Intelligent Control of the Surface Defects Removal in Rolled Products using Water Jet Technology

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Abstract

This paper presents the results of research on the intelligent control of the pressure of the pickling solution for cleaning the rolled surface from defects in metallurgical production. A neural net method of determining the necessary task of the solution pressure during progressive ecologic waterjet processing (WJP) of rolled steel, depending on the fuzzy classification of the defects` thickness, taking into account the temporary changes of the solution properties is proposed. A radial basic network which evaluates the duration of the control voltage signal to perform tasks of changing the pressure of the solution supply through the jets is presented. The presented solution can be implemented in modern pickling lines, increase their profitability and ensure proper environmental protection.

Keywords

Waterjet processing, surface defect, classifier, c-means fuzzy method, RBNN

1. Introduction

The World Economic Forum predicts that most technologies in Industry 4.0 applications will become commonplace by 2027 [1]. Experts highlight such key trends of the Fourth Industrial Revolution as artificial intelligence, robotics and the Industrial Internet of Things (IIoT). It is expected that they will lead to revolutionary changes, when all processes are controlled in a single mode in real time, and full automation of production takes into account changes in external conditions. The IIoT aims to create fully automated industries where traditional engineering models coexist harmoniously with computer intelligence models.

The immediate goal of Industry 4.0 is for major hardware components to be equipped with various sensors, actuators, and intelligent controllers. Collected data is processed and sent to local control systems that monitor physical processes and make decentralized decisions. These local systems can interact in real time, self-adjust and self-learn, as well as be integrated into a single network under the regular control of the personnel of the relevant areas of the enterprise. This allows you to make quick, informed and balanced decisions. But the biggest task is to achieve such a level of automation at the enterprise that machines can work without human intervention in all possible areas. The role of personnel is limited only to responding to emergency situations [2].

Sulfuric acid is one of the most important industrial acids, with global production exceeding 190 million tons in 2008, showing a growth rate of approximately 1.8% per year [3]. One of the many applications is steel pickling. This is the final stage of scale removal in the rolling mill. Number of companies which are the world's largest steel producers used sulfuric acid exceeds the number of companies that use other technologies [4].

In the continuous pickling line, which is the final process in the production of rolled steel, a large amount of aqueous sulfuric acid is used as pickling fluid. Sludge, sour water, iron sulfate, metal salts, and spent acids are byproducts of steel etching with sulfuric acid and are hazardous waste according to

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the EPA [5]. In addition, the solution must be regenerated or discharged into industrial water for neutralization followed by water purification [6, 7] and preparation of a new, fresh solution.

All these measures not only increase the operating, resource and energy costs of the process, but also acidify and salinize the soil.

On the other hand, pickling lines [8] consisting of several pickling baths and input section of WJP treatment are predominant now and meet the technical requirements of Industry 4.0 for energy efficiency and minimization of environmental emissions. WJP is a successful modern machining technique, which is used to produce the precision components in aerospace, automotive and marine applications. In WJP with abrasive, material removal takes place through erosion process, in which water jet accelerates the abrasive particles at high velocity, causes impingement on the target material. It offers, wide range of benefits such as minimal thermal stress, less material distortion, ability to cut any materials, minimum cutting force can be applied on the target material.

In the technological process (TP), to achieve a given target surface finish, expensive abrasives (diamond-containing mixtures, corundum carbide) are often required. At the same time, the changing geometric dimensions and properties of abrasive particles are also evaluated stationary, before being used in repeated TP cycles.WJP of rolled steel products with an pickling solution (PS) is a high-speed jet impact on the treated surface, but over time the PS content and component size of solid products of the acid pickling reaction in the PS increases to 3÷5 mm in time [9] and an uncontrolled polishing effect of metal surface is introduced into the process.

Even though WJP is well established in plastic, ceramic, glass [10], a limited works are carried on the WJP control, especially to such as intelligent control systems of steel strip surface cleaning by WJP technology, is observed.

A thorough review of current WJP approaches and models is given in [11], however, theoretical and experimental studies are focused on multiphase abrasive mixture flow models and fuzzy prediction of flow turbulence characteristics. In [12], ANN and the "random annealing" approach were used to predict the optimal parameters of the WJP process. In [13], the Taguchi method and GONNs (systems of genetically optimized neural networks) were used for the analysis of discrete abrasive flow data and the fuzzy selection of WJP parameters. Recent progress in some relevant methods and experimental applications has been reported in the literature [14-17]. But all these studies as a goal pursue obtaining analytical dependences on certain areas of determining the input variables, and until now there was no reference to the literature in which the problem of regulating the pressure of the PS flow for the processes of abrasive WJP of the surface to a certain depth was discussed.

At present, there is no generalized methodology for the development of WJP automated control systems and the synthesis of WJP quality criteria for surface treatment under conditions of uncertainty in the manifestation of the characteristics and number of surface defects and changes in the abrasive properties of working solutions. So, this paper aims to present a variant of the design of WJP control system using pipelined data processing by intelligent models that estimate the thickness of the defect to be removed, form the required jet pressure, taking into account changes in the abrasive properties of the working solution. If the indicators deviate according to the processing quality criteria, the models can be adjusted.

The way to make modern pickling lines cost-effective and ensure proper environmental protection is to solve the urgent problem of developing modern control systems based on intelligent methods and models.

2. Analysis of the problem of surface defects waterjet removing

The process of removing defects on the surface of rolled carbon steel is carried out by a continuous pickling line in a liquid technological pickling solutions. PS is a diluted sulfuric acid, removes point oxides and films, but also affects the steel surface, partially dissolving one too. When an acute-angled abrasive particle collides with a metal, the process of cutting a micron layer of the entire surface or local scale defects occurs.

One of the TP quality control criteria is the surface cleanliness factor, which uses estimates of the identification of surface defects, and in general it can be presented:

$$q_e = \frac{\sum S_i^{Out} \cdot \delta_i}{\sum S_j^{In} \cdot \delta_j} \quad , \tag{1}$$

where S_i^{Out} is the area of defects of the i-th class with a thickness of δ_i at the exit from the TP;
S_j^{In} is the area of j-th class defects with thickness δ_j at the entrance to the TP.

Exceeding the q_e value set by the TP regulation (r_q < 0.02) during a certain time period of the specified observation window $(t(k); t(k+10))$ indicates the need to change the training rules and parameters of the identification model. The second quality control criterion of TP is q_m – the consumption coefficient of steel mass (regulated by the value $q_m < r_m = 0.05$):

$$q_m = \frac{m^{Out}}{m^{In}} \quad , \tag{2}$$

where m^{Out} and m^{In} are the mass of the steel roll after processing and at the entrance to the TP, respectively.

Therefore, in order to minimize PS consumption and unreasonable metal losses, it is very important to control such process parameters as the dwell time in the PS, the temperature and composition of the pickling solution in the baths, the pressure and speed of the PS in the water jets (WJ).

The parameters of these processes are non-linear, interconnected and indirectly influence each other. The starting energy of the pulse of the PS liquid flow $E_I(\alpha)$ is directly (k-) proportional to the rational root of the tangential stress of the PS flow – $\tau_{st}(P_t)$ created on the surface of the defect due to the supply of PS with the pressure P_t from the distance l from the jet to the surface [9], which can be simplified as:

$$E_I(\alpha) \approx k \cdot l \cdot \sqrt{\tau_{st}(P_t)}\,, \tag{3}$$

where $E_I(\alpha)$ is the momentum energy of the PS flow, which is also nonlinearly present in the Arrhenius equation [9], adapted to the problem of the WJP, replacing the increase in thermal energy E_T during the pickling time Δt:

$$ln\frac{C(t_{n+1})}{C(t_n)} = A \cdot e^{-(\frac{E_a + E_I(\alpha)}{R \cdot T}) \cdot \Delta t} \quad , \tag{4}$$

where $C(t_{n+1})$ – the concentration of sulfuric acid in the bath at the end of digestion after time Δt;
$C(t_n)$ is the initial acid concentration;
$\Delta t = (t_{n+1} - t_n)$ is the irrigation time of the defect;
A is the Arrhenius factor;
$E_a = f(C, T)$ is the reaction activation energy;
R is the universal gas constant;
T is the temperature of PS (ºK).

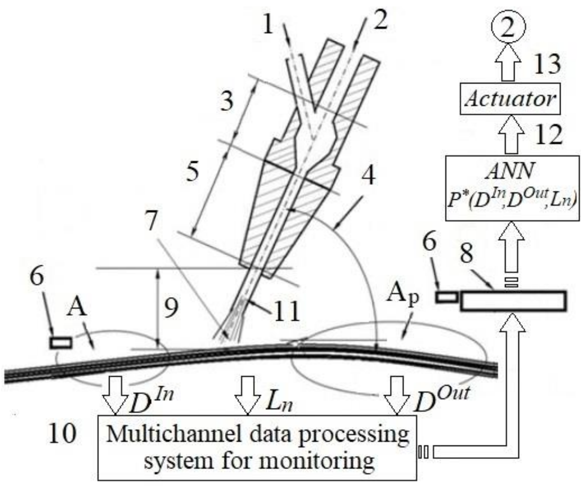


Figure 1: The abrasive WJP control system

The Fig.1 shows the next positions:

1 is the abrasive mixture supply channel (absent in our case); 2 is the PS supply channel under a target pressure; 3 is the abrasive suspension mixing chamber; 4 is the angle of inclination of the jet relative to the processed surface (fixed in our case); 5 is the accelerating nozzle; 6 is the defect identification cameras before D^{In} and after D^{Out} WJP; 7 is the contact area of the PS and the treated surface; 8 is the operator monitor; 9 is the distance from the nozzle cut to the surface; 10 is a microprocessor multi-channel system for processing defect signs and PS signs and forming the $P*$ task; 11 is a PS flow jet; 12 is an artificial neural network (ANN) identifying the $P*$ task; 13 is an executive mechanism that corrects the pressure to $P*$; the area treated by the jet: A – before and Ap – after treatment with the PS; L_n is the length of the *n*-th defect.

The PS pressure is measured by a FESTO SDE1 digital PNP / NPN sensor, the data of which is used to correct the control actions of the circuit - changing the plane of the nozzles through which the PS is supplied. The change in the plane of the irrigation nozzles is carried out by the control voltage of variable duration and polarity, which is supplied by the regulator to the to the executive mechanism (EM) in accordance with the length of the defect L, the speed of winding $V(n)$, and the tasks $P_t^*(\delta)$, which are formed by the reference model-identifier of the thickness of the defect δ according to the code color $(Y(RGB))$. A titanium valve of the H331g type with a full-pass cross-section diameter of 5 mm with a piecewise linearized characteristic [18] is used as a EM, equipped with a short-stroke electric cylinder with a FESTO ESBF-LS-40-30-2.5P linear actuator.

Mostly technological systems can be described as a “black box” characterized by a lack of information about what physical phenomena is happening inside itself. Development of a “black box” model is the formation of the production rule set with a minimum number *k* that describe a mapping of its inputs (the vector X_n) to the output Y, which will provide the most accurate approximation of the real system in the sense of minimum absolute error.

Each production rule specifies some fuzzy point in the display space defined Cartesian product $X_1 \times X_2 \times \ldots X_n \times Y$ in the next form for our task:

$$
\begin{gathered}
R_1{:}\, IF\ (C \approx a_1)\ AND\ (C_n \approx a_2)\ AND\ (T \approx a_3)\ AND\ (\delta \approx a_4)\ THEN\ (P_t^* \approx b_1), \\
\bullet \quad \bullet \quad \bullet \quad \bullet \quad \bullet \\
R_k{:}\, IF\ (C \approx z_1)\ AND\ (C_n \approx z_2) AND\ (T \approx z_3)\ AND\ (\delta \approx z_n)\ THEN\ (P_t^* \approx b_k).
\end{gathered}
\tag{5}
$$

When conducting experimental tests of WJP equipment, the following requirements and conditions are met:

$$
\begin{cases}
(r_q < 0.02) \wedge (r_m < 0.05) \\
\Big(\big(C = (7;\ 14)\big) \wedge \big(C_n = (0;\ 15)\big)\Big), [\%], \\
T = (76;\ 88), [^{\circ}\mathrm{C}]
\end{cases}
\tag{6}
$$

a set of 1200 support points-singletons $(C, C_n, T, \delta, P_t^*)$ was obtained, where C_n is the concentration of reaction products ($FeSO_4$ – solid salts) in PS. An increase in the value of the parameter C_n entails an increase in the abrasive properties of the PS, a deterioration in criterion (2) and an improvement in criterion (1).

The famous FCM (Fuzzy C – Means) algorithm of the Fuzzy Logic Matlab package was used for interpolation of the dependence $P_t^* = f(C, C_n, T, \delta)$. Fuzzy estimation by the FCM method was used to form the fuzzy classifier of pressure task P_t^*, based on Gaussian membership functions [19].

The classifier was tested in a real TP under conditions (6) to obtain an extended a data set $(C, C_n, T, \delta, P_t^*)$. As a result, the numerical values of the required values $P_t^* = f(C, C_n, T, \delta)$ with parameters that lead to a satisfactory level of defect removal with preliminary irrigation of defects with the supply pressure to the jets $P_t^* = (0; 6)$ x 10^6 [Pa] and pressure formation time t_f from the "jet closed" state, were obtained.

The time of a full stroke of the irrigation nozzle needle $h_f = [0; 2] \cdot 10^{-3}$ [m] from the state "closed" to "open" is $t_f = 0.5 \cdot 10^{-3}$s. Table 1 shows a fragment of an obtained data set under conditions (6), where medians of the corresponding *n*-th fuzzy classes of defect thickness and color are respectively – δ_n^M, Y_n^M. The value of the needle travel time t_f from the closed state to some open states under the conditions of reaching the corresponding P_t values (manufacturer's data) is also given in Tab.1.

The fuzzy classifier $\delta(RGB)$ reveals the high applicability and accuracy in the experimental range of the used parameters, the recognition coefficient on the synthesized test set was: $R^2 = 0.9971$.

Table 1
Color classifier (fragment) of surface defects and parameters for their elimination for conditions (6)

n	Defect color X_n	$\delta_n \cdot 10^{-6}$, m	Y_n	Y_n^M	$\delta_n^M \cdot 10^{-6}$, m	$P_t^* \cdot 10^6$, Pa	$t_f \cdot 10^{-4}$, s
1	Matte aluminum	0.1÷0.4	227÷231	229	0.25	0.3	0.2
2	Pale blue	5÷10	218÷226	223	7.5	1.8	1.1
3	Light gray	13÷15	200÷217	209	14.0	3.6	2.2
4	Gray	14÷25	189÷206	198	19.5	3.9	3.0
5	Dark gray 1	24÷36	137÷148	142	25.0	4.5	4.0
6	Dark gray 2 matte	38÷32	45÷ 2	67	35	4.8	4.2
7	Almost black	34÷40	3 ÷ 39	21	37	6.0	5.0

3. The proposed intelligent control system of the surface defects processing

To solve the task of managing the processing of surface defects, an intelligent control system is proposed, the structure and contents of which are shown in Fig.2:

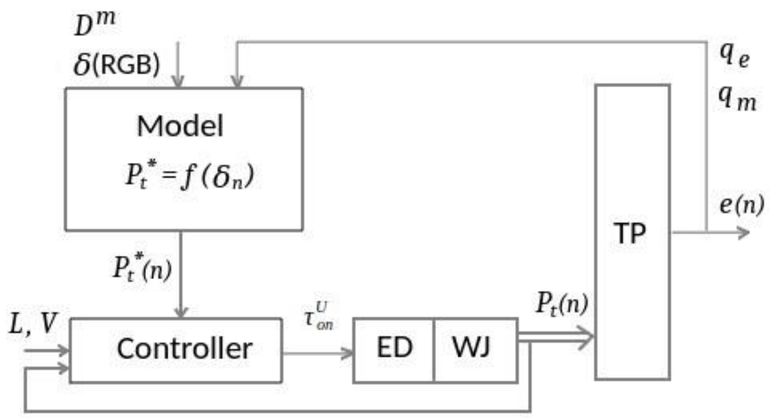


Figure 2: The intelligent control system structure for the surface defects processing

The figure shows: $\delta(RGB)$ is the neural network model-identifier of defect thickness δ by color code obtained from fuzzy classifier, which was made by the *c*-means fuzzy method when processing experimental dataset [20];

D^m – geometric rectangle coordinates of the *m*-th defect;

δ is the defect thickness;

$P_t^*(n)$ are tasks that formed by the reference neural network model-identifier with the structure 4-16-1;

$P_t(n)$ is the value of the real pressure PS at time *n*;

$L \approx (120 \div 240)$ [m] is the specified fixed distance of the rolling stock loop;

V is the still strip winding speed;

τ_{on}^U is the duration of the control voltage suppling to the jet, which is formed by the neural network model of the PS supply pressure regulator with the structure 6-24-1;

ED is the electric drive;
WJ are processing waterjets;
TP is the technological process;
q_e is the surface cleanliness and q_m is the steel mass consumption criteria.

For the creation of such an intelligent system, it is necessary to take into account the nature of the change in input parameters, the architecture of the artificial neural network (ANN) being developed, and data sets for training.

The ability of neural networks to approximate unknown "input-output" mapping regions is widely used for object identification. The properties of the radial ANN are completely determined by the radial basis functions (RBF) used in the neurons of the hidden layer.

RBF nets are the universal approximators and because only one nonlinear hidden layer is present, the parameters of the linear output layer are the subject of adjustment with standard procedures [21]. High speed and filtering properties may be used for their training, which is very useful when processing the "noisy" measurements.

A non-linear input-output mapping may be described by the relation:

$$d = f(x), \tag{7}$$

where x is the $(n+1)$ – input vector, d is the output vector, $f(x)$ is an unknown vector-function, which is evaluated with the help of training sample $\{x(k), d(k)\}, k = 1,2, \dots N$.

The problem of learning the approximating neural network is to find a function $F(x)$ so close $f(x)$ to that:

$$\|F(x) - f(x)\| \leq \varepsilon, \forall x(k)\colon k = 1,2, \dots N, \tag{8}$$

where $F(x)$ is the the mapping realized by the network, ε is a small positive number, that determines the accuracy of the approximation. In this context, the problem of approximation completely coincides with the problem of "training with the teacher" or supervised learning, where the sequence plays the role of the ANN input signal, and $f(x)$ is the training signal.

The process of a model building is divided into two stages - structural and parametric identification, and the application of the ANN also requires solving two problems: determining the network structure and setting (training) its parameters.

Usually, a change in the network structure is made by its gradual complication by adding new neurons, performed each time when an additional identification error $e = d - y$ occurs when a new input signal appears, exceeding the permissible one. Training (parametric identification) consists in determining the network parameters and reduces to minimizing the identification error – as a rule, a quadratic error functional:

$$J(k) = \|\boldsymbol{\varepsilon}(k)\|^2 = \|\boldsymbol{d}(k) - \boldsymbol{y}(k)\|^2. \tag{9}$$

In practice, the most common are discrete learning algorithms of the form:

$$w_{ji}(k+1) = w_{ji}(k) + \eta(k) e_j(k) x_i(k), \tag{10}$$

or in vector form:

$$w_j(k+1) = w_j(k) - \eta_k \nabla_{w_j} E_j(k) = w_j(k) + \eta(k) e_j(k) x_i(k), \tag{11}$$

where $\nabla_{w_j} E_j(k) = -\, e_j(k) x_i(k)$ is the gradient vector of the objective function by the synaptic weights. The speed of the learning process using the algorithm (9), (10) is completely determined by the choice of the parameter η_k that determines the step of the displacement in the space of the tunable parameters. It is natural to choose this parameter so that the rate of convergence of the current values $w_j(k)$ to the optimal hypothetical weights will be maximal. Introducing into consideration, the vector of deviations of the current values $w_j(k)$ from the optimal values in the form:

$$\widetilde{w_j}(k) = w_j - w_j(k), \tag{12}$$

and the differential equation solution:

$$\frac{\partial \left\|\widetilde{w_j}(k)\right\|^2}{\partial \eta} = 0, \tag{13}$$

the optimal value of the step parameter may be obtained in the form:

$$\eta(k) = \|x(k)\|^{-2}, \tag{14}$$

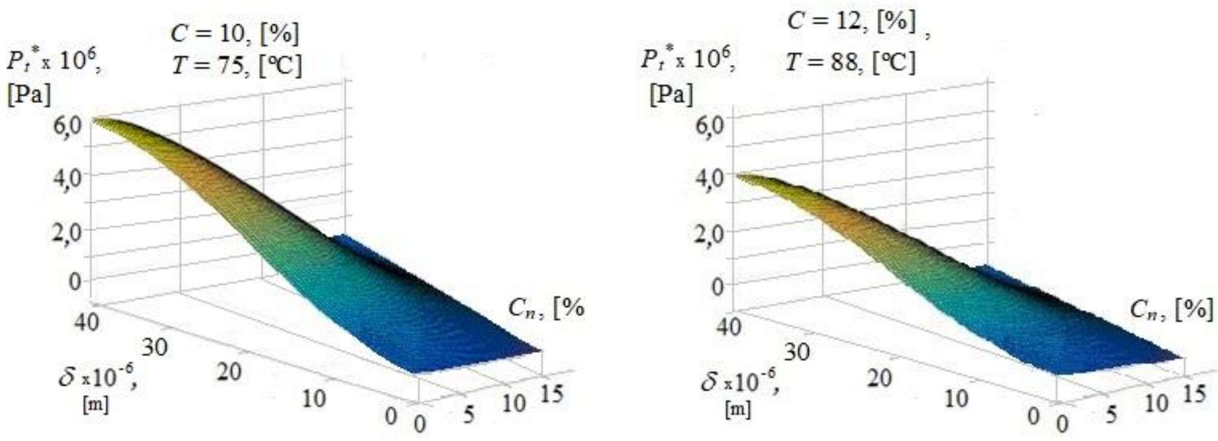
that leads to a one-step learning algorithm:

$$w_j(k+1) = w_j(k) + \frac{e(k) x(k)}{\|x(k)\|^2}. \tag{15}$$

The expression (15) is known as the Kaczmarz – Widrow – Hoff algorithm [22] in the ANN theory.

The cut of the model $P_t^*(k) = f(C, C_n, T, \delta(k))$, reduced by the fixed parameters: temperature T and concentration C of PS, identifies the pressure P_t^*, which is necessary to ensure the given process speed at the current varying values of defects thickness δ, and transmits in the k -th moment of discrete time as the value of task for the WJ regulator.

On the basis of the $\delta(RGB)$ fuzzy classifier, obtained by the FCM method, RBNN (Fig.3)with structure (4-16-1) forming the surface $P_t^* = f(C, C_n, T, \delta)$ was built in the NeuroPh studio package [23], where C_n is the concentration of reaction products ($FeSO_4$ - salts with an abrasive effect) in PS.



a) b)

Figure 3: Fragments of the $P_t^* = f(C, C_n, T, \delta)$ surface

4. A model of intelligent control of the solution pressure in the jet

The limited possibilities of linear pressure control in the jets do not always allow maintaining the required rate of change of the TP output parameters. Dynamic changes in P_t reduce the quality of defect removal. These problems can be solved by improving the control system with the help of RBNN, adjusted to real TP data. For this purpose, it is expedient to simulate the pressure control process P_t.

The neural network model of the PS supply pressure regulator for pre-irrigation of defects forms a control voltage of a certain duration and polarity. In its full form, the RBNN presentation of preliminary irrigation of the non-systemic point defects of steel strip surface (ND) is a rather cumbersome structure:

$$\tau_{on}^U(n) = F_{NN}(C, T, V(n), D^m, \delta_n(Y_n^m), P_t(n-1), P_t(n), \cdot\, t_f(n-1), t_f(n), \Delta t_P)\,, \qquad (16)$$

where $\tau_{on}^U(n)$ is the duration of the control voltage supply to the jet in cycle *n*;

C, T are PS parameters (stable during irrigation);

$V(n)$ is the tape winding speed (constant);

D^m are geometric coordinates of the *m*-th defect;

$\delta_n(Y_n^m)$ is an estimate of the thickness of the defect, which depends on the estimate of the brightness of its color $Y_n(RGB)$ and is estimated by the classifier;

$\Delta t_P = t_f(n-1) - t_f(n)$ is a value entered into the RBNN to calculate the polarity of the control voltage U when $Y(RGB)$ is changing;

$Y(RGB)$ is the evaluation of defects by brightness.

Optimal values of PS parameters are maintained in each control cycle. When using a color classifier of defects, it is possible to estimate the value of the parameter that controls their elimination – the time to adjust the nozzle cross-section to create the necessary PS pressure for irrigation of the defect.

This makes it possible to simplify the model (14), reducing its dimension.

For defects in the rolled strip to be pickled, RBNN by the thickness component $\delta_n(Y_n^m)$ and the geometric coordinates of the defect length $D_y^m = (y_2^m - y_1^m)$ identifies the required supply PS pressure $P_j^*(n)$ through the *j*-th jet:

$$\tau_{on}^U(n) = f_{NN}(V(n), D_y^m(n), P_t(n-1), P_t^*(n), \cdot\, t_f(n-1), t_f(n))\,. \qquad (17)$$

Model is illustrated in Fig.4.

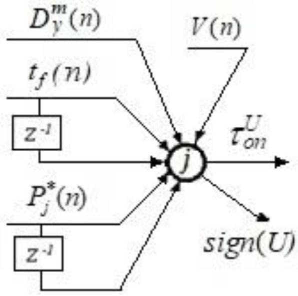


Figure 4: RBNN model of the *j*-th jet voltage control

The representation of the RBNN model of the jet control electric drive activation time has the structure (6-24-1) with a clock delay z^{-1} to take into account the dynamics of parameter changes.

The duration of turning on the electric drive τ_{on}^U to control the area of the passing section of the jet and the pressure at the exit of the PS from the jet by the value ΔP_t, adaptively changes according to an assumed proportional law with coefficients k_n on each segment $(P_n; P_{n+1})$ inside the *n*-th class (Fig.5) – only individual singletons of measured and passport values are known. It is assumed that the continuous function $t_f(P_t)$ increases monotonically and is linearized piecewise in *n* unequal classes on the definition domain $P_t = (0; 6)$ MPa.

The dependences $t_{f(i,i+1)} = F(P_{t(i,i+1)})$ are assumed to be linear for $i = 1, 2, .., n$ in adjacent segments. The assumption about the effect of linear laws $t_f(P_t)$ within n classes makes it possible to determine $t_{f(i)}$:

$$k_n = \frac{t_{f(n)} - t_{f(n-1)}}{P_{t(n)} - P_{t(n-1)}} \quad , \tag{18}$$

$$t_{f(i)} = \frac{P_t(t_i) - P_{t(n-1)}}{k_n} \text{ }, \forall P_t(t_i) \colon P_{t(n-1)} < P_t(t_i) \le P_{t(n).} \quad . \tag{19}$$

The value of the previous iteration is known, then the duration of the supply of the control voltage to change the cross-sectional area of the jet:

$$\tau_{on}^U = \left| t_f(n-1) - t_f(n) \right| . \tag{20}$$

The change in voltage polarity (in the direction of movement of the jet needle) is determined by the sign of the pressure deviation from the operating pressure at the previous moment:

$$sign(U_{on}) = sign(P_{t(n-1)} - P_{t(n)}). \tag{21}$$

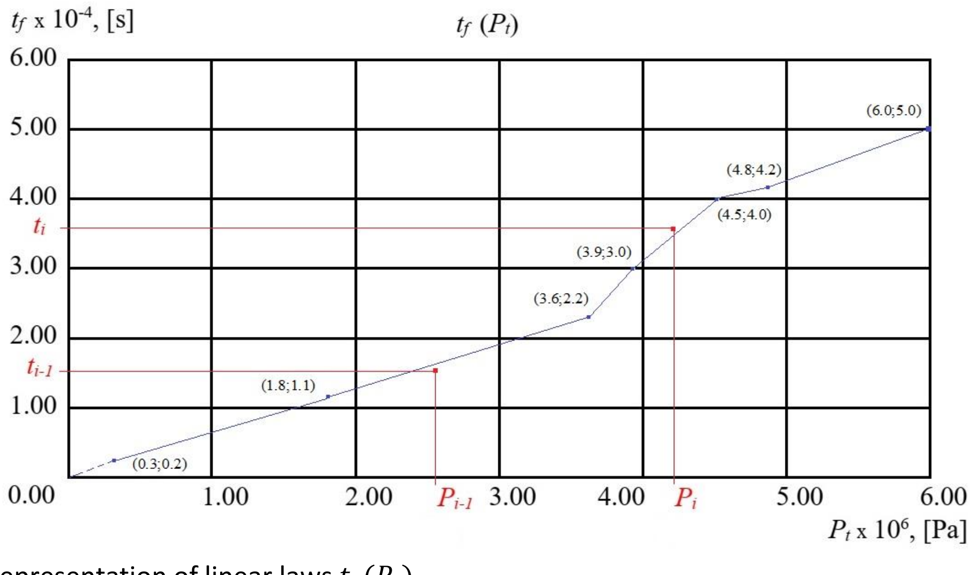


Figure 5: Representation of linear laws $t_f(P_t)$

So situation of pressure change from P_{i-1} to P_i without voltage sign change is illustrated in Fig.5: $\tau_{on}^{U}(i) = \ |3.6 - 1.65| \cdot 10^{-4} = 0.95 \cdot 10^{-4}$ s. Then the marker (Fig.6) of the real time of turning on the jet t_i':

$$t_i' = t_i - \tau_{on}^{U} + \frac{L_{7-3}}{V(n)}, \quad (22)$$

where t_i is a marker of real-time identification of the defect area;
$L_{7-3} \approx$ (120÷240) [m] is the specified fixed distance of the rolling stock loop;
$V(n) = const$ is the conditionally constant regulated speed ≤ 2 [m/s].
This gives the system time to work out the control signals.

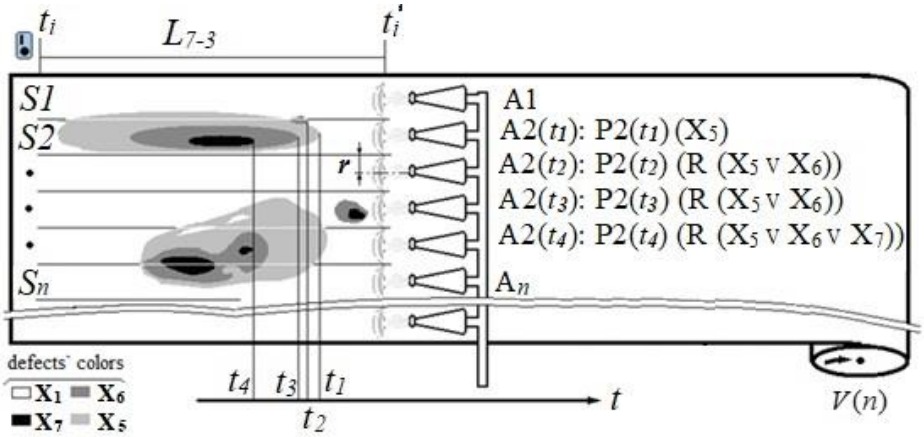


Figure 6: Input segmentation of non-systematic defects of rolled strip

According to the positional coordinates, parts of ND are often assigned to different segments S_j of the rolling strip [15]. In a general form, the logical rule for determining the task of processing the defect fraction for the jet A_j at the moment of time t_i' is the geometrical belonging of the defect fraction to the corresponding rolled segment:

$$A_j \colon P_j(t_i') = R\big(x, y, \delta(X_m)\big) \wedge \big(D_y^m(t_i') \in S_j\big), \quad (23)$$

where R is the determining rule of the preferred alternative, which is specified during the synthesis or training of the regulator and eliminates the ambiguity of the control situation. The width of the segment $S_j = 2r$ (Fig.6) corresponds in size to the part of the surface of the rolled strip irrigated by the jet A_j at the time of the control influence.

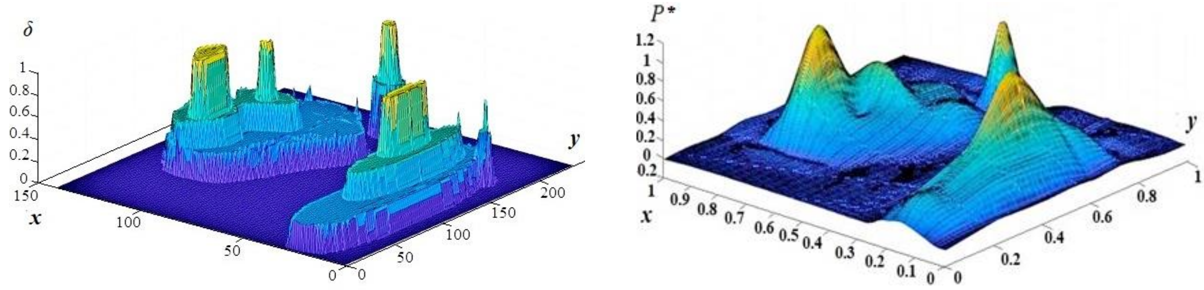
Technically determined restrictions on the number of jets N lead to ambiguous control influences for the processing of parts of defects located in the same sector S_j of the rolled surface, but different in the values of X_m. The physical meaning of the ratio R is as follows: in the sector of the surface S_j treated with the jet A_j, the simultaneous presence of defects with different color characteristics X_m logic control rule is set depending on the priority requirements of the TP: minimum, average or maximum impact on the ND sector (increased pressure in the jet). Fig.6 illustrates the situation of selecting the control rule for jet A2 at the time interval $(t_1; t_4)$, taken as a basis for the synthesis of the regulator R: max (P_t).

When forming training pairs, the determining rule R of the preferred pressure control alternative is finally adopted in the following form - if $\Delta t_P(n)$ can be compared with τ_{on}^{U}, then the control influence is formed based on the assessment of the following defect area $D^m(n+1)$: if $\delta(n+1) >> \delta(n)$, then $P_t = P(\delta(n+1))$. If $\delta(n+1) - \delta(n) < \delta_r$, where δ_r is the regulated value of the current deviations of defect thickness estimates, then the pressure does not change until the next defect region

The output signal of the model $P_t^*(x, y, \delta(Y))$ and signal t_f are used as an input data for RBNN model (17). Basic Gaussian functions with fixed centers and radii are used in the model to approximation of the defect relief $\delta(RGB)$, in the model $P_t^*(x, y, \delta(Y))$ – to generation of control influences and subsequent correction of standards.

For defects of the rolled strip to be pickled, the radial base network $\delta(x, y, Y)$ based on the brightness component and the geometric coordinates forms the image of the defect the task of the supply pressure

$P_t^* = f(C = const, C_n = const, T = const, \delta)$ of the pickling solution through the *j*-th jet is formed (Fig.7). Models obtained by simulation in the Neuroph Studio package.



a) The image of the defect thickness $\delta(x, \mathrm{y}, Y)$ b) Identified by $P_t^*(x, y, \delta(Y))$

Figure 7: Representation of the defect treatment surface

The error in the operation of the regulator $e(n)$ during pressure control in jet (WJ item in Fig.1) is determined by the difference between the current value of the real pressure PS $P_t(n)$ and the task $P_t^*(n)$:

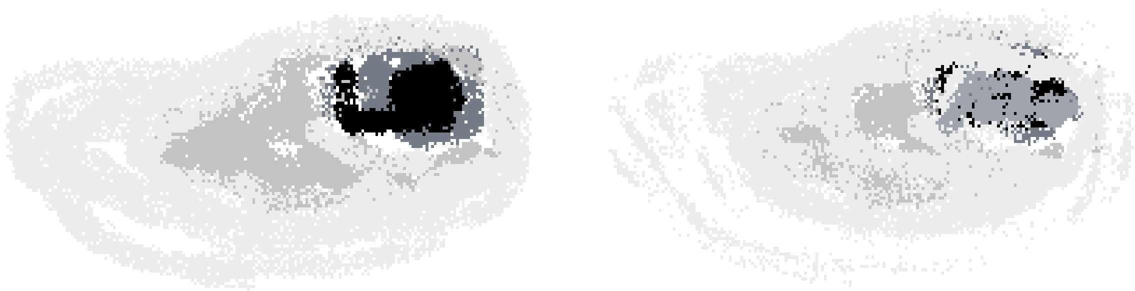
$$e(n) = P_t(n) - P_t^*(n). \tag{22}$$

When the level of accumulated errors $e(n)$ in the control loop is exceeded according to criteria (1, 2), the reference model of task formation $P_t^* = f(C, C_n, T, \delta)$ is adjusted.

5. Results

The images of the original surface defects (a, c, e) on the left, and the images of defects after processing (b, d, f) on the right are shown in Fig.7.

(a) (b)



(c) (d)

Figure 8: Examples of WGP of defects: (a, b, c, d) are scaled 20:1

Figure 7 (b, d) shows the processed ND corresponding to the required criteria (1, 2) values. Figure 8 (d) illustrates an unsatisfactory processing result associated with qualitative differences between defects formed along the edge of the rolled strip and ND. In this case, it is necessary to adjust the models P_t^* and τ_{on}^U: parametric, and possibly also structural.

6. Discussions

In the case when the law of $t_f(P_t)$ is not known with certainty, taking into account the monotonicity of the $t_f(P_t)$ dependence, the construction of a control regulator in the form of an RBNN is the least expensive solution. RBNN approximates unknown values by unipolar sigmoidal functions that are continuously differentiated between known singleton points:

$$t_f(P_t) = \frac{t_n}{1 + e^{-k_n(x-P_t)}} \quad , \tag{23}$$

where k_n is the slope coefficient of the function in the *n*-th class;

P_t is the abscissa of the reference median of this class;

t_n is the time of full travel of the jet needle, median of the *n*-th class according to Fig.5.

A model that structurally reflects the relationship between the measured pressure P_t, the controlling effects of the pressure regulator and the quality of defect processing in real time may be of practical interest. Considering the clearly pronounced concentric-elliptical shape of the ND on the surface of the strip, which is due to the physical nature of their formation, it is possible to apply a preventive forecast of control actions along the horizons of the change in shade on the defect area, as well as system strip defects. Comparative studies of alternative ANN architectures have not been carried out due to the lack of sufficient experimental dataset. To do this, it will be advisable to apply the following approach: to represent the WJP in the form of a recurrent neural network with long short-term memory (LSTM) cells and, as additional input parameters, introduce the class and diameter of the abrasive element into the model, which can be used to estimate the size and hardness of the abrasive element using the procedure identical to the one given in [25].

7. Conclusions

The proposed method of automated WJP of surfaces intelligently takes into account changes of the abrasive properties of the PS and is a promising technology. The method can be used for various types of processing that use an abrasive: rounding of sharp edges; polishing and polishing complex surfaces; deburring and cleaning of welds; surface preparation for coating; removal of organic deposits from propellers and bottom surfaces of sea vessels; removal of contaminated and painted concrete surfaces; removal from the entire surface or locally defective layer (scale); high-precision water cutting of metals.

The proposed solution made it possible to use the abrasive effect of sludge, which is formed over time in the PS without the use of expensive equipment [26] dosed mixing of the abrasive with the liquid flow. Combined with other measures to automate modernized sulfuric acid pickling lines [27], the solution made it possible to reduce sulfuric acid consumption by 23% and increase TP speed $V(n)$ from 1.2 to 1.96 [m/s]. Taking into account the relatively small dimension of the models and the low speed of the TP, the solution can be implemented into IIOT structure of the TP in the form of a low cost microcontroller system.

8. Nomenclature

ANN – artificial neural network.

ED – electric drive.

EPA – United States Environmental Protection Agency.

EM – executive mechanism.

FCM – Fuzzy Classifier Means method.

ND – non-systemic point defects of steel strip surface.

PS – pickling solution.

RBNN – radial based neural network.

TP – technological process.

WJP – waterjet processing.

T – temperature of the solution, (ºC, ºK).

τ_{on}^{U} – duration of switching on the control voltage, (s).

C – concentration of pickling solution, (g/l).
C_n – concentration of reaction products ($FeSO_4$ – salts) in pickling solution, (g/l).
q_e – surface purity coefficient (%).
q_e – consumption coefficient of steel mass (%).

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