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INTELLIGENT MODELS FOR CONTROL OF JET HYDRO-PROCESSING OF ROLLED STEEL DEFECTS

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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 version of Internet of Things (IIoT) aims of which are to create fully automated industries where traditional engineering models coexist harmoniously with computer intelligence models. The biggest task of Industry 4.0 is to achieve such a level of automation at the enterprise that machines can work without human intervention in all possible areas. Collected data should be 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, which responds to emergency situations only [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. The number of companies that are the world's largest steel producers that use 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 (PF). Sludge, sour water, iron sulfate, metal salts, and spent acids are byproducts of steel etching with sulfuric acid and are hazardous waste according to 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. These actions increase the operating, resource and energy costs of the process.

Pickling lines [8] consisting of several pickling baths and hydrojet pickling treatment section are now predominant and meet the technical requirements of Industry 4.0 for energy efficiency and minimization of environmental emissions. Hydrojet processing (HP) of sheet metal with PF is a high-speed jet impact on the treated surface. Over time the content of solid products of the acid pickling reaction in the PF increases and an uncontrolled polishing effect is introduced into the process. The way to make the process cost-effective and ensure proper environmental protection is to solve the urgent problem of developing modern HP control system based on intelligent methods and models.

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. PF 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 technological process (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:

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

where S_i^{Out} – the area of defects of the *i*-th class with a thickness of δ_i at the exit from the TP; S_j^{In} – 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 $q_m < r_m = 0.05$):

$$\{x(k), d(k)\}, k = 1, 2, ..., N, \tag{2}$$

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 PF consumption and unreasonable metal losses, it is very important to control such process parameters as the dwell time in the PF, the temperature and composition of the pickling solution in the baths, the pressure and speed of the PF in the hydro-processing 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 PF liquid flow $E_i(\alpha)$ is directly k-proportional to the rational root of the tangential stress of the PF flow – $\tau_{st}(P_t)$ created on the surface of the defect due to the supply of PF 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 energy momentum of the PF flow, which is also nonlinearly present in the Arrhenius equation [10], adapted to the problem of the WJ, replacing the increase in thermal energy E_T during the pickling time of the defect $\Delta t = t_{n+1} - t_n$:

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

where $C(t_{(n+1)})$ – the concentration of sulfuric acid in the bath at the end of digestion after time τ_{on}^U; $C(t_n)$ – is the initial acid concentration; A – the Arrhenius factor; $E_a = f\,(C, T)$ – reaction activation energy; R – is the universal gas constant; T – the temperature of PF [ºK].

The results of studies of the influence of an uncontrolled increasing of the abrasive content in the PF on the quality of metal surface HP were not found by the authors in the sources of scientific and technical information. Given the above, this work is devoted to the development of an intelligent models for controlling the HP of the surface of carbon steel rolled products defects.

To solve the task of managing of the surface defects processing, an intelligent control system is proposed, the structure and contents of which are shown in Fig.1:

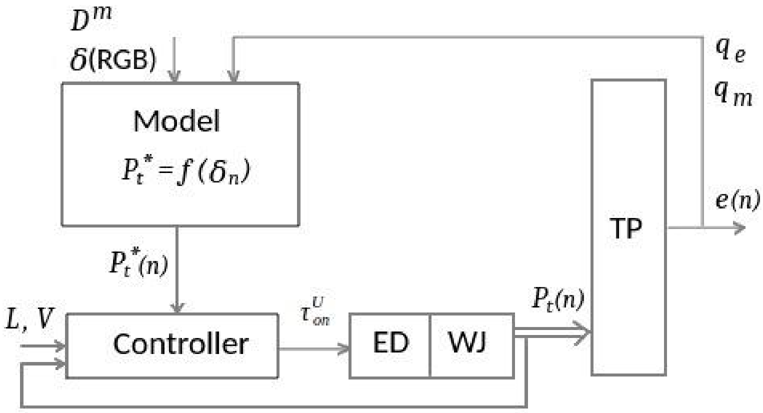


Figure 1 – The intelligent control system structure for the surface defects hydro-processing

The figure shows: $\delta(RGB)$ – neural network model-identifier of defect thickness δ by color code obtained from fuzzy classifier, which was made by the *c*-means fuzzy method [11] when experimental dataset of 1400 points was processed; D^m – geometric rectangle coordinates of the *m*-th defect; $P_t^*(n)$ – tasks that are formed by the reference neural network model-identifier with the structure (4-16-1); $P_t(n)$ – the value of the real pressure PF at time *n*; $L \approx (120 \div 240)$ [m] – the specified fixed distance of the rolling stock loop; *V* – still strip winding speed; τ_{on}^U – the duration of the control voltage suppling to the jet, which is formed by the neural network model of the PF supply pressure regulator with the structure (6-24-1); ED – electric drive; WJ – HP waterjets; TP – technological process; q_e – surface cleanliness and q_m – 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 neural nets (RBNN) 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 [12]. 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:

$$d = f(x), \qquad (5)$$

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

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

$$\|F(x) - f(x)\| \leq \varepsilon, \forall x(k) : k = 1, 2, ..., N, \tag{6}$$

where $F(x)$ – 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. Taking into account the monotonic nature of the abrasive component increasing in the PF content, the approach of dichotomous discrimination of the neurons number in the RBNN hidden layer was applied with an imposed limitation on the accuracy of the model (the recognition coefficient $R^2 = 0.005$). The dichotomous search algorithm on ordered sequences is widely used [13] and saves $N - \log_2 N$ cycles of parameterization when setting up the network compared to a sequential decrement of the number of neurons starting from $N = 200$. Training (parametric identification) consists in determining the network parameters and reduces to minimizing the identification error – as a rule, a quadratic error functional:

$$J(k) = \|\varepsilon(k)\|^2 = \|d(k) - y(k)\|^2. \tag{7}$$

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

$$w_{ji}(k+1) = w_{ji}(k) + \eta(k) e_j(k) x_i(k), \tag{8}$$

or in vector form:

$$w_j(k+1) = w_j(k) - \eta_k \nabla_{w_j} E_j(k) = w_j(k) + \eta(k) e_j(k) x_i(k), \tag{9}$$

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 (7), (8) 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:

$$\tilde{w}_j(k) = w_j - w_j(k), \tag{10}$$

and the differential equation solution:

$$\frac{\partial \left\| \tilde{w}_j(k) \right\|^2}{\partial \eta} = 0, \tag{11}$$

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

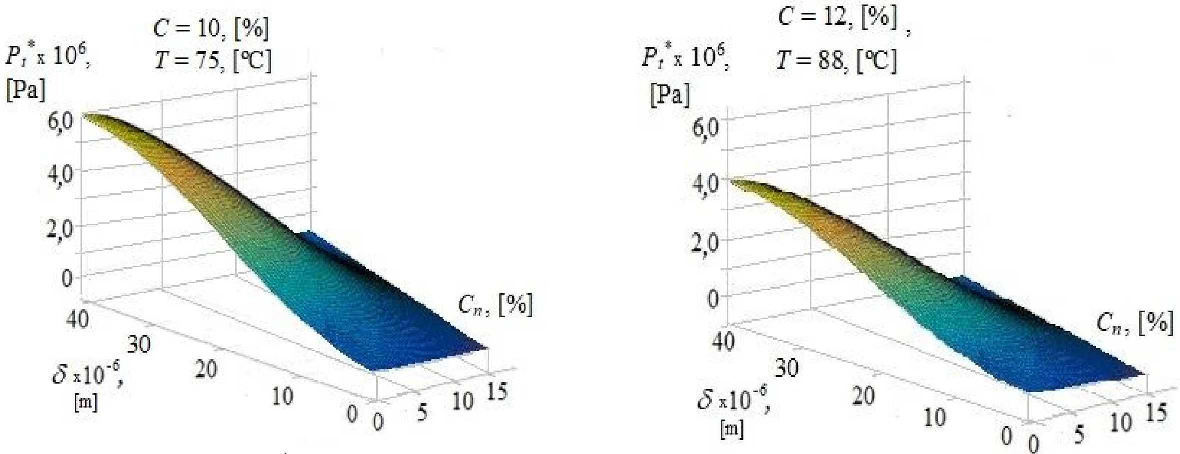
$$\eta(k) = \left\| x(k) \right\|^{-2}, \tag{12}$$

that leads to a one-step learning algorithm known as the Kaczmarz – Widrow – Hoff algorithm [14] in the ANN theory:

$$w_j(k+1) = w_j(k) + \frac{e(k)x(k)}{\left\| x(k) \right\|^2}. \tag{13}$$

The cut of the model $P_t^*(k) = f(C, C_n, T, \delta(k))$ $P_t^*(n)$, reduced by the fixed parameters: temperature T and concentration C of PF, identifies $P_t^*(k)$ – the pressure 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 and Response Surface Methodology [15], RBNN with structure (4-16-1) forming the surface $P_t = f(C, C_n, T, \delta)$ was built in the NeuroPh studio package (Fig.2), where C_n – concentration of reaction products ($FeSO_4$ - salts with an abrasive effect) in PF.



a) b)

Figure 2 – Fragments of the $P_t^* = f(C, C_n, T, \delta)$ surface

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 PF 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:

$$\tau_{on}^{U} = F_{NN}(C, T, V(n), D^{m}, \delta_n(Y_n^m), P_t(n-1), P_t(n), t_f(n-1), t_f(n), \Delta t_P), \tag{14}$$

where τ_{on}^{U} – the duration of the control voltage supply to the jet in cycle n; C, T – PF parameters (stable during irrigation); $V(n)$ – tape winding speed (constant); D^m – geometric coordinates of the m-th defect; $\delta_n(Y_n^m)$ – 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; $\Delta t_P = t_f(n-1) - t_f(n)$ – entered into the RBNN to calculate the polarity of the control voltage U when $Y(RGB)$ – evaluation of defects by brightness is changing.

Optimal values of PF 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 PF 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 (FESTO ESBF-LS-40-30-2.5P model):

$$\tau_{on}^{U}(n) = f_{NN}(V(n), D_y^m(n), P_t(n-1), P_t^*(n), t_f(n-1), t_f(n)). \tag{15}$$

Model is illustrated in Fig. 3.

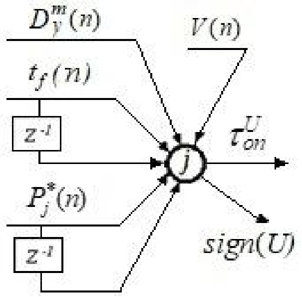


Figure 3 – RBNN model of the j-th jet voltage control

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 PF 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.4) – 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 $P_t = (0;6)\times 10^6$ [Pa]. 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 $t_{f(i)}$:

$$k_n = \frac{t_f(n) - t_f(n-1)}{P_t(n) - P_t(n-1)}, \tag{16}$$

$$t_f(i) = \frac{P_t(t_i) - P_t(n-1)}{k_n}, \forall P_t(t_i) : P_t(n-1) < P_t(t_i) \le P_t(n). \tag{17}$$

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:

$$\tau_{on}^U = \left| t_f(n-1) - t_f(n) \right|. \tag{18}$$

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:

$$sign(U_{on}) = sign(P_t(n-1) - P_t(n)). \tag{19}$$

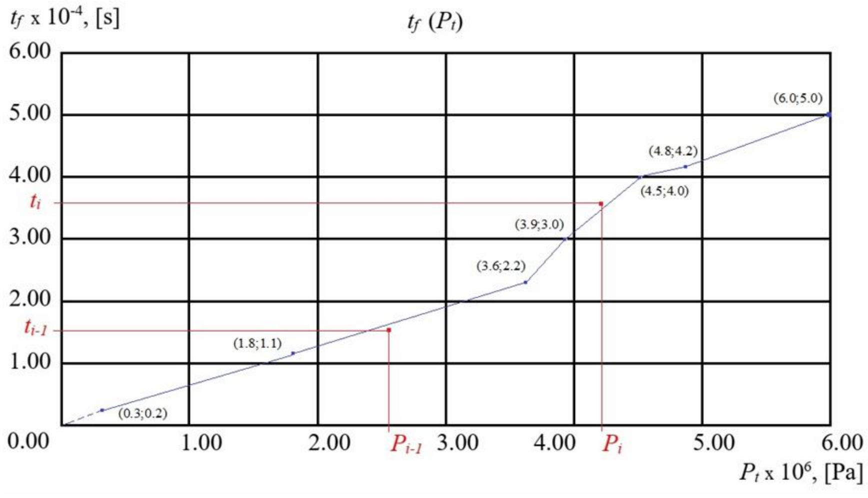


Figure 4 – Representation of linear laws $t_f(P_t)$

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

$$t_i^{'} = t_i - \tau_{on}^{U} + \frac{L_{7-3}}{V(n)}, \tag{20}$$

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

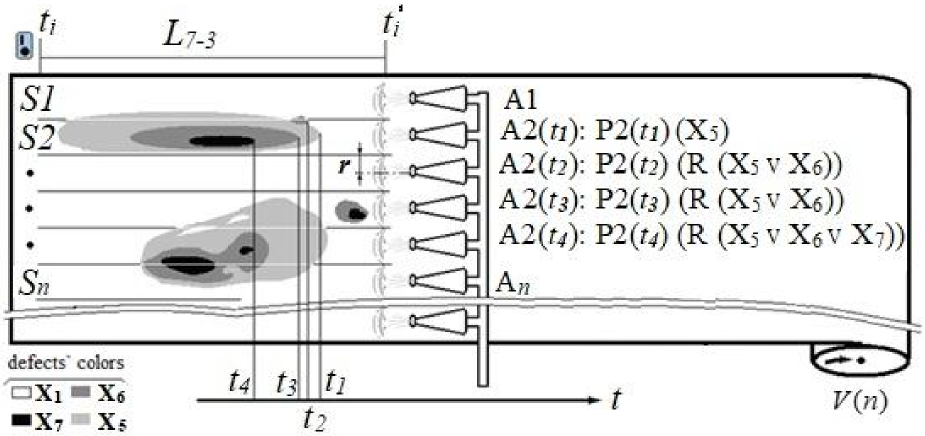


Figure 5 – Input segmentation of non-systematic defects and hydro-processing of rolled strip

According to the positional coordinates, parts of ND are often assigned to different segments S_j of the rolling strip [16]. 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:

$$A_j : P_j(t_i^{'}) = R(x, y, \delta(X_m)) \wedge (D_y^m(t_i^{'}) \in S_j), \tag{21}$$

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. 5) 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. 5 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 $P_t = P_t^*(\delta(n+1))$. 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 (15). Basic Gaussian functions with fixed centers and radii are used in the model for approximation of the defect relief $P_t^* = (x, y, \delta(Y))$, model (15) – generation of control influences and subsequent correction of identification 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. Models obtained by simulation in the Neuroph Studio package.

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 PF $P_t(n)$ 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. Taking into account the 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 forecasting model of controlling influences along the horizons of the color change of the defect area.

The structure of an intelligent control system for the hydro-processing of surface defects in rolled products is presented, which corresponds to the concept of the European program "Industry 4.0" in the direction of energy saving and total automation of processes.

The considered local RBNN hydro-processing models are tuned using the Kaczmarz-Widrow-Hoff algorithm. The model for identifying the current task of the pressure of the processing fluid takes into account the relationship between the thickness of the processed defect, changes in the composition of the processing fluid and, as a result, its abrasive properties. To form a given pressure in the corresponding jet, the following neural model estimates the duration and polarity of the voltage that controls the electric drive of the jet control valve in real time.

The small-dimensional models' conveyor is a promising solution for controlling waterjet processing of metals in such areas as rounding sharp edges; grinding and polishing complex surfaces; deburring and cleaning of welds; surface preparation for coating; removal of defects from the surface; high-precision waterjet cutting of metals [18]. In combination with other measures to automate the modernized sulfuric acid pickling lines [19], the solution will reduce the consumption of sulfuric acid and increase the TP speed ($V(n)$) from 1.2 to 1.96 [m/s]. Taking into account the small dimensions of the models and the relatively low speed of the TP, a software application based on the proposed models can be implemented in the control system for the hydro-processing of rolled metal products in the form of an inexpensive IIOT microcontroller module.

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ІНТЕЛЕКТУАЛЬНІ МОДЕЛІ КЕРУВАННЯ СТРУМЕНЕВОЮ ГІДРООБРОБКОЮ ДЕФЕКТІВ ПРОКАТУ

Надано структуру інтелектуальної системи управління гідрообробкою поверхневих дефектів прокату, яка відповідає концепції загальноєвропейської програми «Індустрія 4.0» за напрямом енергозбереження та автоматизації технологічних процесів.

Розглянуті локальні RBNN моделі гідрообробки налаштовані за допомогою алгоритму Качмажа-Відроу-Хоффа. Модель ідентифікації поточного завдання тиску робочої рідини враховує взаємозв'язок між товщиною оброблюваного дефекту, змінами складу робочої рідини та, як наслідок, її абразивних властивостей. Для формування заданого тиску у відповідному соплі наступна нейромодель оцінює тривалість і полярність напруги, що управляє електроприводом регулюючого клапана сопла в режимі реального часу.

Конвеєр малорозмірних моделей є перспективним рішенням для керування гідроабразивною обробкою металів таких напрямків як заокруглення гострих кромок; шліфування та полірування складних поверхонь; видалення задирок та зачищення зварних швів; підготовка поверхні до нанесення покриття; видалення дефектів із поверхні; високоточне гідроабразивне різання металів. У комплексі з іншими заходами щодо автоматизації модернізованих ліній сірчанокислотного травлення рішення дозволить знизити витрати сірчаної кислоти та збільшити швидкість ТП з 1,2 до 1,96 [м/с]. З урахуванням малої розмірності моделей та відносно невисокої швидкості ТП програмний додаток, заснований на запропонованих моделях, може бути реалізований у системі керування гідрообробкою металопрокату у вигляді недорогого мікроконтролерного модуля ІІОТ.

Ключові слова: струменева гідрообробка, поверхневий дефект, інтелектуальне керування, нечіткий класифікатор, метод c-means, РБНМ.

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ИНТЕЛЛЕКТУАЛЬНЫЕ МОДЕЛИ УПРАВЛЕНИЯ СТРУЙНОЙ ГИДРООБРАБОТКОЙ ДЕФЕКТОВ ПРОКАТА

Представлена структура интеллектуальной системы управления гидрообработкой поверхностных дефектов проката, которая соответствует концепции общеевропейской программы «Индустрия 4.0» по направлению энергосбережения и автоматизации.

технологических процессов.

Рассмотренные локальные RBNN модели гидрообработки настроенны с помощью алгоритма Качмажа-Видроу-Хоффа. Модель идентификации текущего задания давления рабочей жидкости учитывает взаимосвязь между толщиной обрабатываемого дефекта, изменениями состава рабочей жидкости и, как следствие, ее абразивных свойств. Для формирования заданого давления в соответствующем сопле следующая нейромодель оценивает длительность и полярность напряжения, управляющего электроприводом игольчатого клапана сопла в режиме реального времени.

Конвейер малоразмерных моделей является перспективным решением для управления гидроабразивной обработкой металлов таких направлений: скругление острых кромок; шлифовка и полировка сложных поверхностей; удаление заусенцев и зачистка сварных швов; подготовка поверхности к нанесению покрытия; удаление дефектов с поверхности; высокоточная гидроабразивная резка металлов. В комплексе с другими мероприятиями по автоматизации модернизированных линий сернокислотного травления решение позволит увеличить скорость ТП с 1,2 до 1,96 [м/с]. С учетом малой размерности моделей и относительно невысокой скорости ТП программное приложение, основанное на предложенных моделях, может быть реализовано в системе управления гидрообработкой металлопроката в виде недорогого микроконтроллерного модуля IIОТ.

Ключевые слова: струйная гидрообработка, дефект поверхности, интеллектуальное управление, нечеткий классификатор, метод с-средних, РБНС.

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INTELLIGENT MODELS FOR CONTROL OF JET HYDRO-PROCESSING OF ROLLED STEEL DEFECTS

The structure of an intelligent control system for the hydro-processing of surface defects in rolled products is presented, which corresponds to the concept of the European program "Industry 4.0" in the direction of energy saving and total automation of processes.

The considered local RBNN hydro-processing models are tuned using the Kaczmarz-Widrow-Hoff algorithm. The model for identifying the current task of the pressure of the processing fluid takes into account the relationship between the thickness of the processed defect, changes in the composition of the working fluid and, as a result, its abrasive properties. To form a given pressure in the corresponding jet, the following neural model estimates the duration and polarity of the voltage that controls the electric drive of the jet control valve in real time.

The small-dimensional models' conveyor is a promising solution for controlling waterjet processing of metals in such areas as rounding sharp edges; grinding and polishing complex surfaces; deburring and cleaning of welds; surface preparation for coating; removal of defects from the surface; high-precision waterjet cutting of metals. The solution will increase the speed of TP from 1.2 to 1.96 [m/s]. Taking into account the small dimensions of the models and the relatively low speed of the TP, a software application based on the proposed models can be implemented in the control system for the hydro-processing of rolled metal products in the form of an inexpensive IIOT microcontroller module.

Keywords: jet hydro-processing, surface defect, intelligent control, fuzzy classifier, c-means method, RBNN.