sqrt{\frac{2\alpha}{v}}\sigma_f \sqrt{\alpha^2 + \beta^2} Q(t) - \frac{1}{v^2}\frac{d^2 f(t)}{dt^2} - \frac{2\alpha}{v}\frac{df(t)}{dt}}{\alpha^2 + \beta^2}; \quad (7)$$

For simulation disturbances caused by ground conditions, the differential equation (7) is implemented as a subsystem of MATLAB / Simulink. This subsystem is applicable to both continuous and discrete models for bulldozer workflows. Modeling disturbances from soil heterogeneity, i.e. fluctuations in the resistance force on the working organ P_f, is accomplished similarly to (7).

Mathematic model is developed to describe the influence of soil surface micro profile coordinates derivation on the end-effectors coordinates as well as on the digging depth, taking into consideration bulldozer's major geometrical parameters and its velocity.

Average digging depth is also influenced by the distance between the blade side shift and the turning table L_{vi} as follows:

$$h_{sr} = h_n + \frac{h_l - h_n}{G}\left(\frac{G}{2} - L_v\right) = h_n + (h_l - h_n)\left(0{,}5 - \frac{L_v}{G}\right); \quad (8)$$

Simulation model realization to show (Figure 3) correlations between geometrical parameters and velocity v allows to estimate the influence of perturbation actions (stochastic changes in surface altitudes of the right $f_n(t)$ and left $f_l(t)$ tracks) on the end-effectors altitude $y_n(t)$ and $y_l(t)$, as well as on the average digging depth $h_{sr}(t)$.

Dynamic model is developed to form traction prism and to describe the dependence of prism volume V_{nr} and digging depth variable h and bulldozer's moving velocity variable v. Analytical expression for prism volume at the given moment of time t is obtained:

$$V_{np}(t) = B \sin\alpha \int_{t_0}^{t} v(t)h(t)dt - \\ - \frac{\sin\alpha\cos(\alpha+\rho)}{\cos\rho}\int_{t_0}^{t}\int_{t_0}^{t} h(t)v^2(t)\left\{1 - \exp\left[-p\frac{B\cos\rho}{v(t)\cos(\alpha+\rho)}\right]\right\}dtdt; \quad (9)$$

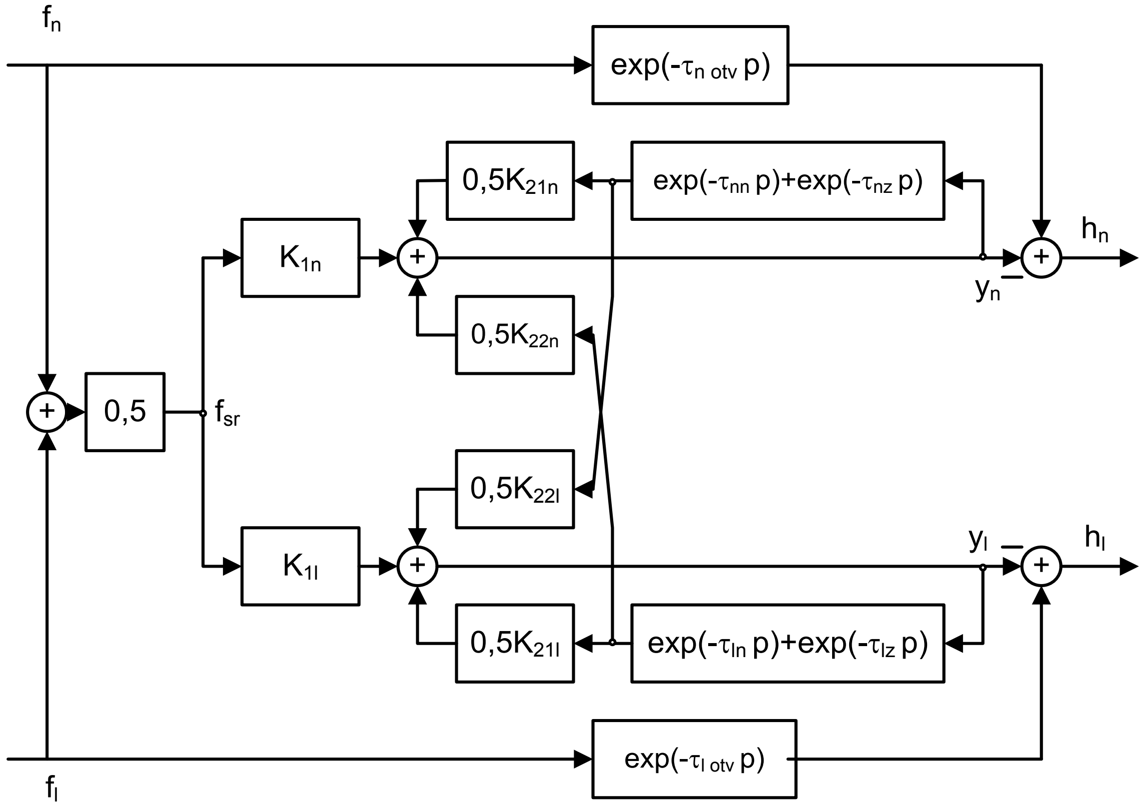

Figure 3. Dependences Model Functional Scheme for Geometric Parameters of Bulldozer.

where *B*– is the blade width; α – is the entrance angle; ρ – is the soil inner friction angle; p – is Laplace operator.
The developed models for bulldozer workflow elements are to be used for separate bulldozer units study with the help of analytical dependences be
tween 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 4).

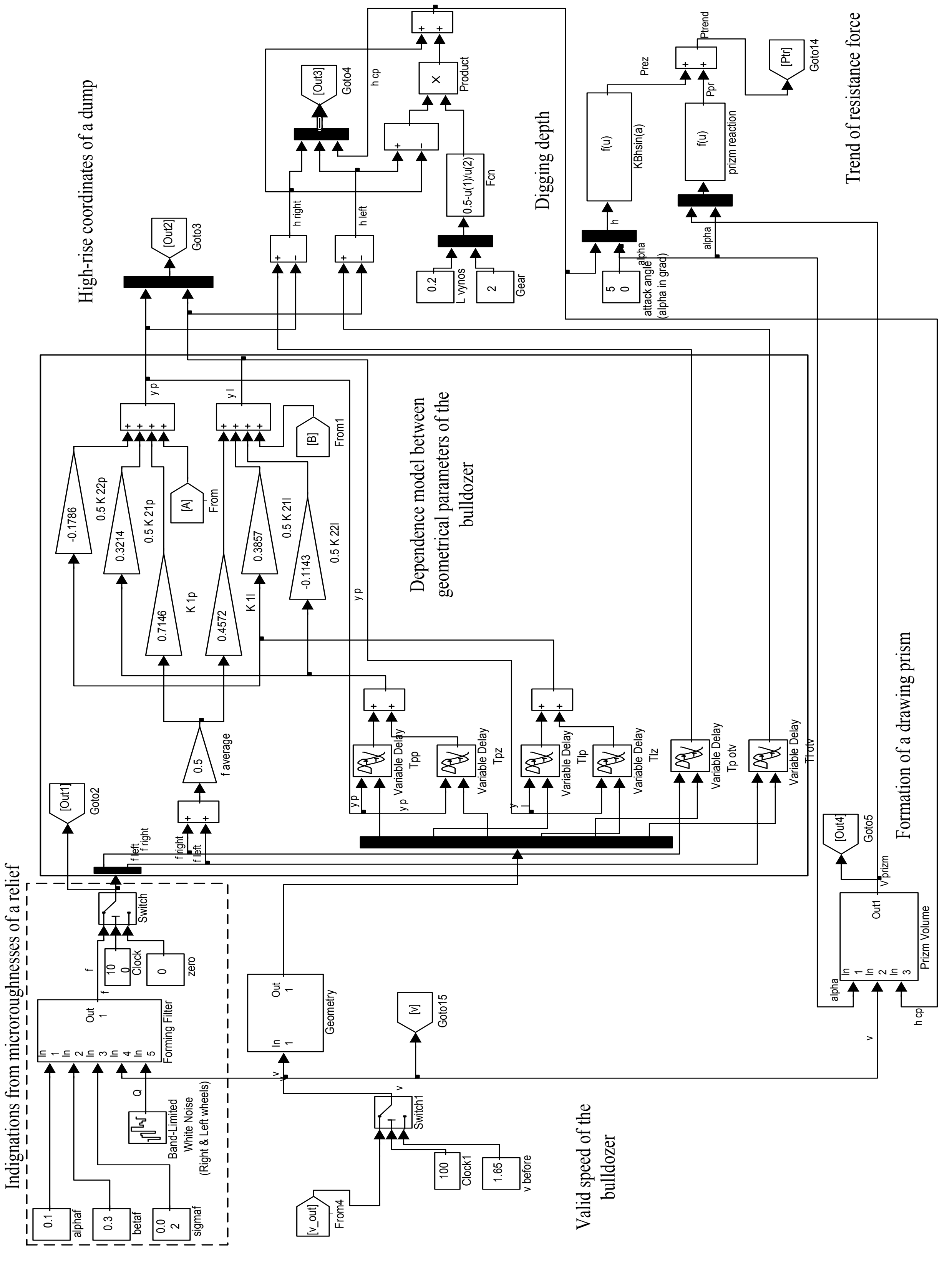

Figure 4. Simulation Model for Bulldozer Workflow.

3 Neural Network Model of Bulldozer Workflow

The Autoregressive model structure with external inputs (Figure 5) 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 5).

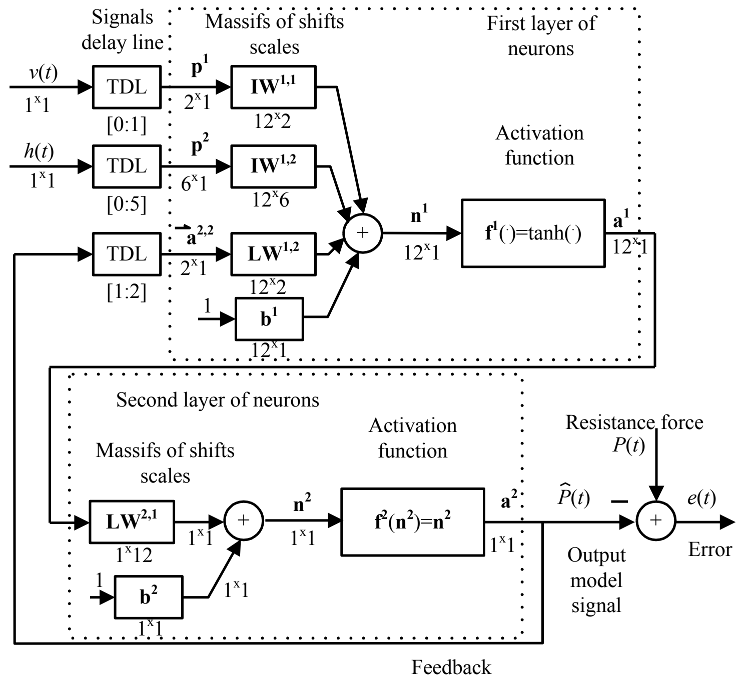

Figure 5. Neural network model for bulldozer's bogie workflow.

Vector for adaptive model adjustable parameters comprising weights and displacements of neural network,

$$\mathbf{X} = \left[\mathbf{b}^1; \mathbf{b}^2; \mathbf{IW}^{1,1}; \mathbf{IW}^{1,2}; \mathbf{LW}^{1,2}; \mathbf{LW}^{2,1}\right]; \qquad (10)$$

Criterion for neural network model optimal tuning, i.e. current learning error at a given moment of time we take as follows:

$$F(\mathbf{X}) = e(t) = P(t) - \mathbf{a}^2(t) \rightarrow 0; \qquad (11)$$

The network learning task is the task of multiple non-linear optimisation

$$\mathbf{X} = \arg\min_{\mathbf{X}} |F|; \qquad (12)$$

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[6,7]. 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. 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:

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

$$= -\nabla \mathbf{a}^2 = -\frac{\partial \mathbf{a}^2}{\partial \mathbf{X}} = -\left[\frac{\partial \mathbf{a}^2}{\partial \mathbf{b}^1}; \frac{\partial \mathbf{a}^2}{\partial \mathbf{b}^2}; \frac{\partial \mathbf{a}^2}{\partial \mathbf{IW}^{1,1}}; \frac{\partial \mathbf{a}^2}{\partial \mathbf{IW}^{1,2}}; \frac{\partial \mathbf{a}^2}{\partial \mathbf{LW}^{1,2}}; \frac{\partial \mathbf{a}^2}{\partial \mathbf{LW}^{2,1}} \right]; \quad (13)$$

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:

$$\mathbf{X}(t) = \mathbf{X}(t-\Delta t) - \mathbf{P}(t-\Delta t) \times \nabla F(t) \times e(t); \quad (14)$$

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

$$\mathbf{P}(t) = \mathbf{P}(t-\Delta t) - \frac{\mathbf{P}(t-\Delta t) \times \nabla F(t)}{\left\langle \left\{ \lambda + [\nabla F(t)]^T \times \mathbf{P}(t-\Delta t) \times \nabla F(t) \right\} \times [\nabla F(t)]^T \times \mathbf{P}(t-\Delta t) \right\rangle \lambda}; \quad (15)$$

4 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 $P(t)$ being estimated, the average relative error after learning the network is 4.5 %.

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

Input model signal, used for training, simulation and verification is presented in Figure 6. 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 7, 8) are accomplished, as well as the forecast for another 0.5 seconds is developed.

Figure 9 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 $N(t)$ has been estimated; the average relative error being 14.7 % on an interval from 7 to 10 s.

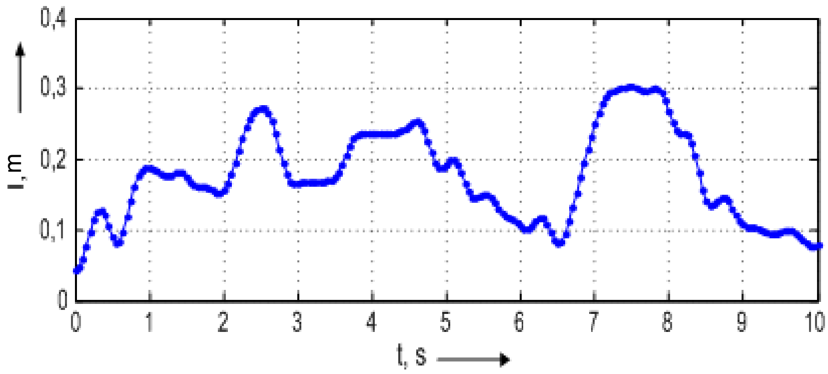

Figure 6. Deepening Dozer Blade.

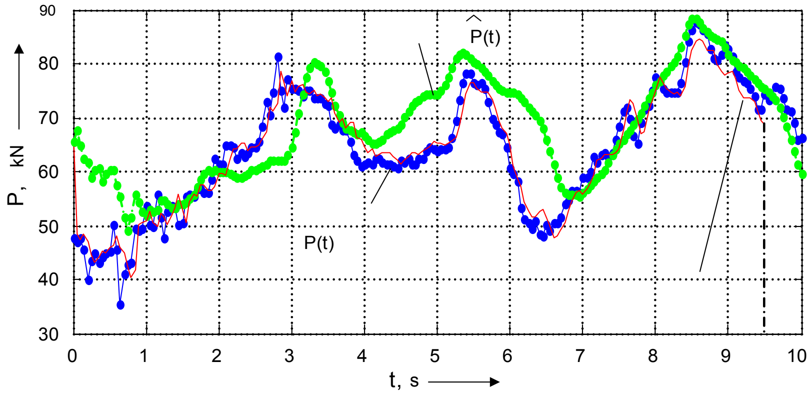

Figure 7. Digging Resistance Force Simulation.

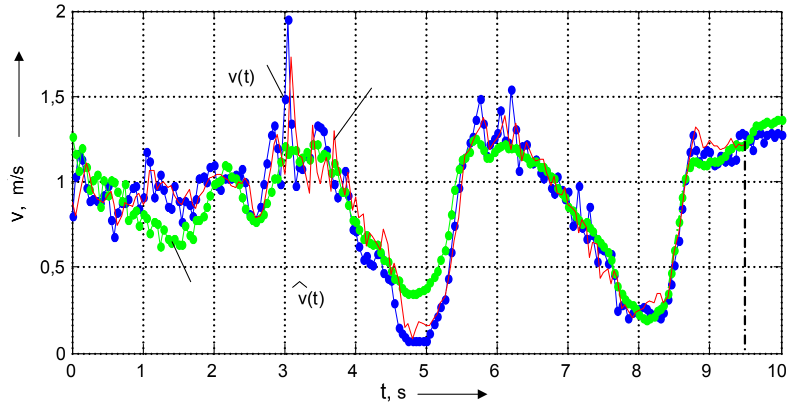

Figure 8. Bulldozer Current Velocity Simulation.

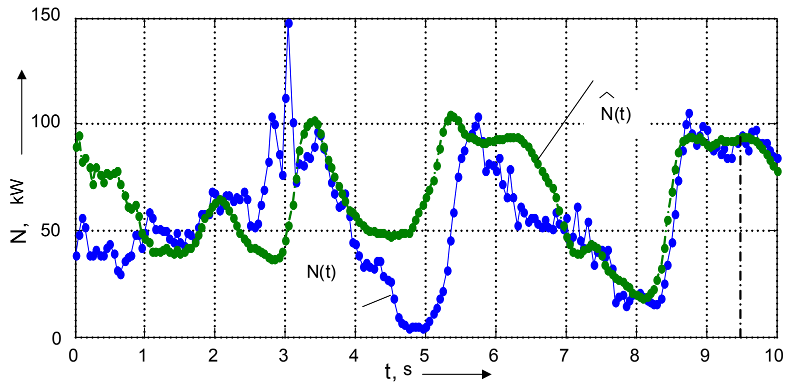

Figure 9. Bulldozer Pulling Power Simulation.

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.

References

[1] Bulgakov A.G., Tokmakov G.E. The analysis of the control systems for building site, problems, possible solutions. VII Internationally scientific conferences: Realisation of the European

scientists; 17th-25th of July, 2011. Sofia. S. 43-44.

[2] Krapivin D.M., Nefedov V.V., Tokmakov G.E. Mathematical model for the movement of mechatronischen devices for the intelligent building site, Mechatronik, Lik, Nowotscherkassk, 2010.- S. 50-54.

[3] Min-Yuan Cheng, Hsing-Chih Tsai, Erick Sudjono. Evolutionary fuzzy hybrid neural network for construction industry. Automation in Construction 21 (2012) S. 46-51

[4] Bulgakow A.G., Jehle P., Tokmakov G.SCM-logistic and mechatronics systems for ensuring the smooth construction process//Innovation in Mechanical Engineering - Shaping the Future: 56-th International Scientific Colloquium, 12-16 September 2011: Conference Proceedings/Ilmenau University of Technology. - Ilmenau, 2011.- Session 2.1.

[5] M.E. Georgy, L.M. Chang, L. Zhang, Prediction of engineering performance: a neurofuzzy approach, Journal of Construction Engineering and Management 131 (5) (2005) 548–557

[6] T.M. Cheng, C.W. Feng, M.Y. Hsu, An integrated modeling mechanism foroptimizing the simulation model of construction operation, Autom. Constr. 15 (2006) 327–340.

[7] Tokmakov G. Anwendung von RFID-Technologien in Bauprozess//Materialien des wissenschaftlichen Seminars von Stipendiaten der Programme "Michail Lomonosov II" und "Immanuel Kant II" 2010/11: 28-29 April 2011, Moskau, DAAD, S.-190-191.