Mechatronic Control System for Leveling of Bulldozer Blade

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Abstract – Recently, it began the spread of bulldozers using information technology during controlling the machine to increase the efficiency of the entire execution of work, including avoiding the usually necessary final surface treatment. Blade control mechatronic system for leveling work of bulldozer blade enables the bulldozer to effectively perform a ground leveling work or a grading work with high accuracy in a minimum amount of time. The system compensates for pitching of a tractor portion of the bulldozer, and for variations in the amount of earth to be moved by a blade of the bulldozer.

The biggest feature of this mechatronic system is automation of digging and soil carrying work by optimally controlling a load applied to the work equipment even if there is digging depth to some extent up to the finishing surface, while the work application range of conventional bulldozers was limited mainly to finishing leveling work under light load. Seamless automatic execution without concern for damage to a finishing surface has been enabled by automatically switching from digging control to leveling control as the work progresses and approaches the finishing surface.

This will reduce operator fatigue during operation, and will also allow even an inexperienced operator to perform work equivalent to the work of a qualified operator.

Keywords – Mechatronic system; Bulldozer blade; Leveling control; Design surface

1 Introduction

Industries such as mining and construction in which earthmoving plays a fundamental role are constantly under pressure to improve productivity (amount of work done), efficiency (cost of work done in terms of labor and machinery), and, safety (injury sustained by workers). Mechatronics and robotics offers the possibility of contributing to each metric but has been slow in being accepted. Until recently, it has been possible to make gains using traditional means— over the last four decades earthmovers have become progressively larger and their mechanisms more efficient. Also, automation of fieldworthy earthmovers is a difficult problem.

These machines must operate in unstructured, dynamic, outdoor environments, often in poor visibility conditions and inclement weather. However, after decades of increases in size and power, practical limits have been reached and now automation is being sought for further improvements. At about the same time, several enabling technologies relevant to earthmovers, particularly in the area of environmental perception, are becoming reliable and affordable. Computing technology has also reached the stage where fast, compact and rugged components can match the bandwidth of sensory data.

The cycle of operation for a mechatronics machine is: sense, plan, and execute. First, a machine must sense its own state and the world around it. Next it must use this information along with a description of a goal to be achieved to plan the next action to be taken. In some cases the mapping from sensing to action is direct, and, can take the form of a pre-determined control law. In other cases, deliberation, or the use of models (sensors, mechanisms, and, actions) is necessary. Finally, the action must be executed via the mechanism. Since, relatively few systems are fully autonomous, depending on human input or control to achieve some of their function, this article examines various aspects of the enabling technologies used by partially automated systems [1].

The cycle of operation for a fully autonomous machine is: sense, plan, and execute. First, an automated machine must sense its own state and the world around it. Next it must use this information along with a description of a goal to be achieved to plan the next action to be taken. In some cases the mapping from sensing to action is direct, and, can take the form of a pre-determined control law. In other cases, deliberation, or the use of models (sensors, mechanisms, and, actions) is necessary. Finally, the action must be executed via the mechanism [2].

Bulldozers equipped with modern navigation and information systems are mobile mechatronic objects, and they can be integrated into general process of intellectual construction [3]. The integration will provide optimal efficiency of the construction cycle and will ensure lean production process [4,5].

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 [6, 7], 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 - mathematical description as mobile mechatronic object

When researching a dozer's working process usually a number of design schemes are considered – straight line, thread milling, wedge and exponential cutting. Meanwhile, a dozer moves along the surface that is formed by its blade. Therefore, when driving onto any surface roughness resulting from the dozer blade control or the change in its position due to any reason, causes position changes of the machine frame and along with the cutting edge that is any face deviation from a straight line in some extent is copied by the dozer.

Observations [8] show that quite often while designing a face its roughness is progressing, reaching a size at which the control over the workflow is lost. In this case, the operator has to align the face deliberately, trying to ensure its "tranquil" profile that allows doing excavation works smoothly, without frequent control system switching and reducing the dozer's operating speed that causes a slowdown and shows inferiorities of the blade control system. Obviously, if the control system operates in the antiphase towards deviations of the tractor frame with sufficient accuracy, the initial face roughness will not evolve and will be gradually cut. One of the most likely causes of the opposite phenomenon observed in practice, is the disparity between the velocity of the dozer V_p and actual conveying speed of the working body V_{ot} required in certain areas S_i of the digging operating cycle, where *i* – is the number of the speed change V_{ot}. Speed ratio depends on the dozer's geometrical dimensions (Figure 1) and its control system.

Mathematical model of the dozer's movement on a straight line tracking (frame alignment) is built using the Lagrange equations of the 2nd kind, under the assumption that the contribution to the dynamics of the drive gears and a track is small, compared with the

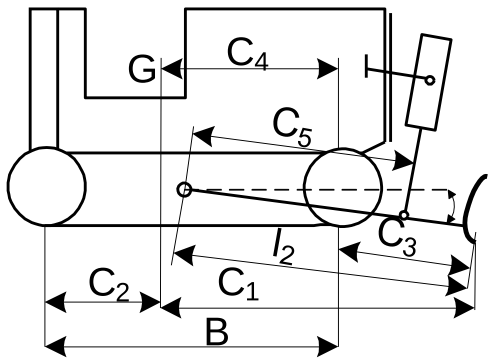

Figure 1. Dozer's geometrical dimensions

contribution of the remaining parts of the dozer.

$$\begin{cases} \frac{d}{dt}\left(\frac{\partial T}{\partial \dot{x}}\right) - \frac{\partial T}{\partial x} = Q_x , \\ \frac{d}{dt}\left(\frac{\partial T}{\partial \dot{\varphi}}\right) - \frac{\partial T}{\partial \varphi} = Q_\varphi . \end{cases} \quad (1)$$

where kinetic energy:

$$T = \frac{1}{2}m_1\dot{x}^2 + \frac{1}{2}m_2\big(\dot{x}^2 + (l_2 l_{c2}\dot{\varphi})^2 + 2\dot{x}l_2 l_{c2}\dot{\varphi}\sin(\varphi)\big) + \frac{1}{2}J_{c2}\dot{\varphi}^2 + \frac{1}{2}\sigma hx\big(\dot{x}^2 + (l_2\dot{\varphi})^2 + 2\dot{x}l_2\dot{\varphi}\sin(\varphi)\big) + \frac{1}{2}\sigma hx i_{rz}^2\dot{\varphi}^2, \quad (2)$$

generalized forces acting on a dozer:

$$\begin{aligned} Q_x &= -\sigma hgl_2\sin\varphi + F_т - F_s , \\ Q_\varphi &= -(m_2 l_{c2} + \sigma xh)gl_2\cos\varphi + M. \end{aligned} \quad (3)$$

m_1 – tractor mass; m_2 – blade frame mass; σ – soil surface density; $F_т$ machine pulling power; F_s ground cutting resistance; h – depth of the soil cutting; l_{c2} – center of the blade mass; i_{rz} - gyration radius of the dumping soil.

$$m_1\ddot{x} + m_2\ddot{x} + m_2 l_2 l_{c2}\ddot{\varphi}\sin\varphi + m_2 l_2\, l_{c2}\dot{\varphi}^2\cos\varphi + \sigma h\dot{x}^2 + \sigma hx\ddot{x} + \sigma h\dot{x}l_2\dot{\varphi}\sin\varphi + \sigma hxl_2\ddot{\varphi}\sin\varphi + \sigma hxl_2\dot{\varphi}^2\cos\varphi - \frac{1}{2}\sigma h\dot{x}^2 - \frac{1}{2}\sigma hi_{rz}^2\dot{\varphi}^2 - \frac{1}{2}\sigma h(\dot{x}^2 + l_2^2\dot{\varphi}^2 + 2\dot{x}l_2\dot{\varphi}\sin\varphi) = -\sigma hgl_2\sin\varphi + F_т - F_{сопр}. \quad (4)$$

$$m_2 l_2^2 l_{c2}^2\ddot{\varphi} + m_2\ddot{x}l_2 l_{c2}\sin\varphi + m_2\dot{x}l_2 l_{c2}\cos\varphi\dot{\varphi} + J_{c2}\ddot{\varphi} + \sigma h\dot{x}l_2^2\dot{\varphi} + \sigma hxl_2^2\ddot{\varphi} + \sigma h\dot{x}l_2\sin\varphi + \sigma hxl_2\cos\varphi\dot{\varphi} + \sigma h\dot{x}i_{rz}^2\dot{\varphi} + \sigma hxi_{rz}^2\ddot{\varphi} - m_2\dot{x}l_2 l_{c2}\dot{\varphi}\cos\varphi - \sigma h\dot{x}l_2\dot{\varphi}\cos\varphi = -(m_2 l_{c2} + \sigma xh)gl_2\cos\varphi - (m_2 l_{c2} + \sigma xh)gl_2\cos\varphi + M. \quad (5)$$

The system (1) solution allows getting the differential equations (4) and (5) that describe the dozer's movement on a straight line track, and determining control actions through the parameters of the machine in areas S_i of the digging operating cycle as the coefficients a_i in the dependence $V_{ot} = a_i V_p$. Such a dependence is typical for dozers with a single-motor drive with a hard pump hydraulic drive connection to the motor shaft.

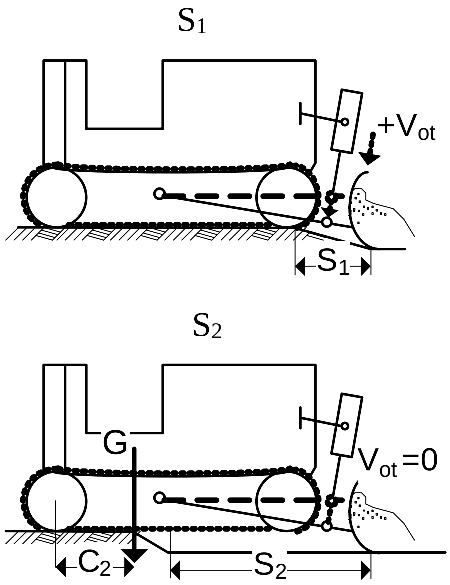

Figure 2. The movement of the tractor frame the beginning of digging.

At the beginning of digging (Figure 2), the frame of the tractor makes a strictly forward movement over a distance of S_1+S_2 without hesitation relatively its mass center. The blade cutting edge in the area S_1 dives into the soil to a depth equal to a predetermined cutting thickness *h*. Thus, the control action a_1 may be determined by the formula:

$$a_1=\frac{30 i_{tr} m\, l_2}{\pi r_k F_z i_{pr} C_5 n} \quad , \tag{6}$$

where i_{tr}, i_{pr} - tractor transmission and hydraulic pump ratios; n - number of hydraulic cylinders; m - fluid mass in the hydraulic cylinders;

In the area S_2 the movement is made with a_2=0 until the mass center of the tractor won't move to the buttonhole edge.

On further movement the dozer "dives" in the drawn buttonhole (Figure 3), so in the area S_3 it is necessary to lift the blade at a rate of V_{ot}, determined by the coefficient a_3:

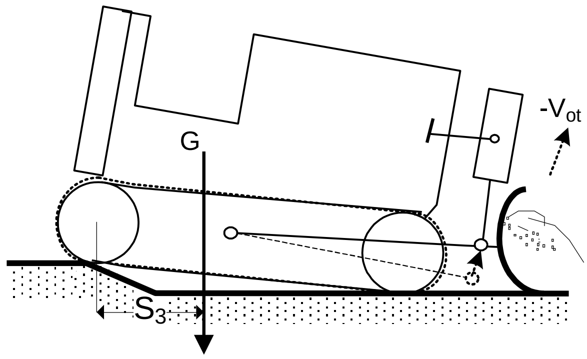

Figure 3. The movement the dozer "dives" in the drawn buttonhole

$$a_3 = \mathrm{tg}\,\beta\left[e^{\frac{aV_п t}{C_1+V_п t}}\left(1+\frac{aC_1}{C_1+V_п t}\right)-1\right]. \tag{7}$$

The area S_3 ends after the dozer's back gear hits the edge of the face and reverse alignment of tractor frame starts. Length of the alignment area is $S_4 \approx S_1$. Obviously, during this period it is necessary to start dropping the blade. The a_4 determines the rate of dropping the blade in the given area:

$$a_4 = \frac{C_3 S_1}{(C_4+S_3+V_п t)^2}. \tag{8}$$

To implement control actions a_i = f (S_i, t, h) the dozer must be equipped with a vertical blade control system.

3 Adaptive control principles for a mechatronic bulldozer blade control system

The article proposes the bulldozer workflow neural network model adaptive learning algorithm based on the recurrent least square method (exponential forgetfulness method) and on the algorithm of Forward Perturbation or dynamic back propagation.

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 $\vartheta(t)$ 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).

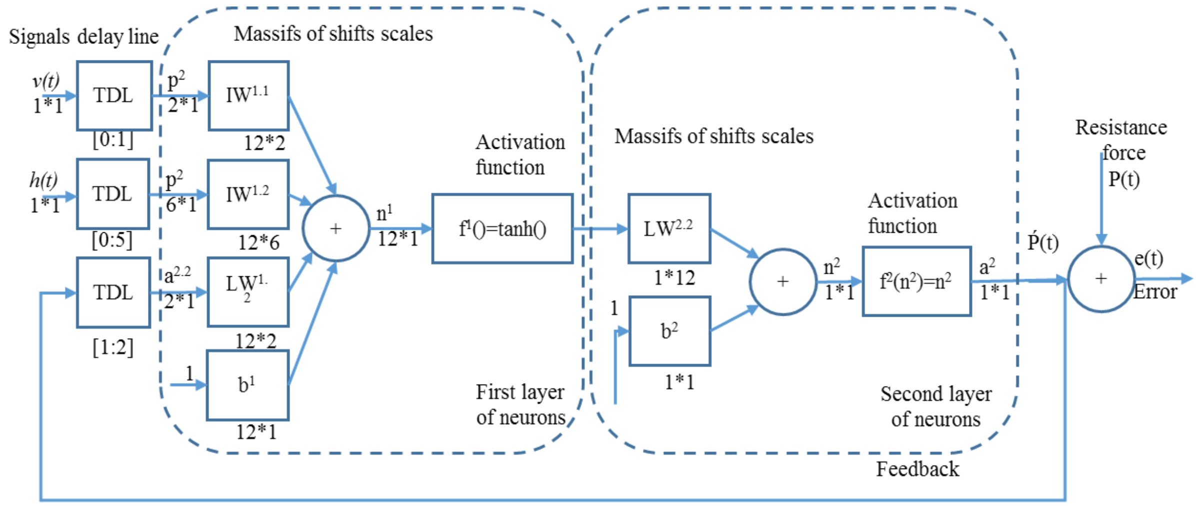

Figure 4. Autoregressive model structure

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.

It is a method of random search with elements of adaptation, which is based on principles similar to the Darwin's evolution process of biological organisms. In this case, three types of operations are performed: crossing, mutation, selection. The fitness degree (how the population corresponds to the given task) is defined through the fitness function that can also include penalty functions for violation of additional restrictions on variable variables. There are various forms of crossing [8]. They make a selection of the fittest specimen, which constitute a parental pair and the crisscrossing of the chromosomal chains takes place, i.e. the descendant line code inherits fragments of codes of parental chromosomes. The mutation operator produces a local change in the line code of chromosomes with a given probability, which is one of the configurable parameters of the genetic algorithm [9, 10].

The selection operator allows creating a new population from a set of specimen, generated and modified descendants of specimen after mutation. The genetic algorithm is used to adjust the membership functions that are defined within the accuracy of a few changeable parameters, such as triangular, trapezoidal, radial functions. When simultaneously configuring several membership functions, the parameters of each of them are coded by their own segment of the chromosome, so that during the process of crossing the code sharing occurs only between chromosome segments of the same type. To configure a rule base to a specific chromosome fragment, some variant of the rule base is corresponded and in accordance with the accepted coding the choice of the genetic operators' type is performed.

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 %[11-13].

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 5a. 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 5b, 5d) are accomplished, as well as the forecast for another 0.5 seconds is developed.

Figure 5c 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 [14]. 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 [15-16].

The development methodology of the adaptive control systems of bulldozer workflows is based on the application of neural network technology [17].

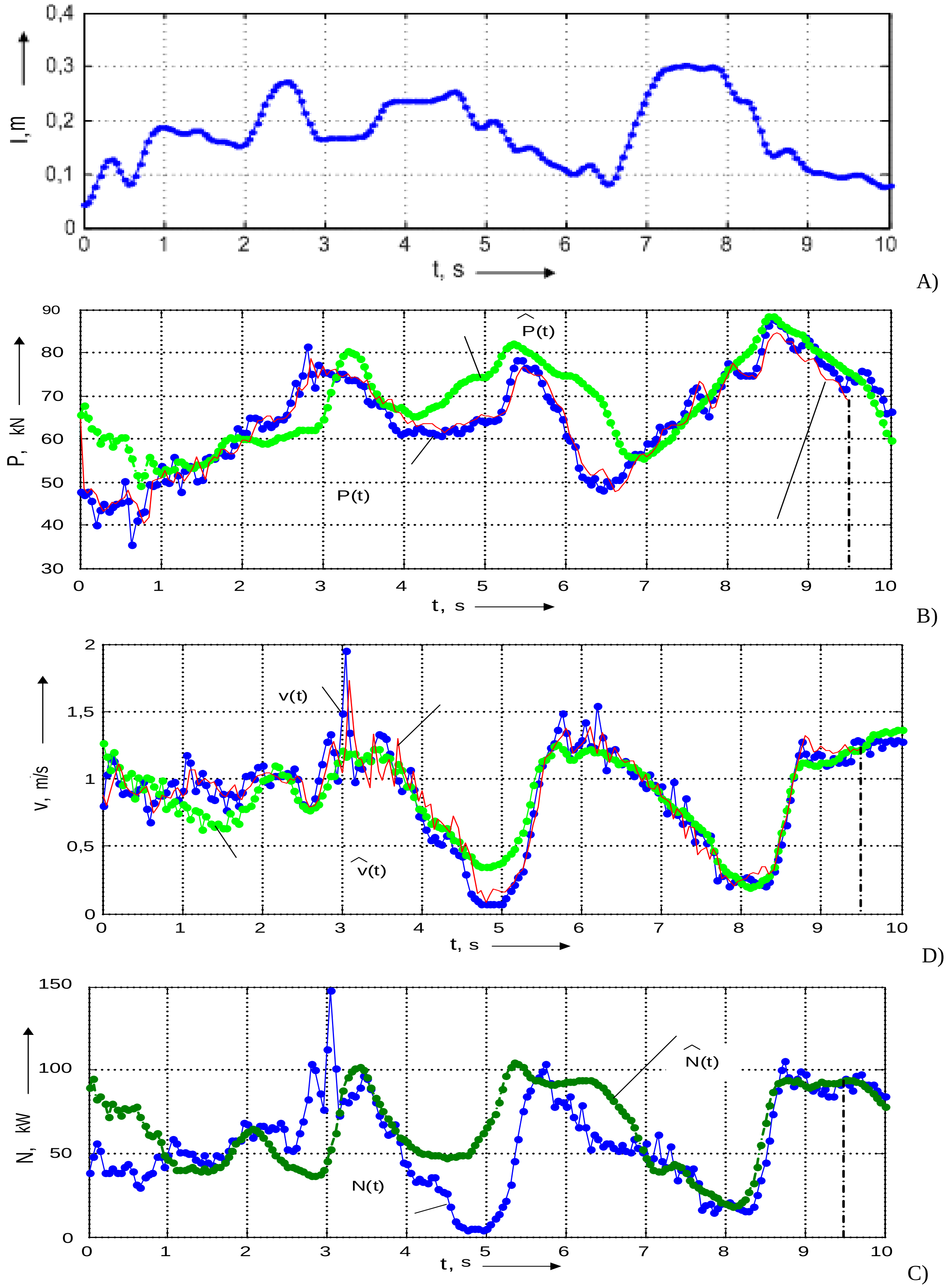

Figure 5. Comparison of Bulldozer operational parameters obtained with the Model and actual operational parameters: A) Deepening Dozer Blade; B) Digging Resistance Force; D) Bulldozer Current Velocity; C) Bulldozer Pulling Power.

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. Based on the obtained results of practical measurements and the simulation carried out on their basis, the team set the following goal as the practical testing of the machine in real working conditions.

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