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APPLICATION OF INTELLIGENT PROCESSING OF DATA FLOWS UNDER CONDITIONS OF RIVER NAVIGATION

V. Panin
Doctor of Technical Sciences, Professor, Rector*
E-mail: academy@maritime.kiev.ua
V. Doronin
PhD, Associate Professor
Department of Technical Systems and Control Processes in Navigation *
E-mail: doronin_vladimir@ukr.net
I. Tykhonov
PhD, Associate Professor
Department of Navigation and Ship Management*
E-mail: itykhonov@i.ua
M. Alieinikov
Postgraduate student
Department of Technical Systems and Control Processes in Navigation*
E-mail: Alieinikov@ukr.net
*State University of Infrastructure and Technologies
Kyrylivs'ka str., 9, Kyiv, Ukraine, 04071

Розглянуто реалізацію контекстно-орієнтованого підходу під час інтелектуальної обробки потоків навігаційних даних при експлуатації водних транспортних засобів. Початкова вибірка обробки потоків даних в умовах діючого лоцманського методу навігації не відповідає закономірностям функціонування складного об'єкта при сучасному інструментальному методі навігації. Вирішення завдання полягає в подоланні труднощів шляхом визначення комплексних проблем процесів, що відрізняються від простої суми властивостей елементів з однотипними багаторівневими зв'язками.

Запропоновано спосіб обробки потоку навігаційних даних у безперервному режимі. У процесі дослідження розглянуто комбінування інформації з багатьох джерел із знаходженням більш точних і достовірних даних. Методом оцінки вирішення завдань застосований критеріальний метод, де кожна окремо взята альтернатива оцінюється конкретним числом (критерієм, цільовою функцією). Порівняння альтернатив зводиться до порівняння відповідних чисел. Враховані різні варіанти вибору альтернатив і критеріїв оптимальності: критерії Байєса, Вальда, Джейнса, Лапласа. Використаний метод характеризується умовами багатокритеріальності. Застосовані методи прийняття рішень в іграх із зовнішнім середовищем, нормалізації, використання нейронних мереж, основою яких є контекст. Побудована архітектура штучної нейронної мережі.

Дослідження проводились з метою отримання стабільної структури системи з певними класами вхідних сигналів на штучних нейронних мережах. Цікавим з теоретичної точки зору є отримання параметричної варіації параметрів у заданих межах критеріїв оптимальності. Проведені експерименти підтвердили ефективність використання запропонованих методів. Найбільш конструктивним серед напрямів інтелектуальної обробки потоку навігаційних даних є контекстно-орієнтований підхід. Реалізація підходу гарантує високу якість дотримання критеріїв точності в умовах річкової навігації суден.

Прикладним аспектом використання отриманого в процесі дослідження результату є можливість відмовитися від лоцманського методу судноводіння, від установки берегових і плавучих засобів навігаційного обладнання. Важливим результатом є отримання диференційованого відображення масиву глибин на електронній карті. Одержані результати дають підстави стверджувати про можливість впровадження запропонованого контекстно-орієнтованого підходу в реальне судноплавство

Ключові слова: безпека судноплавства, електронна навігація, критерії руху, штучний інтелект, нейронна мережа

1. Introduction

River transport plays one of the key roles in maintaining sustainable development of the transport complex and improving the state's defense potential. An effective mechanism for the operation of water transport means is the transition to an instrumental navigation method (INM) instead of the existing pilotage method. The purpose of this transition is increasing the traffic safety on inland water ways (IWW) of Ukraine.

The transition to a modern navigation method includes harmonized measures for acquisition, integration, exchange, representation, and analysis of information on ships and in coastal services with the help of information technologies [1]. When the INM is used, information from many sources is combined and reliable data on the situation are found. These data are more precise than those obtainable from separate sources.

In this case, intelligent processing of navigation data flows is used to solve in the first place the weakly structured problems of implementation of the INM system, that is, the problems in which composition of elements and relationships between them are established just partially and they usually arise in situations characterized by the presence of an uncertainty factor. These problems include both formalized and non-formalized elements. There are no universal procedures and methods for intelligent processing of navigation data flows. Determination of the system functioning regularities, options of the data stream structure and choice of the best option are common for all procedures of data flow processing. In addition, the context-oriented approach is the most constructive of all ways of intelligent processing of navigation flow data. Such an approach involves application of the methods and models of the decision-making support system (DMSS) for practical application of these decisions [2].

Problematic situations occurring in navigation of water transport means (WTM) on Ukrainian IWW require elimination of contradictions and conflicts inherent in conventional technologies of using data of the inland electronic chart system, or Inland ECDIS, and introduction of the latest methods of information technology (IT) [3].

The relevance of this study consists in obtaining higher probability of safe navigation of WTM by a differentiated plotting of an array of depths on an electronic chart. The most important aspect of the studies is the possibility of abandoning the installation of coastal and floating means of navigation equipment, which will ensure a significant economic effect at a national scale. In addition, it should be noted that introduction of the present-day navigation method will ensure a rapid closure of navigation on the fairway and piloting only selected vessels over a special period.

2. Literature review and problem statement

The problem of using the system for providing the INM on the IWW of Ukraine which is currently under study was not completely elucidated till now. Some of its issues have been explored superficially and cursorily. As the analysis showed, a scientifically grounded approach to this issue was considered just in the form of hypotheses without theoretical substantiation [4].

The issues of the primary and secondary positioning used in the ECDIS system were considered in [5]. However, only the standard positioning methods were described. The problem of ensuring automatic and manual realization of the received positions in the ECDIS was considered in a form of discussion.

The potential risks identified in the course of study were associated with a lack of knowledge of the ECDIS operators. Ideas on implementation of the captain's mate module in a mobile navigation system for inland waters were set forth in [6]. The proposed solutions of the problem were based solely on the mobile charts in the navigation systems and did not cover functioning of the system in general. The problems of developing and implementing electronic charts and information systems were outlined in [7] but the proposed architecture primarily concerned the use of the ECDIS in improvement of environmental protection. Realization of other aspects of navigation was considered in part and did not cover functioning of the system in general. In 2014, materials of a discussion concerning the introduction of electronic navigation were published [8]. The materials are based on the studies of revision of the current navigation concept. Issues of functioning of electronic navigation were touched indirectly, in a form of general information on river safety. A modern method for assessing the risk and vulnerability of water transport was presented in [9]. The studies conducted over the last sixty years have taken into account the specifics of navigation solely along the Danube River. Publication [10] is of the greatest interest. Importance of data, both static and dynamic, becomes more understandable. The comprehensive architecture of integration of various data flows in the S-100 format was presented as a conceptual framework for the overall structure. A general understanding of key players in the arena of electronic river navigation without concretizing was presented. Paper [11] proposed a method for eliminating disadvantages of existing radiotelephony and obtaining new advantages in the field of communication and navigation within the frames of existing common means. The proposed innovation was based on updating of the ECDIS software. At the same time, the standard ECDIS and Inland ECDIS configurations are different.

When applying the context-oriented approach to processing flows of navigation data, variants of choosing alternatives and optimality criteria were taken into account [12]. Such criteria are in a linear shell of elements of the linear space in conditions of uncertainty of Bayes, Wald, Jains and Laplace criteria [12, 13]. However, this concept does not refer to the given object but only to some of its properties. Numerous methods of decision making analysis [14] characterized by multicriteria conditions, for example, the methods of making decisions in games with environment, the method of normalization, the method of using neural networks were developed for many systems. However, in absence of information on the probability of environment states, there are no unambiguous and mathematically precise recommendations on the choice of decision-making criteria.

The classical theory of the use of multi-layered artificial neural networks provides criteria with the help of which the fact of use in the system can be established [15–17]. At present, a number of applied studies are known, which propose only simulation of dynamics of vessel movement based on the methods of neural network construction [18]. Paper [19] suggests construction of a neural network that predicts speed of the ship's drift under the influence of external factors, a procedure of forming samples for training and testing. In addition, study [20] addresses the problems of synthesis of neural network systems that predict parameters of vessel movement under conditions of influence of controlling and disturbing influences. The study deals with the synthesis of neural networks that predict drift acceleration and a derivative of angular speed of turning in time under conditions of external perturbations. At present, hybrid systems are increasingly being used to preserve the benefits of neural networks and fuzzy systems. Examples of hybrid neural-fuzzy systems that predict only kinematic parameters of the ship are described in [21].

In addition, it should be noted that the problems associated with the system of providing the INM were considered in [25], which proposed only the most important stage of introduction of a modern navigation system: a comprehensive implementation of system analysis of the problem situation taking into account specificity of movement of water transport means.

The problem is as follows. In order to achieve the set objective, it is necessary to sequentially solve a number of tasks related to the implementation of a distributed information and telecommunication system. The most important step in solving problems is the context-oriented intelligent processing of navigation data flows.

Let there be an initial sample of the task of processing navigation data flows in conditions of the current pilot navigation method (PNM):

$$A=\{a_k\},\ Z=\{z_{kn}\},\ P_{\mathrm{PNM}}=\{p_k\ (a_k,\ z_{kn})\},\ P^{(\mathrm{PNM})}=f(A,Z),$$

where $A=\{a_k\}$ is the set of the system elements; $Z=\{z_{kn}\}$ is the state of system elements; PPNM is the stream of navigation data in the conditions of the current PNM; P(PNM) is the processed stream of navigation data in conditions of the current PNM.

This does not correspond to the regularities of functioning of a complex object under the current INM because of existing local and branch tasks and principles of ensuring its life cycle. Solution of the problem consists in determining complex problems of the system object and the processes which differ from the simple sum of properties of elements with the same type of multilevel links. The initial sample for the task of processing navigation data flows in conditions of IMN takes the form:

$$\begin{aligned}&A=\{a_i\},\ Z=\{z_{ij}\},\ Q=\{q_{ij}\},\ D=\{A,\ Q\},\\&Z(t_1)\to Z(t_2)\to Z(t_3)\to \ldots,\ Z(t)=Fc\ [X(t)],\\&P_{\mathrm{INM}}=\{p_k\ (a_k,z_{kn},k_k)\},\\&P^{(\mathrm{INM})}=f(A,Z,K),\end{aligned} \qquad (1)$$

where $k\neq i,\ j\neq m$; $Q=\{q_{ij}\}$ is the set of links between the system elements; $D=\{A,\ Q\}$ is the set of the system elements and the links between them; P_{INM} is a stream of navigation data in conditions of a modern INM; $P^{(\mathrm{INM})}$ is the processed stream of navigation data under conditions of modern INM; K, k are the criteria of optimality.

It is necessary to solve the task of processing the flow of navigation data and functioning of the system in a continuous mode

$$f(x_0-0)=f(x_0+0)=f(x_0),\ \forall x\in R\ x(t)=T_t\,x(t_0),$$

where $x(t)$ is the attribute of a dynamic system under conditions of significant uncertainty and influence of environment on it; T_t is the evolution operator.

The criterion method is used as the method of assessing solution of the problems of context-oriented intelligent processing of the continuous stream of navigation data [17, 23] where each individual alternative is evaluated by a specific number (a criterion, a target function). Comparison of alternatives is reduced to a comparison of the corresponding numbers, that is, the target function $Z=f(x)$ is introduced for the whole set of alternatives $X=\{x_n\}$ and $Z'=f'(x)\Rightarrow$max or min. The values of $Z_{\min}<Z<Z_{\max}$ alternatives are expressed through scalar, vector, and plural quantities. Apply scales of intervals:

$$\frac{x_1-x_2}{x_3-x_4}=\frac{f(x_1)-f(x_2)}{f(x_3)-f(x_4)}=\mathrm{const},$$

where $f(x)=ah+b$ are the permissible linear transformations.

The main scale type is the scale of intervals since this type contains scales that are unique with an accuracy to a multitude of permissible positive linear transformations.

3. The aim and objectives of the study

The study objective was to determine the context-oriented approach to intelligent processing of data flows at the stage of implementation of the system of providing the INM on Ukrainian IWW which guarantees high compliance with the accuracy criteria in the conditions of river navigation.

To achieve the study objective, the following tasks were set:

– to define the conditions of safe navigation on Ukrainian IWW;

– to construct a model reflecting a real hierarchy of control tools that are interrelated and interdependent in a single INM system;

– to fix the level of the potential of quality of navigation parameters with the use of artificial intelligence and the use of elements of fuzzy logic;

– to take into account variants of the criteria of the source information for making automated decisions (AD) in conditions of uncertainty and risk;

– to establish stages of construction of a multi-criteria model with establishing a system of subject priorities which are built on artificial neural networks.

4. The materials and methods used in the study of intelligent processing of data flows

4. 1. Features of the context-oriented approach to data processing

The proposed context-oriented approach uses not only peculiarities of reality but also various aspects based on a certain set of problem fields.

The field of AD in this case is a multi-level structure which includes the field of problems, the field of models, the field of the method and the field of realization [24]. To use these features, we used the methodology of development of the DNSS which is based on the context as a means of integration of the methods of system and situational analysis, that is, information that can be used or that characterizes the process of problem solution [14]. Here, the use of the context is defined as a construct consisting of the concepts within corresponding contextual fields.

The proposed contextual structure consisting of contextual concepts that are interconnected through contextual relationships will be used to define essence within the limits of contexts. Based on the revealed properties of the context and the problems that arise when using the context, formulate the following requirements to the context management:

1) the context is described by a standardized method;

2) when presenting knowledge of the process of making AD, adhere to the operations necessary for presentation of the context and its control.

This will provide relevant, real and accessible information for solving a particular task or for understanding the current situation.

4. 2. Implementation of the context-oriented approach in processing of data flows

Implementation of the context-oriented approach during intelligent processing of data flows in the INM conditions is as follows.

1. The necessary condition for a safe pilotage of ships on the IWW of Ukraine consists in provision of a captain's watch assistant with reliable navigational information from the Inland ECDIS. Such information consists of a plurality of alternatives being processed. The integral information is represented in Inland ECDIS in a form of navigation parameters (NP).

The proposed model (Fig. 1) represents the real hierarchy of control tools that are interrelated and interdependent in the system. All these functions are combined into a single INM system which converts the available resources into target effects. It should be noted that the existing conventional navigation systems cannot realize the INM properties in unforeseen extreme situations [1].

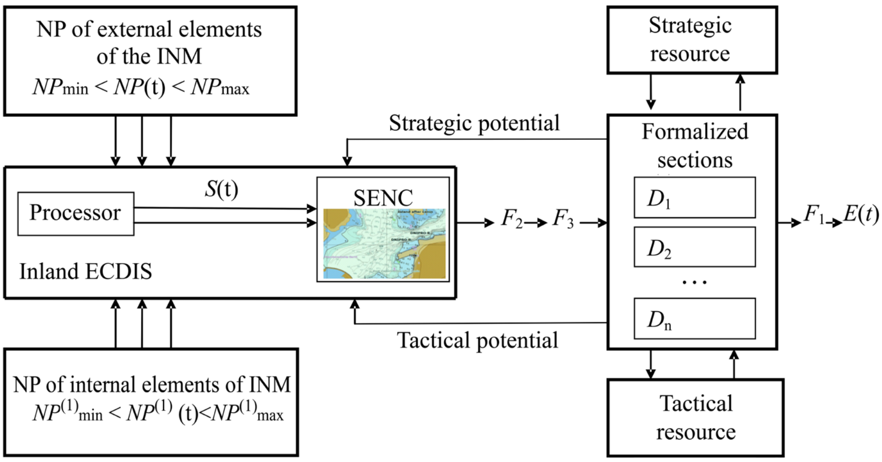


Fig. 1. Model representing a real hierarchy of control means

Designations in Fig. 1:

F1: safe navigation of water transport means (WTM);

F2: precise navigation service within F1 tasks;

F3: guaranteed adaptive control of the INM including movement of WTM.

$$S(t) \to F_2 \to F_3 \to F_1 \to E(t).$$

Let us fix the level of potential of the NP quality for the tasks of stabilizing the vessel movement and the functional stability of the INM system using the methodology of system optimization of the INM structure.

$$NP_{min} < NP(t) < NP_{max},$$

where NP_{min} and NP_{max} are the NP values which are substantiated and guarantee an appropriate quality of control parameters $U(t)$ within F_3 [1].

Taking into account the foregoing, Table 1 shows the NP for displaying navigation information on the system electronic chart (SENC). It should be noted that the choice of NP was made with the help of artificial intelligence using the elements of fuzzy logic. In contrast to the traditional use of fuzzy logic, a hybrid approach was used. With this approach, in various parts of the system there are various actively interacting computing models [2].

2. Depending on completeness of the source information, automated decisions are made by the Inland ECDIS AD both in conditions of certainty and uncertainty. The number of alternatives $A(t)\neq$const, so the choice of AD is made in a presence of two or a small number and a large but finite number of alternatives [13].

Let us consider the elements of *A&K* (optimality criterion) located in the linear shell of the linear space elements

$$\langle A, K \rangle. \quad (2)$$

Solution of expression (2): $A^{opt} \in A: \Leftrightarrow K$. It should be noted that the main source of uncertainty is the external environment $Q=\{Q_j\}$. The environment uncertainty leads to unknown consequences of alternative realization. Thus, the problems of safe ship piloting are created.

Let us present the initial information for making AD in conditions of uncertainty (*vag*) and risk (*R*) as a model of AD (Table 2).

It follows from Table 2 that in different variants of environment development, there is no unambiguous approach to making an optimal decision.

The models of choosing an optimal alternative in vag conditions are analyzed in Table 3.

The measured NP multiply repeat the situation of choice with a known probability of safe movement. These are depths, water level by indications of the water gauge station, bearings, distances to hazards, bridge heights, power lines above water level, etc.

$$P_{sm} = 1 - \exp\,(D_{min}/M)^2, \quad (3)$$

where D_{min} is the shortest distance to the nearest danger; M is RMS error of the computed location of the vessel at the point of the shortest distance to the nearest danger.

Because of the large number of realizations of the model 1 criteria (Table 3), the value of expression (2) is gradually stabilized and the risk will be virtually eliminated. Other models are used when extreme caution is needed and a decision that will give a guaranteed result should be made [24].

3. In real situations, the number of elements of expression (2) and the AD made in vag conditions is strictly limited. Often, the situation with WTM movement is unique [19]. For modeling of making decisions under *var&R* conditions, a method of games with environment is offered.

Let us construct a game matrix A to realize the context-oriented approach. The decision-making methods in games with environment depend on the nature of *vag&R*.

For example, the captain's watch mate using the electronic chart system Inland ECDIS has m possible strategies: $A_1, A_2 \ldots A_m$ and the coastal infrastructure (environment) has n possible states: $Q_1, Q_2, \ldots, Q_n$ and risks r_{ij}

$$A = \|a_{ij}\|_{mn} \Rightarrow R = \|r_{ij}\|_{mn},\ r_{ij} = \beta_j - a_{ij} = \max_{1\le i\le m} a_{ij} - a_{ij}. \quad (4)$$

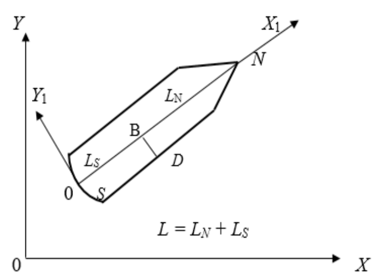
For example, for the passage of the route section from the Dnieper River (0 km Rvach River – Kakhovka gateway (electronic charts (ENC) UA5N0000, UA7N0005, UA8N0017, UA8N0023, UA7N0036, UA7N0047, UA7N0059, UA7N007) matrices A and R are obtained.

$$A = \left(\begin{array}{ccccc} & Q_1 & Q_2 & Q_3 & Q_4 \\ A_1 & 3 & 5 & 4 & 5 \\ A_2 & 4 & 6 & 3 & 4 \\ A & 5 & 3 & 6 & 3 \end{array}\right) \Rightarrow$$

$$\Rightarrow R = \left(\begin{array}{ccccc} & Q_1 & Q_2 & Q_3 & Q_4 \\ A_1 & 2 & 1 & 2 & 0 \\ A_2 & 1 & 0 & 3 & 1 \\ A_3 & 0 & 3 & 0 & 2 \end{array}\right). \quad (5)$$

Table 1

NP for the tasks of stabilization of vessel movement and functional stability of the INM

No.	*NP*	Accuracy	Symbolic properties
1	2	3	4
1	B: bearing	$\Delta D=\left.\frac{m_B\cdot d}{57{,}3\cdot\sin\Theta}\right\|_{30<\Theta<150}^{m_B\le 1^0}$ mB: root mean square (RMS) error	$M_o=\frac{m_B^o}{57{,}3^o\cdot\sin\theta}\sqrt{D_1^2+D_2^2}\le 10$ m $tgB=\frac{\Delta\lambda\cdot\cos\phi_m}{\Delta\phi}$ B∨D: $f(x_0-0)=f(x_0+0)=f(x_0)$, $\forall x\in R\ x(t)=T_t\,x(t_0)$ M_0: RMS error in determining location T_t: operator of evolution
2	D: distance	m_D<10 m (RMS eror)	$M_o=\frac{1}{\sin\theta}\cdot\sqrt{m_{D1}^2+m_{D2}^2}\le 10$ m D∨B: $f(x_0-0)=f(x_0+0)=f(x_0)$, $\forall x\in R\ x(t)=T_t x(t_0)$
3	$A=\{a_x,a_y\},\quad i=\overline{1,n_a}$, $B=\{b_x,b_y\},\quad i=\overline{1,n_b}$, $C=\{c_x,c_y\},\quad i=\overline{1,n_c}$, … The set of SENC points	$\delta_{dig}=\max_{N\in M,N,M_{i+1}} d\left(N,M,M_{i+1}\right)\le 0{,}2$ mm $\delta_{chart}\le 0.5$ mm δdig: digitizing errors δ_S: SENC accuracy	$Xi^*-Xi=EXi,\ Yi^*-Yi=EY$, $\Delta_i=\max(\|E_{Xi}\|,\ \|EYi\|)\approx 0.1-0.2$ mm $M(E_{Xi}=M(E_{Yi})=0$ $Xi^*-Xi=EXi\ ,Yi^*-Yi=EY$ precise coordinates, $M(E_{Xi})=M(E_{Yi})=0$: mathematical expectations
4	Actual depths $h(t)$. ΔZ: depth corrections for SENC	$m_{Z0}\le 0.1$ m, (СКП), $\delta_S\le 0.5$ mm (SENC accuracy) $\Delta z=\Delta z_f+\Delta z_{meas}+\Delta z_\alpha+\Delta z_M$, $m_{zO}=\sqrt{m_{meas}^2+m_{zM}^2}$, $\forall M\overset{def}{=}\delta_S$	$h(t)=\underbrace{\frac{1}{\det(pE-A)}S(p)}_{(C)_{i,j}}\cdot B+$ $+\underbrace{y_{01WS}+h_{10}}_{const}+\left\\|(\delta y_{01WS})_{i,1}\right\\|$ (pE−A), S(p): matrices: characteristic, union def (pE−A): power polynomial of Laplacian variable p of the n-th order δy_{01WS}: depth deviation from zero, y_{01WS}: values of water level, h_{10}: zero of depths
5	Signals from satellite positioning systems (SPS): GLONASS GPS, DGPS	$M_{GLONASS}$=20÷35 m (RMS error), M_{GPS}=36 m (RMS error) M_{DGPS}=1÷5 m (RMS error) at P=95 %	$M_{\det}=m_{\det}\sec\cdot h_{aver}\cdot\sqrt{\frac{3}{\sum\sin^2\Delta A}}=m_{\det}\cdot G$, 1.5<G <5 (geometric factor)
6	Locations of GPS antennas on the ship	$m\le 0.05$ m (RMS error)  	Setting coordinates of point D of the ship by the signals of the spaced-apart GPS antennas $x_D=(x_S+x_N\gamma)/(1+\gamma)\pm d/L(y_N-y_S)$ $y_D=(y_S+y_N)/(1+\gamma)\pm d/L(x_N-x_S)$ $\alpha=L_S/L,\ \beta=L_N/L,\ \gamma=\alpha/\beta$
7	Mathematical model of the ship movement $S'(t)=\begin{cases}S_L, & \varepsilon>\varepsilon_0,\\ S_0, & \varepsilon\in\varepsilon_0,\\ S_R, & \varepsilon<\varepsilon_0\end{cases}$	$M_{mov}=M_0<10\ m$ $\forall S'(t)\forall! S_L\vee S_o\vee S_R\ :t=t_i$. S_L, S_0, S_R: sets of movement states (to the left, no deviation, to the right)	$\frac{d^2y}{dx^2}+p(x)\frac{dy}{dx}+q(x)y=0$, $t=t_0\Rightarrow\forall M\in x0y\mapsto N\in u\ 0\ v:\begin{cases}U=u(x,y)\\ V=\nu(x,y),\end{cases}$ $I=\begin{vmatrix}\frac{\partial u}{\partial x} & \frac{\partial u}{\partial y}\\ \frac{\partial\nu}{\partial x} & \frac{\partial\nu}{\partial y}\end{vmatrix}\ne 0,\ I=\left(\frac{\partial\nu}{\partial x}\right)^2+\left(\frac{\partial\nu}{\partial y}\right)^2>0$.

Continuation of Table 1

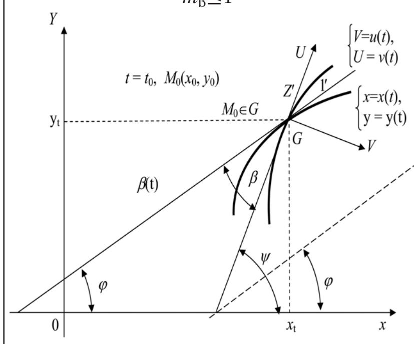
1	2	3	4
8	Angle β	$m_\beta \le 1^0$  *x, y* & *V, U*: the set arcs of the defined curves	$\begin{cases} x = x(t) \\ y = y(t) \end{cases} \Rightarrow \begin{cases} V = \bar{u}(t) \\ U = \bar{v}(t) \end{cases}$ $\beta = arctg \dfrac{\dfrac{\partial V}{\partial x}\dfrac{\partial x(t)}{\partial t}}{\dfrac{\partial V}{\partial y}\dfrac{\partial y(t)}{\partial t}} = -arctg \dfrac{\dfrac{\partial U}{dy}\dfrac{\partial y(t)}{dt}}{\dfrac{\partial U}{dx}\dfrac{\partial x(t)}{\partial t}}$. $\beta = f\left[U'(x,y) \,\&\, V'(x,y)\right]\Vert$
9	Automatic SENC correction or manual correction from RIS	$\delta_{dig} = \max\limits_{N\in M,N,M_{i+1}} d\left(N,M,M_{i+1}\right) \le 0{,}2$ mm $\delta_{chart} \le 0.5$ mm	$Xi^* - Xi = EXi$, $Yi^* - Yi = EY$, $\Delta_i = \max(\lvert E_{Xi}\rvert, \lvert EYi\rvert) \approx 0.1-0.2$ mm $M(E_{Xi}) = M(E_{Yi}) = 0$

Table 2

The AD model under conditions of risk R

$A^R=\{A^R_i\}$	$Q^R=\{Q^R_j\}$			K^R
	$P_1\ (Q^R_1)$	$P_j\ (Q^R_j)$	$P_m\ (Q^R_m)$	
A^R_1	$Y^R 11$	Y^R_{1j}	Y^R_{1m}	K^R_1
…	…	…	…	…
A^R_i	Y^R_{ij}	Y^R_{ij}	Y^R_{im}	K^R_i
…	…	…	…	…
A^R_n	Y^R_{n1}	Y^R_{nj}	Y^R_{nm}	K^R_n

Table 3

Models of choosing an optimal alternative in vag conditions

No.	Model	Criteria	Explanation of alternatives
1	Model 1	$A_B^{vag} = \arg\max\limits_i K_i$, $K_i = \sum\limits_j Y_{ij}\, xP_j$	Characterized by a max value of mathematical expectation of probability of safe movement P_{sm}>95 %, *x*: single optimal solution Bayesian criteria
2	Model 2	$A_C^{vag} = \arg\max\limits_i K_i$, $K_i = \min\limits_j Y_{ij}$	Characterized by the choice of max values from among min results of mathematical expectation of probability of safe movement Wald criteria
3	Model 3	$A_{opt}^{vag} = \arg\max\limits_i K_i$, $K_i = \max\limits_j Y_{ij}$	Characterized by the choice of max values from among max results of mathematical expectation of probability of safe movement. Optimism criteria

Then, regardless of the game matrix type, the optimal strategy is chosen.

A list of vag states of environment at the time of making the AD is presented in Table 4.

Optimal strategy:

$$A = \Vert a_{ij} \Vert_{mn} \Rightarrow p_j\left(Q_j\right) \Rightarrow \max_{1\le i\le m} \sum_j^n p_j a_{ij} \;\&\; \min_{1\le i\le m} \sum_j^n p_i r_{ij}.$$

In the absence of information on the probability of environment state, there are no unambiguous and mathematically clear recommendations on the choice of decision-making criteria.

4. In the INM, the decision-making models are characterized by multicriteria conditions. Such source information for making decisions in vag conditions is associated with a large number of criteria [24].

The decision-making model under multicriteria conditions is presented in a tabular form (Table 5). The following additional symbols are used in the table: $N=\{N_a\}$ is the set of criteria for evaluating alternatives; K_i is the resultant estimate of A_i; V_a is an estimate of importance of the a-th criterion $\left(\sum\limits_a V_a = 1\right)$, Fia is the estimate of the advantage of A_i by the *a*-th criterion, $\left(\sum\limits_a F_{ia} = 1\right)$.

Next, a model based on the criterion of total efficiency is obtained:

$$A_{TE} = \arg\max_i K_i\ ,$$
$$K_i = \sum_a F_{ia} x V_a, \qquad (6)$$

where ATE is the alternative optimal by the criterion of total efficiency.

Expression (6) means that an optimal solution to a multicriteria problem is an alternative characterized by the highest value of the criterion of total efficiency [17].

One of the most important stages in solving a multicriteria problem is formation of a set of criteria. In the instrumental navigation method, the set of criteria (estimation of functionals) must be complete.

The characteristic of the estimation functional is the ingredient (*Ing*): positive $Ing=F=F^+$ (maximum value) and negative $Ing=F=F^-$(minimum value) [24].

Let us consider the stage of constructing a multicriteria model of estimation of AD options and identification of the system of subject priorities.

Determine making of a multi-purpose decision in a form of expression $\{X, F\}$ where $X=(x_1, x_2,..., x_n)$ is the set of solutions, are the vectors of the estimation functionals.

To solve this problem, apply the normalization method (Table 6); the weight method (Table 7) and the folding method (Table 8).

Application of the normalization method is explained by the fact that the evaluation functionals in the INM have different units of measurement or different orders of magnitudes that are measured. Table 6 presents mathematical expressions of reducing to one dimensionless scale of the measurements that were used.

Set the priority of local criteria using the priority vector and the weight vector (Table 7). Priority of estimation functionals is reduced to adjustment of the compromise scheme and establishment of the degree of importance of the objects. Select a series of binary priority relations (RV) and a vector of weight factors of the priority (U). Apply the principle of flexible accounting of the priority. As a result, practical realization is reduced to a transformation of the space of homogeneous objects regarded as coordinates in the corresponding space. Under the priority correlation (u), there will be the vector of weight coefficients (u_1,..., u_q) on the components of corresponding detailed indicators.

Table 4

List of information situations related to var of environment

Information situation	Vag	Decision making criteria (W, S) on the example of matrices (4)
IS_1	Unconditional probability on the set Q elements	Model 1 (Table 3)
IS_2	Probability with unknown parameters of the Q set parameters	Model 2 (Table 3)
IS_3	Unknown distribution of probabilities on the set Q elements	Jain, Laplace criteria
IS_4	Opposite environment interests in the decision-making process	$W=\max\limits_{1\le i\le m}\min\limits_{1\le j\le n}a_{ij}=3,$ $S=\min\limits_{1\le i\le m}\max\limits_{1\le j\le n}r_{ij}=2$
IS_5	Intermediate information situation between IS_1 and IS_5 during the environment's choice of its states	$W=\max\limits_{1\le i\le m}\left\{p\min\limits_{1\le j\le n}a_{ij}+(1-p)\max\limits_{1\le j\le n}a_{ij}\right\}$ $0\le p\le 1,$ $p=0\Rightarrow W=6,$ $p=1\Rightarrow W=3.$ $S=\max\limits_{1\le i\le m}\left\{p\min\limits_{1\le j\le n}r_{ij}+(1-p)\max\limits_{1\le j\le n}r_{ij}\right\}.$ $p=0\Rightarrow S=3,$ $p=1\Rightarrow S=0$

To determine the rating of an object within the sample, apply an integrated indicator in a form of a folding criterion w. The set of elements of the given sample is ordered by this indicator. Folding criteria for the INM are given in Table 8. local objective of the decision made.

Table 5

Decision making model under multicriteria conditions

$A=\{A_i\}$	$Q^R=\{Q^R_j\}$			K_i
	$N1\,(V1)$	$N_a(V_a)$	$N1\,(V1)$	
A_1	Y_{11}	Y_{1a}	Y_{1m}	K_1
…	…	…	…	…
A_i	Y_{j1}	Y_{ia}	Y^R_{im}	K_i
…	…	…	…	…
A_p	Y_{p1}	Y_{pa}	Y^R_{nm}	K^R_n

One of the set of decisions $\overline{F}$ should be chosen from the domain Ω_X. In accordance with the foregoing, each chosen decision is evaluated by a plurality of criteria f_1, f_2,..., f_K. The criteria vary in coefficients of relative importance λ_1, λ_2...., λ_K. Criteria $f_q, q=\overline{1,k}$ form the vector criterion of optimality $F=\{f_q\}$. The coefficients $F=\{f_q\}$ form the vector of importance $\Lambda=\{\lambda_q\}$. Each local criterion characterizes some.

Table 6

The methods of normalization of criteria in the INM conditions

Normalization method	Mathematical expression
Change of functional methods based on the change of Ing for an opposite $F=F^{-}\&F=F^{+}$, $F=\left\{F^1,...,F^Q\right\}=\left\{f_k^q\right\}_{q,k=1}^{Q,m}$	$f_k^{q^\pm}\to\left(-f_k^q\right)^{\mp},\ f_k^{q^\pm}\to\left(1/f_k^q\right)^{\mp}$
Choice of an ideal vector 1) $F^{ideal}=\left\{f_q^{ideal}\right\},\ q=\overline{1,k},$ 2) $F^{ideal}=F_{\max}=\left\{f_{1\max},f_{2\max},...,f_{k\max}\right\},$ 3) $F_q^{ideal}=f_{q\max}-f_{q\min},\ q=\overline{1,k}$	$f_k^{q^\pm}\to\left(\dfrac{f_k^q}{f^{ideal}}\right)$
Comparison of evaluation functionals. Normalization of environment	$f_k^{q^+}\to\left(f_k^q-\min\limits_k f_k^q\right)^+,$ $f_k^{q^-}\to\left(\max\limits_k f_k^q-f_k^q\right)^+;$ $f_k^{q^-}\to\left(\dfrac{f_k^q}{\min\limits_k f_k^q}\right)^-,\ f_k^{q^+}\to\left(\dfrac{f_k^q}{\max\limits_k f_k^q}\right)^+$ $f_k^{q^\pm}\to\left(\dfrac{f_k^q-\min\limits_k f_k^q}{\max\limits_k f_k^q-\min\limits_k f_k^q}\right)^\pm$
Averaging of vectors of the evaluation functionals	$f_k^{q^\pm}\to\left(\dfrac{f_k^q}{\operatorname{average}\limits_k f_k^q}\right)^\pm$
Normalization of vectors of the evaluation functionals according to Savage	$f_k^{q^\pm}\to\left(\dfrac{\max\limits_k f_k^q-f_k^q}{\max\limits_k f_k^q-\min\limits_k f_k^q}\right)^\mp$

Table 7

Methods of accounting priority of the estimation functionals under INM conditions

Principle of flexible accounting of the priority	Mathematical expression
Linear principle	$u_q \cdot f_k^q$
Power principle	$\left(f_k^q\right)^{u_q}$
Reduction of the problem dimension-ality	$F=\left\{F^q\right\},\ q\in Q^0,\ Q^0=\left\{q=\overline{1.Q}/\left(F^q \succ F^{q_0}\right)\right\}$

Then the optimal decision will take the form:

$$\overline{F}=\overline{F}\left(\overline{X}\right)=\underset{X\in Q_X}{\mathrm{opt}}\left|F(X),\Lambda\right|,$$

where $\overline{F}$ is the optimal value of the integral criterion; opt is the optimization operator.

5. An important component of INM on IWW of Ukraine is the use of coastal and ship information systems (IS). The IS types that exist on IWW of Ukraine and used for movement of WTM include systems for processing operations, management information systems and DMSS (Inland ECDIS, RIS, AIS, GPS, Inland Radar) [1]. The new generation of IS has not been applied yet on IWW of Ukraine. These are primarily the systems built on artificial neural networks (NN) with processor elements (Fig. 2). The presence of complex problems under INM conditions requires intelligent adaptive control systems. These systems are able to adapt to a very wide range of external conditions which is more effective than conventional methods. A key aspect of NN is the ability to learn in the process of solving navigational problems [16].

Table 8

Folding criteria under INM conditions during intelligent processing of data flows

v	Mathematical expression
$v1$	$v^+=\max\limits_k \min\limits_q f_k^{q^+}$, $v^-=\min\limits_k \max\limits_q f_k^{q^-}$ Wald and Savage criteria
$v2$	$v=\max\limits_k \max\limits_q f_k^q$
$v3$	$v=f_{k_0}^1=f_{k_0}^2=\ldots=f_{k_0}^q$
$v4$	$v=\max\limits_k \sum\limits_q f_k^q$
$v5$	$v=\max\limits_k \prod\limits_q f_k^q$

Let us consider the stage of construction of a multicriteria model for determining the estimates of AD variants and identifying the system of priorities of the subject for INM conditions.

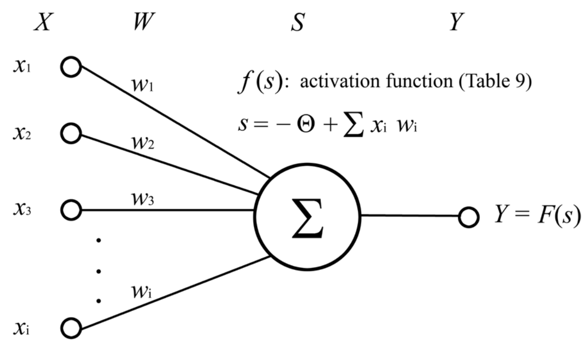
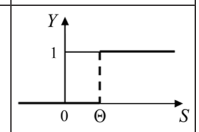
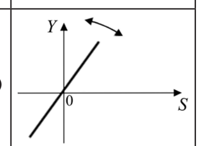
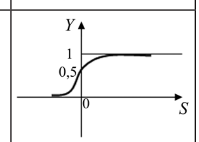
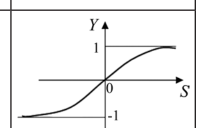
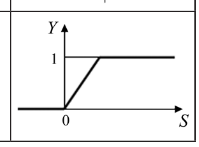


Fig. 2. Applied artificial neural model

Table 9

Applied neural activation functions

No.	Function name	Mathematical expression	Range of values	Graphical explanation
1	Threshold function	$f(s)=\begin{cases}0, s<\Theta;\\ 1, s\geq\Theta\end{cases}$	{0.1}	
2	Linear function	$f(s)=ks$	$(-\infty;+\infty)$	
3	Logistic function	$f(s)=\frac{1}{1+e^{-as}}$	(0.1)	
4	*th*	$f(s)=\frac{e^{as}-e^{-as}}{e^{as}+e^{-as}}$	(–1.1)	
5	Linear threshold	$f(s)=\begin{cases}0, s<\Theta;\\ ks, 0\leq s<\Theta;\\ 1, s\geq\Theta\end{cases}$	(0.1)	

One artificial neuron performs the recognition procedure while neural computations are performed from the joining of neurons in INM network. Such a network will consist of a group of neurons that form layers. Calculation of the source vector **Y** (components: outputs of neurons y_i) can be reduced to a matrix multiplication.

$$\mathbf{Y}=F(\mathbf{XW}). \quad (7)$$

The multilayer INM network is formed by cascades of layers. Moreover, output of one layer is input of another layer. Such multilayer network can be replaced by an equivalent single-layer network. Calculation of expression (7) is as follows. The input vector is multiplied by the first weight matrix. Next, the resultant vector is multiplied by the second weight matrix taking into account the activation function *F* (Table 9).

Training will be carried out by sequential presentation of the input vectors with adjustment of weights. In this training process, weights of the network become such that each input vector produces an output vector [21]. In the

INM network, it is advisable to use training algorithms with and without a trainer.

To construct the architecture of the artificial neural network of INM (Fig. 3), use a model that is mapping real hierarchy of control means (Fig. 1) and NP for the problems of stabilizing the vessel movement and the functional stability of the INM (Table 1).

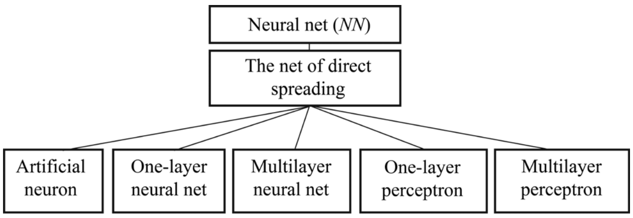


Fig. 3. Architecture of the artificial neural network of the INM

Classes of input signals in NN of INM are shown in Fig. 4.

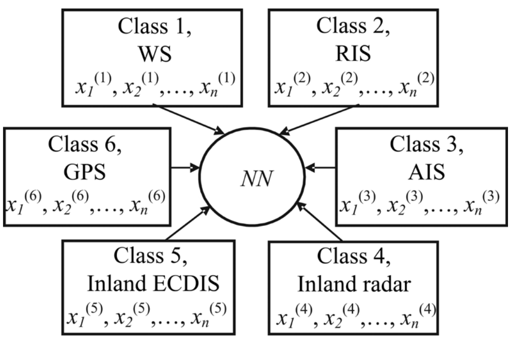


Fig. 4. Classes of input signals in NN of INM

The problem of automating synthesis of a data flow model for pattern classification by attributes is solved as follows. Known methods for synthesizing neural-fuzzy nets require download of entire training sample into the Inland ECDIS memory. This limits the use of neural-fuzzy models in practice. Given that the flow of navigation data in the INM includes a large amount of heterogeneous information, synthesis of the structure of neural-fuzzy networks is proposed to be done by partitioning the space of attributes into clusters. Moreover, rules of belonging to a cluster are formed for each cluster. Clusters and formed rules are mapped in the structure of the neural-fuzzy network. The proposed method of synthesis belongs to ultimate definite neural-fuzzy models. There is no need to download the entire training sample into the Inland ECDIS memory. This provides an acceptable level of data generalization. The methodology consists in calculation of the cluster centers in the space of attribute intervals. Belonging of clusters to classes is determined by the training sample. In this case, there may be such situations when the following is covered by observations:

1) not all clusters;
2) all clusters.

In the first case, belonging is determined by the maximum potential induced for this cluster. In the second case, it is determined by the maximum frequency of copies of the corresponding classes in the cluster. The resulting set of cluster-rules is mapped in the structure of the neural-fuzzy Mamdani network and its parameters are adjusted based on the parameters of partitioning of attributes and cluster centers.

$$X =< x,y > \underset{y(x)}{\overset{S}{\rightarrow}} x = \left\{x^{(s)}\right\}, \quad y = \left\{y^{(s)}\right\}, \quad s = 1,\ 2,\ldots,S;$$

$$S \underset{y(x)}{\overset{N}{\rightarrow}} x = \left\{x_j\right\},\ j = 1,\ 2,\ldots,N;$$

$$s =< x^s, y^s > \overset{K>1}{\rightarrow} x^s = \left\{x_j^{(s)}\right\}, \quad y^{(s)} \in \left\{1,\ 2\ldots.,K\right\};$$

$$QED\ F(): f\left(F(NN)\right),\ w,\ < x,y > \rightarrow \text{opt},$$

where X is the set of precedents; x is the set of input precedent vectors; y is the original attribute; $x^{(s)}$ is the set of input attributes of the s-th precedent; $y^{(s)}$ is the set of output attributes of the s-th precedent; x_j is the j-th input attribute; $x_j^{(s)}$ is the value of the j-th input of the s-th precedent; S is the sample size; s is the number of the sample copies; N is the number of input attributes; K is number of classes; w is parameters of the neuro-model; $F(NN)$ is the structure of the neuro-model; $f(F(NN))$ is the criterion of model quality.

Network error for the problems with a discrete output will take the form:

$$E = \frac{1}{S}\sum_{s=1}^{S}\left|y^s - F\left(w,x^s\right)\right| \rightarrow \min.$$

The ultimate definite neural-models based on a regular partitioning of attributes are shown in Fig. 5–8.

A two-layer NN for input signals of class 1.

Fig. 5 presents a two-layer NN obtained from a single-layer NN [14]. The input receives signals from WS via the synapses that form one layer, which outputs three signals

$$y_1 = f\left[\sum_{i=1}^{n} x_i w_{i1}\right],\ y_2 = f\left[\sum_{i=1}^{n} x_i w_{i2}\right],\ y_3 = f\left[\sum_{i=1}^{n} x_i w_{i3}\right]. \quad (8)$$

Reduce weight coefficients $W^{(i)}$ of one layer of neurons to a matrix according to expression (7) by adding the second layer consisting of one neuron.

The following is obtained:

$$\overline{Y} = F\left(\overline{XW^{(\Sigma\ )}}\right) = F\left(\overline{V}\right) = \sum_{i=1}^{m} v_i \sigma\left(\sum_{j=0}^{n} x_j \cdot w_{ji}\right), \quad (9)$$

where $\sigma(s) = \frac{1}{1+e^{-as}}$ is the logistic function of neuron activation (Table 9).

A full expression is obtained for differential corrections $h(t)$ to the measured depths, which are denoted in SENC [25]

$$h(t) = \underbrace{\frac{1}{\det\left(pE-A\right)} S\left(p\right)\cdot}_{(C)_{i,j}} \quad + \underbrace{y_{01WS} + h_{10}}_{const} + \left\|(\delta y_{01WS})_{i,1}\right\|,$$

$$y_{1WS} = f\left(h_{01WS}, \delta y_{01WS}\right),\ y_{2WS} = f\left(h_{02WS}, \delta y_{02WS}\right),$$

where $S(p)$ is *adj* (union matrix) for $(pE–A)$; $(pE–A)$ is the characteristic matrix for the state matrix A; $\det(pE–A)$ defines the power polynomial of Laplace variable p of order n;

$(C)_{i,j}$ is a matrix with the value of changes of instantaneous water level relative to 2WS; B is the matrix $n'm$ of the vessel location B according to the data taken from the ENC; h_{01WS} is the constant component equal to zero of depths $h_{01WS}=$ $=h_{02WS}$; h_{10} is the constant component equal to possible changes of zero of depths relative to the absolute coordinate system $h_{10}=h_{20}$; y_{01WS} is zero of depths of 1WS, $y_{01WS}=$ $=y_{02WS}$; δy_{01WS} is instantaneous water level relative to y_{01WS}; $\|(\delta y_{01WS})_{i,1}\|$ is matrix-column of changes δy_{01WS} of instantaneous water level relative to 1WS.

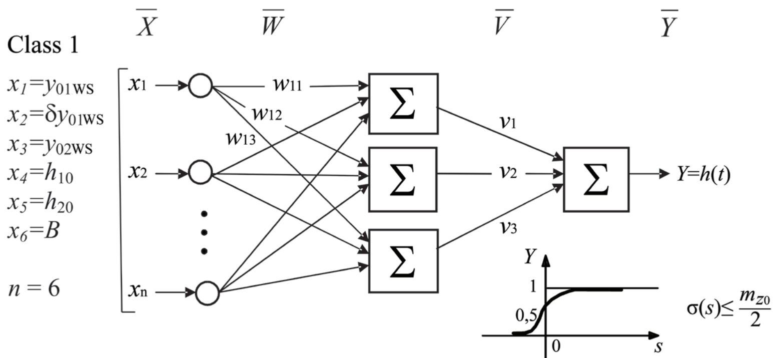


Fig. 5. Two-layer NN for input signals of class 1

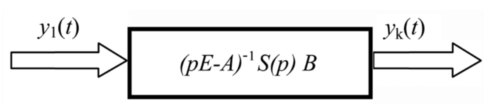


Fig. 6. The scalar transfer function from the input to the output

The matrix transfer function C_{ij} is a rectangular matrix with dimensions $m\times n$. Each element of this matrix is a scalar transfer function from the input to the output (Fig. 6). All scalar transfer functions have the same characteristic polynomial. Therefore, analysis of the data flow from WS is reduced to the analysis of this polynomial roots. For automated mapping of actual depths in the Inland ECDIS, the distance between WS is divided into conditional zones. The difference between the heights of the instantaneous level at two extreme points of the conditional zone $\sigma(s)$ shall not exceed half the accuracy of measurement of the depths m_{Z0}.

The single-layer NN for input signals of class 2.

The block diagram of the NN for input signals of class 2 (Hopfield network) is shown in Fig. 7.

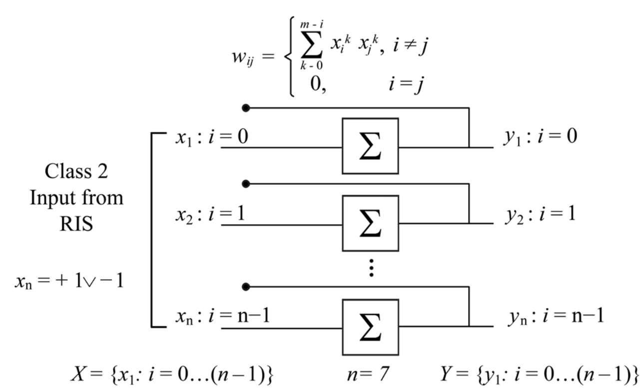


Fig. 7. Block diagram of NN for input signals of class 2

Functioning of NN:

1) $y_i(0)=x_i$, $i=0,\ldots,(n-1)$;

2) $s_j(p+1)=\sum_{i=0}^{n} w_{ij}y_i(p),\ j=0,\ldots,(n-1)$;

3) $y_j(p+1)=f\left[s_j(p+1)\right],\ f\to table\ 9_{1,5}$.

The two-layer NN of inverse propagation (input signals of classes 3 to 6).

Similarly, construct the NN for input signals of classes 3–6. Features of its construction are shown in Fig. 8 and in Table 10.

Table 10

Elements of constructing NN for input signals of classes 3–6 under INM conditions

Class of input signals	Number of layers in the NN	W (n×m)	V (m×p)	Throughput
Class 3 $x_1^{(3)}, x_2^{(3)},\ldots, x_n^{(3)}$ Inland AIS	2 Hidden, output	42×20	20×10	Up to 2,000 messages per minute
Class 4 $x_1^{(3)}, x_2^{(3)},\ldots, x_n^{(3)}$ Inland radar	2 Hidden, output	15×12	12×8	3,000 imp/s
Class 5 $x_1^{(3)}, x_2^{(3)},\ldots, x_n^{(3)}$ Inland ECDIS	2 Hidden, output	72×60	60×9	One message per second
Class 6 $x_1^{(3)}, x_2^{(3)},\ldots, x_n^{(3)}$ GPS	2 Hidden, output	12×8	8×6	One message per second

Notes: W: a matrix of weight coefficients wij from inputs to a hidden layer; V: the matrix of weight coefficients vjk from the hidden layer to the outpus

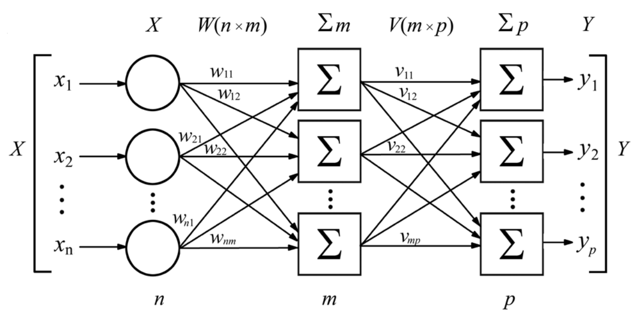


Fig. 8. NN of inverse propagation (input signals of classes 3 to 6)

Training of NN.

Sample: (X^t, D^t), $t=\overline{1,T}$.

$$E(W,V)=\frac{1}{2}\sum_{k=1}^{p}\left(y_k-d_k\right)^2,$$

$$w_{ij}^{N+1}=w_{ij}^{N}-\alpha\frac{4}{4w_{ij}},\ v_{jk}^{N+1}=v_{jk}^{N}-\alpha\frac{4}{4v_{jk}},$$

$$E(W,V)=\frac{1}{2}\sum_{k=1}^{p}\left(y_k-d_k\right)^2,$$

$$w_{ij}^{N+1}=w_{ij}^{N}-\alpha\frac{4}{4w_{ij}},\quad v_{jk}^{N+1}=v_{jk}^{N}-\alpha\frac{4}{4v_{jk}},$$

where y_k is the value of the k-output; d_k is the required value of the k-output; α is the training speed parameter; s is the weighted sum of neuron inputs.

Calculate

$$\frac{\partial E}{\partial v_{jk}}\ \&\ \frac{\partial E}{\partial w_{ij}}.$$

$$\frac{\partial E}{\partial v_{jk}}=\frac{\partial E}{\partial v_k}\frac{\partial y_k}{\partial s_k}\frac{\partial s_k}{\partial v_{jk}}\Rightarrow s_k=\sum_{j=1}^{m}v_{jk}y_j^c\ \&\ \frac{\partial s_k}{\partial v_{jk}}=y_j^c,$$

$$y_k=f\left(s_k\right)\Rightarrow\frac{\partial y_k}{\partial s_k}=f\left(s_k\right)\left(1-f\left(s_k\right)\right)=y_k\left(1-y_k\right),$$

$$\frac{\partial E}{\partial y_k}=y_k-d_k\Rightarrow\frac{\partial E}{\partial v_{jk}}=\left(y_k-d_k\right)y_k\left(1-y_k\right)y_j^c.$$

Similarly:

$$\frac{\partial E}{\partial w_{ij}}=\frac{\partial E}{\partial y_j^c}\frac{\partial y_j^c}{\partial s_j}\frac{\partial s_j}{\partial w_{ij}},$$

$$s_j=\sum_{i=1}^{n}w_{ij}x_i,\quad\frac{\partial s_j}{\partial w_{ij}}=x_i,\quad\frac{\partial y_j^c}{\partial s_j}=y_j^c\left(1-y_j^c\right),$$

where y_j^c is the value of output of the j-th neuron of the hidden layer; x_i is the i-th component of the training sample.

5. Results of studying the intelligent processing of data flows

The developed context-oriented approach to the intelligent processing of data flows under INM conditions makes it possible to consider the proposed system as six functionally interconnected components of the subsystem F_1, F_2,...F_6 (Fig. 4) with certain input signal classes in the *NN*. The result of interaction of the six subsystems F_1, F_2, ... F_6 is fulfillment of the set tasks with the probability of safe navigation $P_{sm}\geq95$ % according to expression (3) for specific conditions of movement of water transport. Experimental studies of modeling of the proposed approach to intelligent processing of navigation data flows were performed on the simulator of the SeeMYENC electronic river charts system.

Fig. 9–12 show graphs of the obtained dependences.

When modeling a situation, non-optimal values were set to certain elements of the system. In this case, optimality of the system in general was determined. The possible parametric variation was controlled in the specified limits of optimality criteria. Calculation of navigation parameter criteria with the ability to be rebuilt according to external conditions for optimal achievement of the general goal was carried out using the formulas of the above tables. The stability domain in the vector space was calculated according to the ENC information. The fundamental point of modeling was the fact that removal of the consequences of extraordinary situations was carried out by redistribution of existing resources including changes in the mode of operation of its subsystems. The performed experiments confirmed operability and practical applicability of the proposed method.

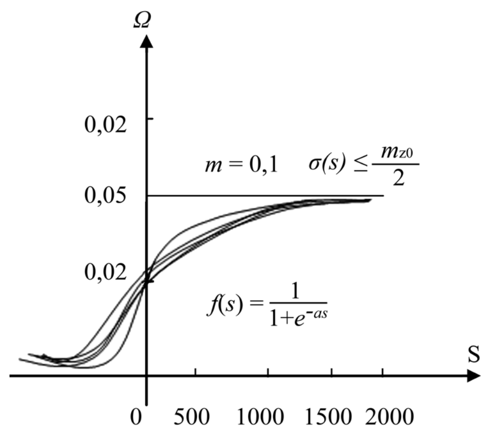


Fig. 9. The Ω vs. S graph for input signals of class 1

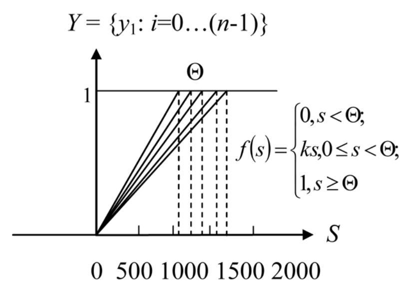


Fig. 10. The Y vs. S graph for input signals of class 2

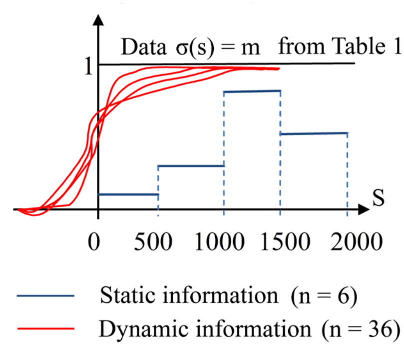


Fig. 11. The Y vs. S graph for input signals of class 3

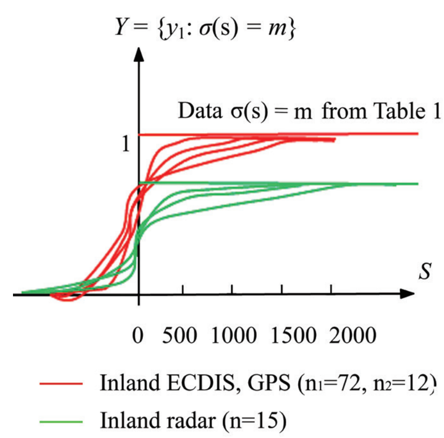


Fig. 12. The Y vs. S graph for input signals of classes 4, 5

6. Discussion of results obtained using the proposed approach to intelligent processing of data flows

The existing visual pilotage method was not based on solution of the problems with application of a scientific approach to the introduction of a modern navigation system on the inland waterways of Ukraine. Hence, the methods of intelligent processing of navigation data flows featured simplicity. For example, processing of navigation data flows in the pilotage method was based on its consideration not as a system object but as a simple sum of properties of elements with the same type of multilevel links [17]. This does not correspond to the regularities of functioning of a complex object in the modern method of navigation through existing local and branch tasks and principles of ensuring its life cycle.

Functioning of the modern navigation method is based on an analysis of a number of factors that are currently not taken into account due to the use of approximate models [4]. It should be noted that the problem of determining the context-oriented intelligent processing of data flows in such a complex organizational system as the system of providing INM on inland waterways of Ukraine remains open today.

The issues in the navigation data stream network affect reliability of information. In addition, the problem lies in that the channel of support for data transmission networks is the main line of transmission of navigation information between objects of coastal infrastructure and the electronic chart system.

In this work, the proposed method of synthesis of neuro-fuzzy models by precedents can give ultimate definite neuro-models based on regular sectioning of attributes. The resulting set of cluster-rules is mapped in the structure of the neuro-fuzzy Mamdani network and its parameters are configured based on the parameters of sectioning of attributes and cluster centers. Implementation of the method does not require loading of the entire training sample into the Inland ECDIS memory, multiple reviewing of the training sample and significantly accelerates the process of model synthesis.

The prospects for further studies consist in the further construction of an expert system in application of the *NN* for the mathematical support of a wide range of practical problems of diagnostics and pattern recognition. For example, in the information system of processing navigation data flows which should promptly detect network anomalies and suggest possible solutions to eliminate anomalies, joint use of expert systems and *NN* is effective. This set of qualities enables *NN* and expert systems to form a hybrid intelligent system (neural-network dynamic expert systems). In a similar system, a trained *NN* is used instead of a knowledge base. Unlike conventional knowledge based expert systems, a system of this type can operate with invalid and incomplete data. Knowledge of the problem area can be used for network training. After training, *NN* will play the role of a set of rules IF-THEN – KNOWLESGE BASE. Artificial *NN*s do not use logic. Their work does not require introduction of experience and expertise of an expert. They imitate human brain training processes to find the relationships between incoming and outgoing data. This is not set by the developer. The interaction of *NN* and the expert systems will minimize disadvantages of diagnostic models of network anomalies. Combining of these approaches results in an advantage over other diagnostic models.

This approach addresses in the first place the weakly structured problems characterized by presence of an uncertainty factor, they contain both formalized and non-formalized elements. Combination of information is made from multiple sources with acquisition of more precise and reliable data on the situation compared to the data obtained from these sources separately. Various options for choosing the optimality criteria were taken into account: Bayes, Wald, Jains, Laplace.

Advantage of the conducted studies is ensuring much greater accuracy of prediction of ship location, elimination of significant ambiguities, vagueness and unpredictability of situations of extreme, risky nature. Theoretical incompleteness and possibility of various interpretations in practice lead to dangerous statistics of disasters, accidents, unwanted events with passengers, crews, cargo and environmental pollution. The performed calculations confirm increase in the probability of safe traffic to 97 %.

Disadvantages include greater duration of forming a sample than with the method for visual (pilot) navigation and effectiveness of application depends on computing resources.

The work contains materials on scientific studies in the field of river transport in the part of definition of mechanisms for structuring and processing flows of navigation data in the conditions of modern navigation methods. The proposed approach is a continuation of the previous study on the application of system analysis of implementation of an instrumental navigation method on inland waterways of Ukraine [25].

The obtained results give grounds to assert the possibility of introducing the proposed method into real navigation on inland waterways of Ukraine.

7. Conclusions

1. The ways to provide much more accurate prediction of vessel location, eliminate significant ambiguity, vagueness and unpredictability of situations of extreme, risky nature were determined. The performed calculations confirm the increase of the probability of safe traffic to 97 %.

2. A model was proposed that represents a real hierarchy of management tools that are interrelated and interdependent in the system. All these functions are combined into a single INM system which converts the available resources into target effects. It should be noted that existing conventional navigation systems cannot realize the INM properties in unforeseen extreme situations.

3. With application of the methodology of system optimization of the INM structure, the level of quality potential of the navigation parameters for the tasks of stabilization of the vessel movement and functional stability of the system was fixed. The given problem was solved employing artificial intelligence and the elements of fuzzy logic.

4. Various options of choice of alternatives and optimality criteria in the linear shell of linear space elements under uncertainty were considered: the criteria of Bayes, Wald, Jains, Laplace. This enabled the application of cri-

teria for the source information to make automated decisions under conditions of uncertainty and risk.

5. The stages of application of the multicriteria model constructed on artificial neural networks were determined. The architecture of the artificial neural network of INM was elaborated. This has allowed us to get a model that reflects the real hierarchy of control means for the tasks of stabilizing the vessel movement and functional stability of the system.

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