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NEURAL NETWORK MODELING OF HYDRODYNAMICS PROCESSES IN THE CENTRIFUGAL PUMP AND OIL PIPELINE

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Abstract. Artificial neural network using for hydrodynamics processes studying is presented by two fundamentally different approaches. The first one is the neural network using for the direct differential hydrodynamics equations solution. Theses equations describe the 2D and 3D turbulent isothermal flow of the viscous incompressible liquid in centrifugal pump flowing area model.

Neural network solution results of hydrodynamic equations for the computational zone that consists of two sub-domains are given below. One of these is rotating, and the second one is immobile. In this case at the neural network algorithm realization it is not required to specify the conjugate conditions at the two sub-domains border. The second approach consist in neural network structures application for the computational experiment results approximation obtained after using of traditional methods of computational hydrodynamics and for obtaining of hydrodynamic processes multifactor approximation models.

The present approach is illustrated by the hydrodynamics processes neural network modeling in pipeline in the case of medium leakage through the wall hole.

Keywords: centrifugal pump; pipeline; hydrodynamics; neural network modeling

I. Introduction

The idea of application of ANN methodology for the mathematical physics equation solution is not a new one and it is presented in the number of publications, which are reviewed in the reference book [1]. It is also noted there that the application of ANN for hydrodynamics problem simulation is very limited. In particular, among of 2342 publications mentioned in [1], only one [2] deals with hydrodynamics. Some other techniques of neural networks CFD methods have been described in papers [3-5]. Artificial neural network using for hydrodynamic processes studying is presented by two fundamentally different approaches. The first one is the Neuronet's Method of Weighted Residuals (NMWR) using for the direct differential hydrodynamics equations solution. The NMWR description and its example realization for Navier-Stokes equations solution is given in papers [6-8]. Theses equations describe the 2D laminar isothermal flow of the viscous incompressible liquid. In the paper [9] the NMWR is used for simulation of flows in a channel with permeable wall. Neural network solution results of hydrodynamic equations for the 2D computational zone that consists from two sub-domains are given in [10]. One of these is rotating, and the second one is immobile. In this case at the NMWR algorithm realization it is not required to specify the conjugate conditions at the two sub-domains border. Neural network modeling results for the 3D rotating cylindrical zone are given below.

The second approach consist in neural network structures application for the computational experiment results approximation obtained after using of traditional methods of computational hydrodynamics and for obtaining of hydrodynamic processes multifactor approximation models. The present approach is illustrated by the hydrodynamics processes neural network modeling in pipeline in the case of medium leakage through the wall hole.

II. Study algorithm

To investigate the ANN approximated capabilities the perceptron with the single hidden layer (SLP) has been chosen as a basic model which performs nonlinear transformation of the input space into the output space in accordance with the formula [11]:

$$y(\mathbf{w},\mathbf{x}) = \sum_{i=1}^{q} v_i f_\sigma\left(b_i + \sum_{j=1}^{n} w_{ij} x_j\right) + b_0, \tag{1}$$

where $\mathbf{x} \in \mathbf{R}^n$ – network input vector, made up of the values x_j; q – the neuron number of the single hidden layer; $\mathbf{w} \in \mathbf{R}^S$ – all weights and network thresholds vector; w_{ij} – weight entering the model nonlinearly between j-m input and i-m neuron of the hidden layer; v_i – output layer neuron weight corresponding to the i-neuron of the hidden layer; b_i, b_0 – thresholds of neurons of the hidden layer and output neuron; f_σ – activation function (in our case the logistic sigmoid is used). ANN of this structure already has the universal approximation capability, in other words it gives the opportunity to approximate the arbitrary analog function with any given accuracy. The main stage of using ANN for resolving of practical issues is the neural network model training, which is the process of the network weight iterative adjustment on the basis of the learning set (sample) $\{\mathbf{x}_i, y_i\}$, $\mathbf{x}_i \in \mathbf{R}^n$, $i = 1,\ldots,k$ in order to minimize the network error – quality functional

$$J(\mathbf{w}) = \sum_{i=1}^{k} Q\big(f_\varepsilon(\mathbf{w}, i)\big), \tag{2}$$

where w – ANN weight vector; $Q(f_\varepsilon(\mathbf{w},i)) = f_\varepsilon(\mathbf{w},i)^2$ – ANN quality criterion as per the i-training example; $f_\varepsilon(\mathbf{w},i) = y(\mathbf{w},\mathbf{x}_i) - y_i$ – i-example error. For training purposes the statistically distributed approximation algorithms may be used based on the back error propagation or the numerical methods of the differentiable function optimization.

Suppose that some equation with exact solution $\bar{y}(x)$

$$L(\bar{y}) = 0 \qquad (3)$$

for not digital value y^s (3) presents an arbitrary $\mathbf{x}^s$ in learning sample. We have $L(y)=R$ with substitution of approximate solution (1) into (3), where R is equation residual. R is continuous function $R=f(\mathbf{w},\mathbf{x})$ and it is a function of SHL inner parameters. Thus, ANN training under outlet functional consists in inner parameters definition through trial solution (1) for meeting the equation (3) goal and its solution is realized through the corresponding modification of functional quality (2) training.

Usually total squared error at net outlets is presented as a objective function at neural net training and an argument is the difference between the resulted 's' net outlet and the real value that is known a priori. This approach to neural net utilization is generally applied to the problems of statistical set transformation and the reveal of the unknown a priori function values (net outlet) from the argument (net inlet). As for simulation problems, they are connected with mathematical representation of physical laws and modification of them to the form being applied in practice [12,13]. Usually, it is connected with the necessity of development of digital description of the process to be modeled [14]. Under such conditions we meet the necessity to exclude from objective function the computation result known a priori and the transfer to its functional task. Then the objective function during known law simulation will be defined only by the inlet data and the law which we simulate:

$$E = \frac{1}{2}\sum_S \left(y^s - f\left(\mathbf{x}^s\right)\right)^2 . \qquad (4)$$

The parameters optimization of the neural network trial solutions is achieved by the application of several optimization strategies and subsequently by choosing the maximum effective one [15]. The first strategy is the application of totality effective gradient methods "starting" from various initial points. The second strategy is the application for the ANN training of the structural-parametrical optimization based on an indirect statistic optimization method on the self-organizing (IOSO) basis or parameters space research [16].

Any versions of multi-criterion search of several equations system solution are based on different methods of generating of the number of solutions, satisfying Pareto conditions. The choice of candidate solution out of Pareto-optimal population must be based on the analysis of hydrodynamic process and is similar to identification procedure of mathematical model. In any case the procedure of multi-criterion optimization comes to the solution of composition of single-criterion problems, out of which a lot of possible solutions are formed.

In each specific case, the use of NMWR requires the preliminary systematic study, aimed at: 1) defining the number of calculation nodes (i.e. the size of the calculation grid), 2) finding the number of neurons in the network, necessary for attaining proper approximating power, 3) the choice of initial approximations for training neural network test solution; 4) the selection of the additional criteria in the goal function for regularization of the training procedure, as to avoid possible non-uniformity of the solution; 5) the analysis of possibilities of applying the multi-criteria algorithms of optimization in search of neural network solution parameters (provided that several criteria of optimization are available).

III. Modeling Flows in Rotating Ring Zone. The Equations That are Applicable to Rotating reference Frame

For this flow, NMWR solves conservation equations for mass and momentum.

Continuity equation

$$\frac{\partial \overline{u}_j}{\partial x_j} = 0. \tag{5}$$

Momentum equations

$$\frac{\partial}{\partial x_j}\left(\overline{u_i u_j}\right) + \frac{\partial}{\partial x_j}\left(\overline{u_i' u_j'}\right) = -\frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j}\left[\mu\left(\frac{\partial \overline{u_i}}{\partial x_j} + \frac{\partial \overline{u_j}}{\partial x_i}\right)\right] + f_i. \tag{6}$$

For flows in rotating domain (fig. 1), the equations for conservation of mass and momentum are written for the relative velocity formulation, where f_i in right hand side is given by

$$\vec{f}_i = -\rho\left(2\vec{\omega} \times \vec{u} + \vec{\omega} \times \left(\vec{\omega} \times \vec{r}\right)\right).$$

The absolute velocity formulation is used in the not rotating domain, and f_i=0. Thus, the standard k-ε turbulence model is used.

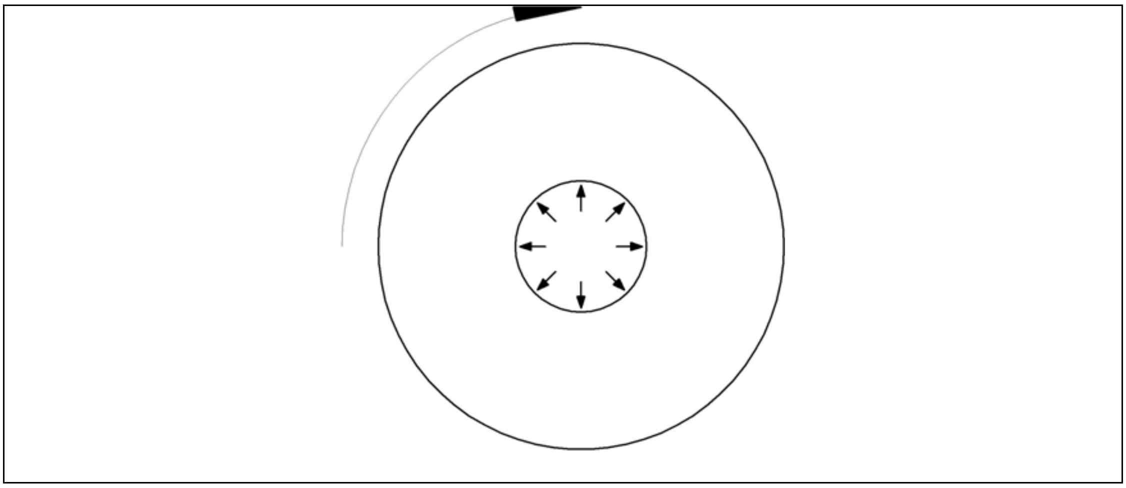

Figure 1. Rotating Domain

Let's understand under equations solution the neural network functions $\bar{u}_i, p, k, \varepsilon = f_{NN}(\mathbf{w}, x, y)$, where $\mathbf{w}$– all weights and network thresholds vector that assure summary quadratic residuals minimums for each equation in optional totality of computation nodes which coordinates on each neural network solution learning iteration are generated using the random number generator.

The search process efficiency of neuronet learning solution parameters depends on problem dimension, i.e. weights and perceptron thresholds varying adjusted quantity. The more important neurons quantity in the trial solution, the more artificial neural network (ANN) approximate capacity, but it is more difficult to achieve the high approximation accuracy.

At the same time the neuron quantity depends not only on simulated function complexity, but also on calculation nodes quantity in which the residual equation is calculated. It is the known fact that generally the point's quantity increase in the statistical set used for neural network construction results in increase in necessary neurons network quantity. Consequently, the dense calculation grids application results in nonlinear programming problems, at the application of rare calculation grids it is necessary to check the solution realization between calculation nodes, i.e. there is a problem of the learning solution procedure standardization. In the neuronet solution reception context on the known equation it is convenient to use the traditional additional parameter of the training neural model quality - a control error which is calculated on the set of additional calculation nodes taking place between calculation grid nodes. The number of these additional calculation grid nodes can be much more important and they should cover all calculation area because the nodes number increase in which the control error on known network parameters does not result in essential computing expenses growth. Hence, at the learning solution neuronet parameters reception there is a problem of solving the multi-criterion problem of the nonlinear optimization and to minimize simultaneously both the summary residual in control points, or the control error can appear as a restriction parameter, in the limited set of calculation nodes and in this case the neural network solution parameters reception is reduced to the conditional nonlinear optimization problem.

On figure 2 it is presented the vector of distribution of velocities in the current random computation nodes of revolving ring on one of the iteration of the neural network training of the decisions of the equations (5)-(6).

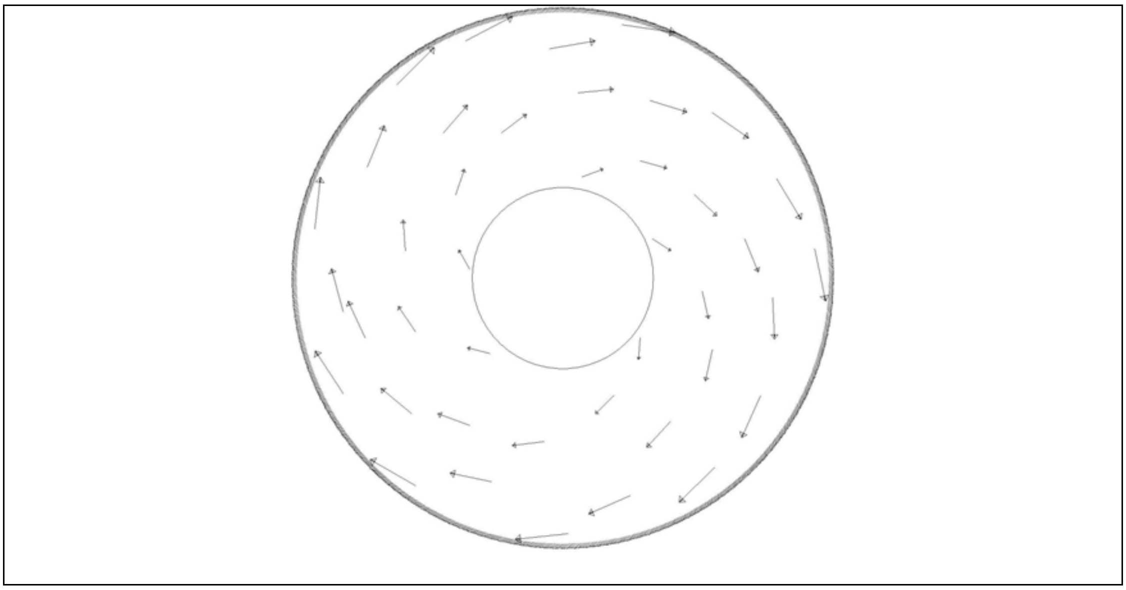

Figure 2. Velosity distribution on one of the iteration of the neural network training

The contours of stream function in the computational zone obtained with the NMWR using are presented in the fig. 3.

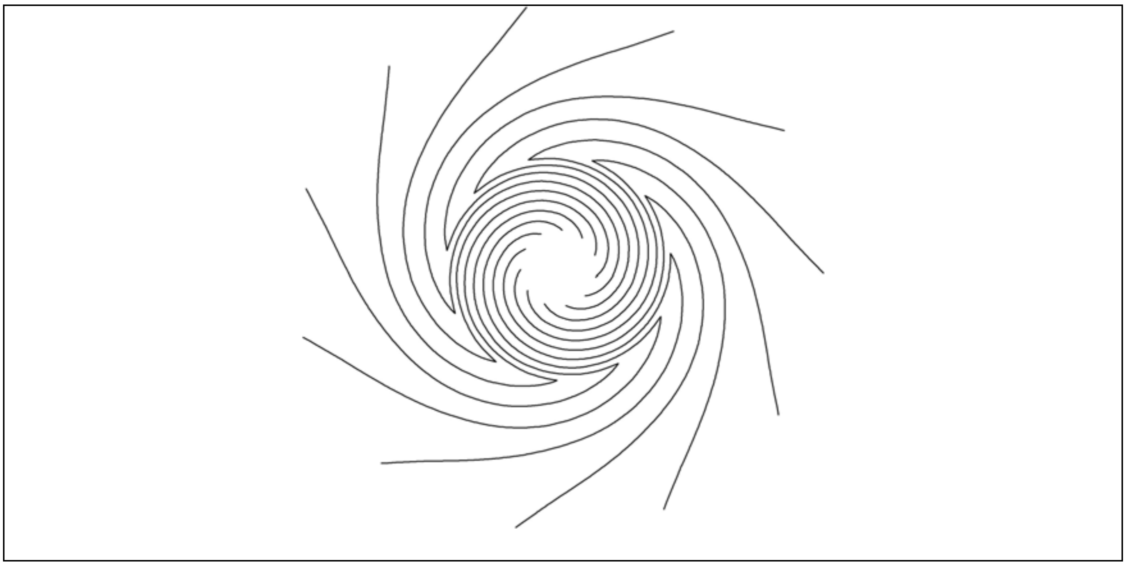

Figure 3. The contours of stream function

The stated method is easy for generalizing on a three-dimensional case. In this case it is possible to use the geometrical model represented in fig. 4. I.e. instead of a rotating ring for 2D models the rotating "liquid" cylinder with certain angular speed which can be varied is used. The liquid supply is carried out symmetrically from the cylinder opposite sides. Thus the centrifugal pump with two inputs is modelled. Similar results for 3D case are resulted in figures 5-7.

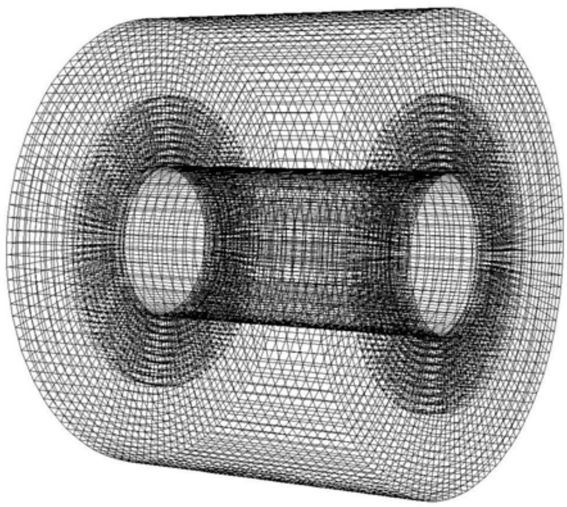

Figure 4. Geometrical model of the rotating "liquid" cylinder

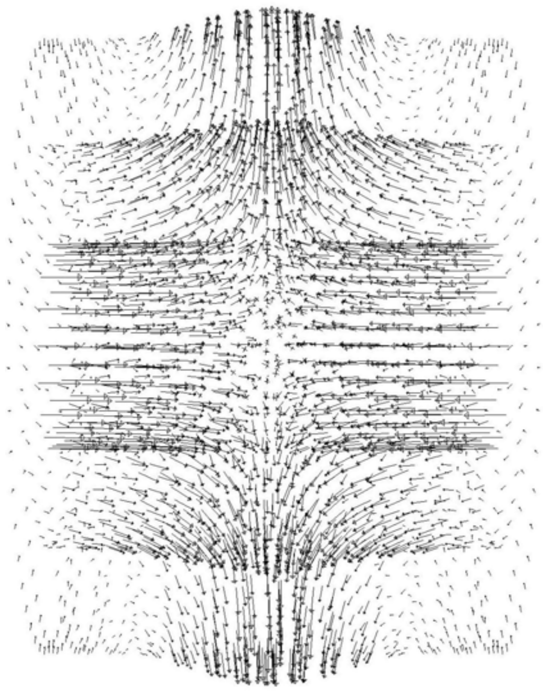

Figure 5. Vectors of velocity distribution

In figure 6 t is represented such four blades located with angular step of 90 degrees from each other.

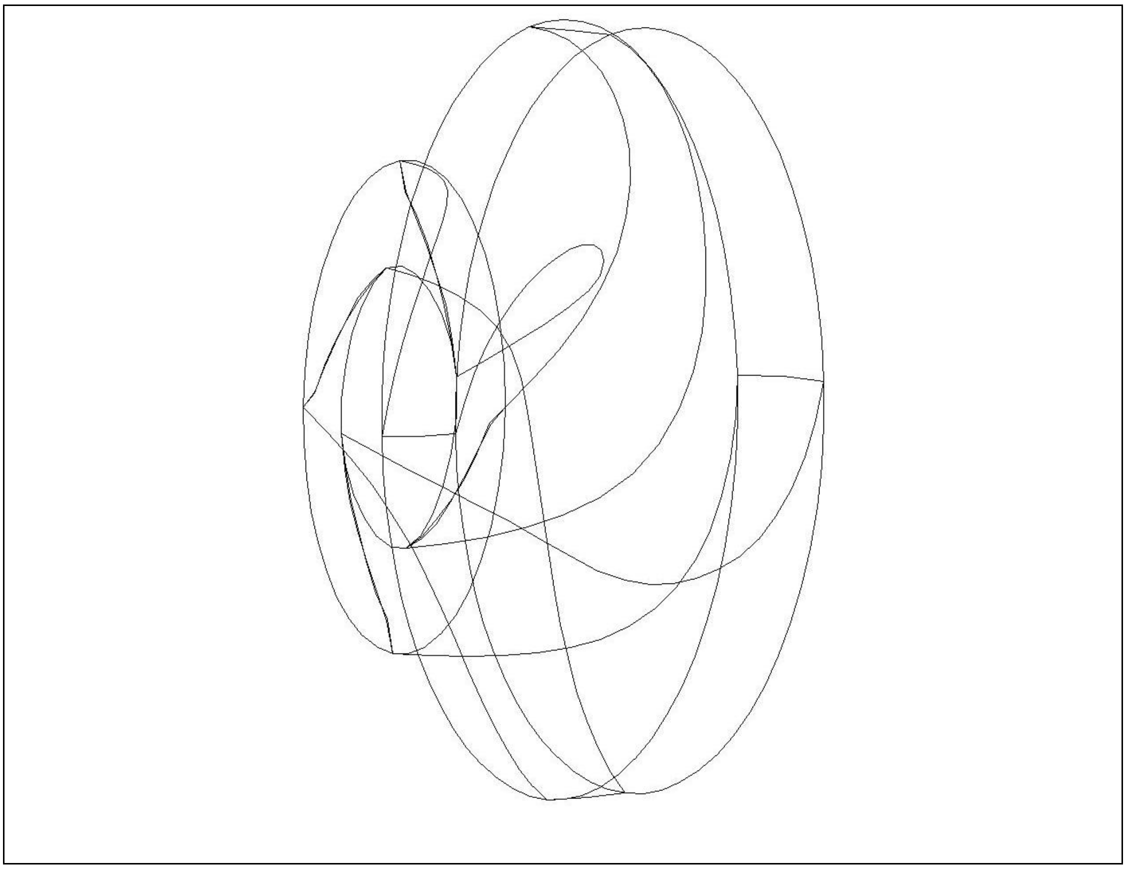

Figure 6. Four centrifugal blades

IV. Modeling Leakage in a Oil Pipeline

For definition of the leakage position from the pipeline the method of the zone location of leakages [17] which generalizes the known method of detection of the leakages by the salient point of the hydraulic gradient line can be used. By the use of "base" variant of the method of the zone location it is supposed that in case of stationary process hydraulic gradients i_1 and i_2 before and after the leakage is constant and can be designed by the known values of the charge of liquid on the ends of the controllable site. I.e., the indignation of distribution of hydrodynamical parameters is not taken into account in comparison with the established flow which arises because of the influence of the outflow of environment through the aperture of the leakage. It results in deformation of the profile of speed in the cross sections of the pipeline in the vicinity of the leakage and the nonlinear dependence of the hydraulic gradient in the function of distance from the position of the leakage downwards on the stream. In order that distribution of speed in cross section of the pipe becomes again appropriate to the established flow, the distance up to 40-60 calibres from coordinate of the leakage x_y

can be demanded. The definition of nonlinear dependence of function of the hydraulic gradient in the neighbourhood of the leakage is possible either on the basis of the special experimental researches, or on the basis of the numerical decision of the equations of hydrodynamics in three-dimensional statement. The given function can be added to the algorithm of the method of the zone location for reduction of the error of definition of coordinate of the position of the leakage.

One pipeline section of the 300 meters length and diameter $D = 1\ m$ is used for the nonlinear dependence of the total pressure drop determination along the pipeline length in the leakage neighborhood through the wall hole. The leakage position coordinate is fixed $x_y = 155.5\ m$. On the segment $x \in [140,200]\ m$ computational faces are formed with an interval $h = 1\ m$. In segments $x \in [100,140]\ m$ and $x \in [200,250]\ m$ computational faces are disposed with an interval $h = 10\ m$. Such a leakage location (approximately in the middle of the pipeline sector into a question) and computational faces disposition have been chosen for the influence elimination of the boundary conditions setting in the computational zone inlet and outlet on the flow distribution near leakage position. The leakage hole D_l/D relative diameter during the computational planed experiment is constant. The mathematical model includes conservation equations for mass and momentum enclosed by the standard $k-\varepsilon$ turbulence model. The local hydraulic friction coefficient in any section of the pipeline is defined by the ratio

$$\lambda = -\left[8\mu \left.\frac{\partial u}{\partial r}\right|_{r=R} \right] \Big/ \left(\rho \bar{u}^2\right),$$

where $|\bar{u}| = \frac{1}{R^2}\int_0^R 2urdr$ - the average speed in the design section, μ - the dynamic factor of viscosity of the liquid. The distribution of speed at the turbulent flow in cross section of the pipe is described by the universal logarithmic dependence

$$\frac{u}{u_*} = A \lg \frac{u_* y}{\nu} + B,$$

where $u_* = \bar{u}\sqrt{\frac{\lambda}{8}}$ - the dynamic speed, y - the distance from the wall, ν - the kinematic viscosity.

At the statement of boundary conditions on the input the mass charge m_1 or the speed $\bar{u}_1$ appropriate to this charge is set. In the units of grid belonging to the aperture of the leakage, the speed of outflow of liquid u_y is appointed. The given parameter at the numerical researches varies for the modeling leakages of various intensity. In any point of the calculating area any operational value of pressure $\partial/\partial x$ of all the hydrodynamical parameters are equaled to zero, for the concerning of which differences of pressure will be calculated, is set. On the output from the calculating area the conditions of the established current are set, i.e. the derivatives modeling of the boundary layer the standard wall functions for parameters of turbulence k, ε [18] are used.

The equations discretization is effectuated on the base of finite volumes method in the combination with hexagonal grid.

The plan of computing experiment

If x_1, x_2 - are the coordinates of the beginning and the end of the controllable pipeline sector, i_1, i_2 - are the hydraulic gradients accordingly before and after the leakage, Δp_0 - are the total pressure drop on the sector, so in case of $i_1 = const$ from the beginning of the sector to the leakage and $i_2 = const$ from the leakage up to the end of the sector, in the stationary hydrodynamical mode the coordinate of the leakage is defined by the formula

$$x_y = \frac{\Delta p_0 + \rho g(i_1 x_1 - i_2 x_2)}{\rho g(i_1 - i_2)}.$$

Let's present the total pressure drop nonlinear dependence for its calculation in the leakage neighbourhood in nonlinear function form $i = f_{NN}^i(i_1, i_2, x - x_{NN})$ on the pipeline sector $x \in [x_{NN}, x_{NN} + l_{NN}]$, where for our computational model the left area limit coordinate of the nonlinear leakage function determination $x_{NN} = 150\ m$ and the determination length fragment area $l_{NN} = 60\ m$ (the leakage is situated in the point which coordinate is $x_y = 155{,}5\ m$). In this case total pressure drop in the controlled sector $[x_1, x_2]$ are calculated in correspondence with the following formula

$$\frac{\Delta p_0}{\rho g} = i_1(x_{NN} - x_1) + i_2(x_2 - (x_{NN} + l_{NN})) + \int_0^{l_{NN}} f_{NN}^i(i_1, i_2, x - x_{NN})dx.$$

At the known function $f_{NN}^i(i_1, i_2, x - x_{NN})$ the present equation is nonlinear with one unknown value x_{NN}. After solving this equation we can determinate the pipeline leakage coordinate x_l.

Starting from above-mentioned the computational experiment is effectuated with the purphose of the function determination $f_{NN}^i(i_1, i_2, x - x_{NN})$, i.e. the total pressure drop dependence in the leakage neighbourhood i (criterion) of three variables $i_1^{NN} = \rho g i_1$, $i_2^{NN} = i_2 / i_1$ and $\Delta x_{NN} = x - x_{NN}$ (factors). Earlier the interval of the variation of the factor $\Delta x_{NN} \in [0{,}60]$ was determined. Let's determine the intervals $i_1^{NN} \in [10{,}20]$, $i_2^{NN} \in [0{,}5{,}0{,}95]$. The plan of the computing experiment is made with the points received with the help of the generator of the quasiuniform sequences of numbers of Sobol-Statnikov [19]. The working hypercube of space $\mathbf{R}^3$ is filled by the points $\left(i_1^{NN}, i_2^{NN}, \Delta x_{NN}\right)$ according to LP_τ algorithm [19]. The choice of this algorithm for the formation of the plan of experiment is caused by high efficiency of the method of research of space of the parameters based on the sounding of computational area by points of the uniform distributed sequence.For each variable parameters combination i_1^{NN}, i_2^{NN} from the experiment plan limitation boundary conditions in the computational model are selected by the way of determination of values correspondent of the inlet mass flow $\dot{m}_{in}$ and leakage intensity m_l.

$$\overline{u}_{\theta x} = \frac{4m_{\theta x}}{\rho\pi},\; i_1^{NN} = \rho\lambda\frac{\overline{u}_{\theta x}^2}{2},$$

where the hydraulic friction coefficient is calculated by the implicit formula of Altschul for "smooth" pipes

$$\frac{1}{\sqrt{\lambda}} = -2{,}04\lg\left(\frac{2{,}82}{\mathrm{Re}\sqrt{\lambda}}\right).$$

In result of the computational hydrodynamics equations decision we obtain the value distribution of total pressure drop on the length of the controlled pipeline sector, from which we are exterminating the criteria value *i* for the corresponding value Δx_{NN} from the experiment plan Let's register the obtained vector $\left(i_1^{NN}, i_2^{NN}, \Delta x_{NN}, i\right)$ in database for the posterior generation of neural network dependence $i = f_{NN}^{i}\left(i_1^{NN}, i_2^{NN}, \Delta x_{NN}\right)$.

For the illustration of numerical calculations on figure 7 the distribution of speed in the leakage neighbourhood.

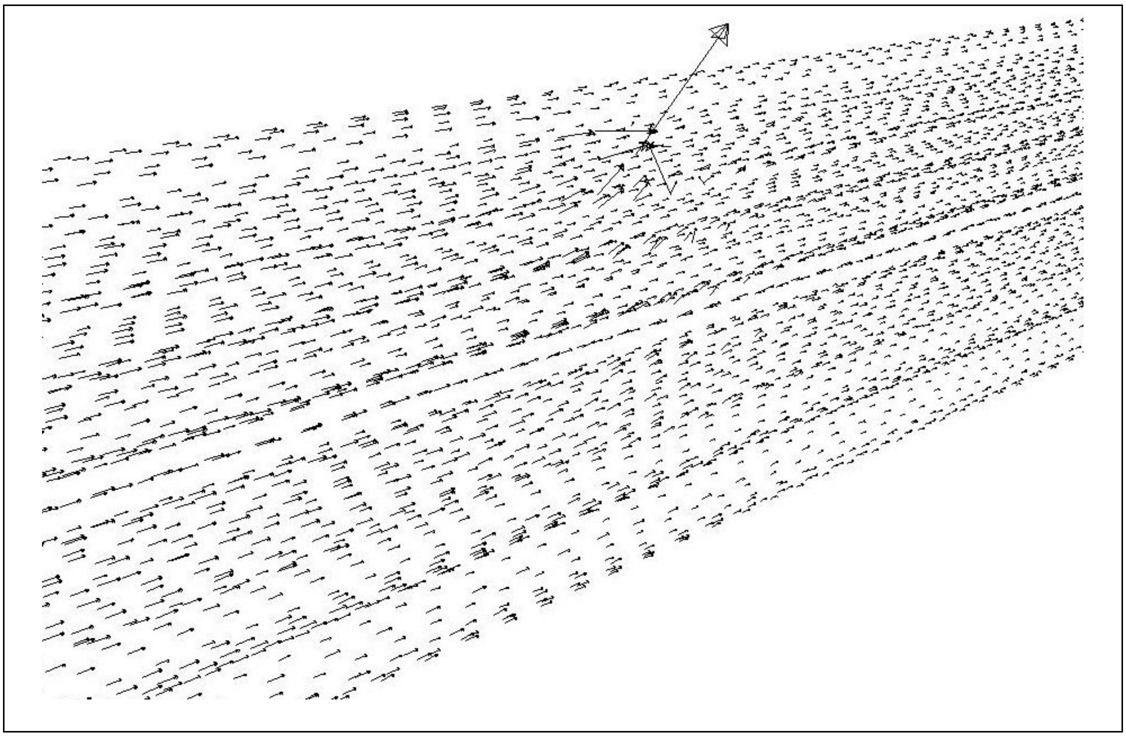

Figure 7. The distribution of speed in the leakage neighbourhood

The neural network regressive model

For the construction of the regressive dependence $i = f_{NN}^{i}\left(i_1^{NN}, i_2^{NN}, \Delta x_{NN}\right)$ the device of the artificial neural networks is used. For the formation of display $i = f_{NN}^{i}\left(i_1^{NN}, i_2^{NN}, \Delta x_{NN}\right)$ the standard structure of the multilayer perceptron (MLP) with 3 inputs, one output and two latent layers with 7 and 5 neurons accordingly was used. At training MLP algorithm of Levenberg-Markardt was used. The sum mean-root square error on 512 points of statistical sample has made *E=0.001*.

The comparative analysis of dependences calculation results obtained for inlet parameters values $\rho g i_1 = 16\,\frac{Pa}{m}$, $i_2/i_1 = 0.9$ is presented in the fig. 8 and $\rho g i_1 = 10\,\frac{Pa}{m}$, $i_2/i_1 = 0.8$ for $\Delta x_{NN} \in [0{,}60]\,m$ from the differential equation computational solution– continuous lines and determined with neural network dependence – markers. It is necessary to note the high approximation precision.

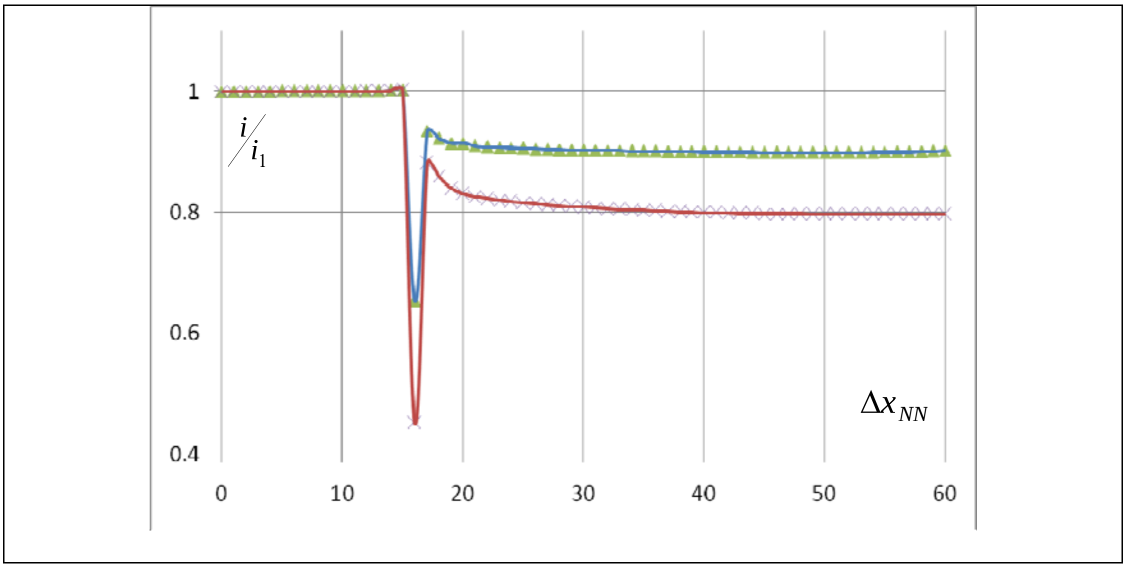

Figure 8. Comparative analysis of neural network data and results of the numerical solution

Conclusion

The results presented in this article concern one of many applications of neural network learning functions to the mathematical physics problems solution - to the solution of the hydrodynamics equations. Neural network learning functions application allows to remove the differential equations errors solution caused by derivatives discretization and the borders low precision representation. The numerical algorithm of Navier-Stokes equations system solution differing from known fluid dynamics methods by an opportunity of the arbitrary formation of the computational grid is developed.

The formation of the finite-elemental models of all extended pipelines or centrifugal pumps and the numerical decision of the equations of movement of the liquid for modeling of the hydrodynamics processes now is limited to the resources of computers as by the quantity of the final elements of the calculated grid of model, so as by the time of finding of the decision. Even at presence of such model, its use for the operative analysis of functioning of system is rather doubtful. However, the numerical models of hydrodynamics processes can be used for the formation of the information databases constructed on the basis of the neural network of computing architecture which after "training" have high speed of realization of calculations. Neural networks are the universal approximation tool of the multivariate nonlinear dependences, capable "to be arranged" under the appearing of the new information of the researched process, i.e. they can serve as the intellectual tool of monitoring which is constantly filled up and clarified. Thus, the introduction of the neural algorithms in the approved and well recommending methods of detection of the leakage in the pipelines and for search of optimum centrifugal pump design is expedient for the increase of the accuracy and the efficiency of the accepted decisions.

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НЕЙРОСЕТЕВОЕ МОДЕЛИРОВАНИЕ ГИДРОДИНАМИЧЕСКИХ ПРОЦЕССОВ В ЦЕНТРОБЕЖНОМ НАСОСЕ И НЕФТЕПРОВОДЕ

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Аннотация. Использование искусственных нейронных сетей (ИНС) для исследования гидродинамических процессов представляется двумя принципиально разными подходами. Первый заключается в использовании численного метода взвешенных невязок (НМВН) на основе нейросетевых пробных функций для непосредственного решения дифференциальных уравнений гидродинамики. Суть метода состоит в модификации выражения для функционала качества работы нейросети таким образом, что ошибка работы сети оценивается как суммарная невязка решаемых уравнений в произвольных точках расчетной области, количество и координаты которых меняются на каждой итерации. В предыдущих работах приводится описание НМВН и пример его реализации для решения уравнений Навье-Стокса, описывающих 2D ламинарные изотермические течения вязкой несжимаемой жидкости. В статье представлены результаты нейросетевого решения уравнений движения жидкости для расчетной области, состоящей из двух подобластей, одна из которых вращается, а другая неподвижна. Результаты моделирования использованы для профилирования пространственной лопасти центробежного насоса. Второй подход заключается в применении нейросетевых структур для аппроксимации результатов вычислительного эксперимента, полученных с использованием традиционных методов вычислительной гидродинамики, и получения многофакторных аппроксимационных моделей гидродинамических процессов. Данный подход иллюстрируется нейросетевым моделированием гидродинамических процессов в трубопроводе при наличии утечки среды через отверстие в стенке.

Ключевые слова: центробежный насос, трубопровод, гидродинамический, нейросетевое моделирование

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