ON CONSTRUCTION OF AN INTELLIGENT SUBSYSTEM FOR ANALYZING THE PARAMETERS OF A MARSHALLING HUB

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ABSTRACT

The article considers the issues of continuous monitoring of the situation at the marshalling yard and detection of the possibility of occurrence of dangerous situations. An approach is proposed for constructing an automated intellectual subsystem for analyzing and timely forecasting the critical utilization of railway sorting units. The solution of the problem is proposed with the help of network communication technologies due to the use of information from automated data collection systems and the neural network decision support subsystem.

Keywords: transport, intelligent system, system analysis, forecasting of critical situations, simulation modeling, sorting node, neural network, information, communication technologies.

Background. *Actual monitoring tasks and prospects for development of rail transport require the use of modern methods of the theory of transport systems, as well as creation of new tools and systems for automated design. In particular, this concerns continuous monitoring of the situation at the marshalling yard, timely notification of possible collisions and increasing the efficiency of loading and unloading operations.*

The main logistics problems at the marshalling yard, for which solution simulation modeling is applied, consist in increasing the capacity of the tracks, searching for promising options that will ensure rational use of resources, minimum costs, reducing the probability of emergency situations on routes and stations, estimating the load of the sorting node.

For such purposes, problem-oriented simulation models, developed, as a rule, in a medium of profile type systems [1–4] are widely used. When developing simulation models, real transport systems are represented in the form of queuing systems. The complexity of solving the management problem is that distribution of resources among the multiple components of the transport system is carried out in the face of changing priorities and intensive interaction of processes, which are extremely difficult to be formulated in the language of formalized rules and sets of actions, and therefore it is difficult or in some cases impossible to build an adequate mathematical model. In this connection, in fact, the solution of these kinds of problems is carried out on the basis of construction of an imitation model that takes into account the probabilistic characteristics of the processes occurring.

Objective. *The objective of the authors is to consider construction of an intelligent subsystem for analyzing the parameters of a sorting node.*

Methods. *The authors use general scientific and engineering methods, simulation modeling, evaluation approach, comparative analysis.*

Results.

I.

The construction of the simulation model of the sorting node allows to carry out system research and evaluation of design and technological solutions for existing and projected nodes, enables to monitor the dynamics of resource movement, their effectiveness, identify bottlenecks, the peculiarities of the station's operation in various conditions (and at critical loads), modeling actions «what if», including on the basis of elements of fuzzy logic and the mathematical apparatus of neural networks.

The analysis showed that the existing simulation models [5–11] require preliminary configuration, manual data entry and significant time costs. Creation of an effective simulation model of the sorting node assumes an adequate description of the specifics of technological processes in all subsystems and their system interaction. In the course of the simulation, equations of the dynamics of the change in the number of cars for the sorting fleet tracks, the known values of car groups on tracks, the predetermined line capacities for the calculated space-time network, etc. are used, however in real time this information is not always available and, accordingly does not allow to build forecasts for the node's load.

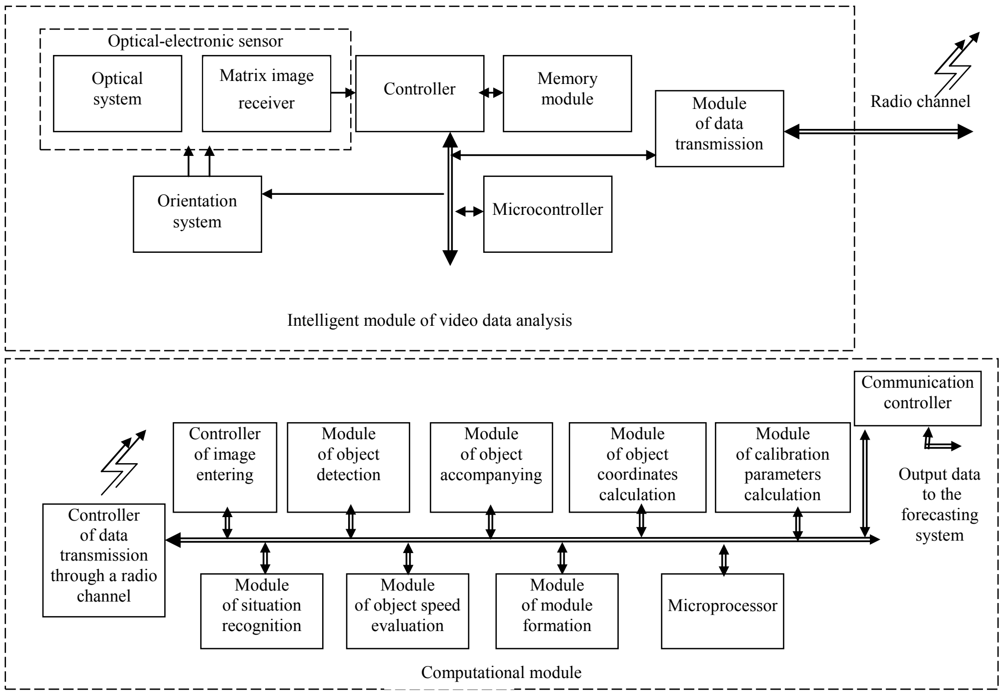
To build a model that is as close as possible to the operating marshalling yard, it is suggested to use the information of the automated control system on the location of cars, the order of formation of trains, as well as information from the technical vision system that automatically analyzes the numbers, the quantity of arriving cars, type of cargoes and type of cars.

There are examples of development of a mathematical model for retrieving data on cargo and passenger transportation by selecting images from geographically distributed sources that allows to describe, and simulate the processes of their analysis and recognition for the purpose of measuring characteristics and classifying objects. Image processing algorithms are also created in programmable logic integrated schemes and specialized processors for conditions of limited computing resources [12].

Thus, simulation modeling of the work of a marshalling yard, on the one hand, can be used to optimize the functioning processes taking into account selected targets, and on the other hand, for working out various non-standard scenarios and critical load modes. However, the application of this approach for forecasting the critical load of a railway sorting unit in real time is not always convenient and possible, especially if it is necessary to implement it within the framework of the global traffic regulation system. In this regard, there is a need to build an automated subsystem for monitoring of the values of the parameters that characterize the current workload and the mode of operation of the sorting unit, as well as for forecasting and early warning of a risk of occurrence of a critical situation, including taking into account the planned arrival of freight trains.

II.

As a mathematical apparatus of the intelligent subsystem for analysis and forecasting, it is proposed



Pic. 1. Structural and functional organization of the system of technical vision.

to share the methods of logical inference, the main representative of which are methods of fuzzy logic and decision trees, as well as neural network information processing methods. This is due to a large number of different types of parameters that can affect the capacity of the railway sorting node, as well as the property of neural networks that allow modeling non-linear processes, work with noisy data, adapt to operating conditions, generalize and extract essential features from incoming information. A key role is also played by the automation of decision-making and forecasting.

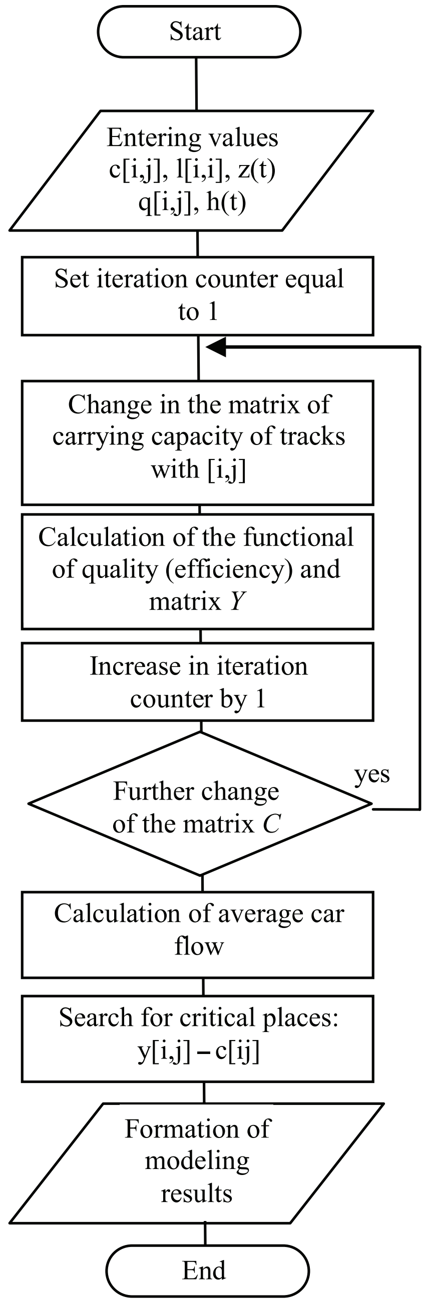
As a source of visual data on the current location of rolling stock and cargoes it is suggested to use network (IP) video cameras located in key nodes of the sorting station and integrated into a single network. To combine data from different video cameras, specially developed algorithms for forming a single workspace are used, including algorithms for calibrating and calculating the positions of each car in three-dimensional space based on analysis of their movement along railway tracks when viewed from various IP cameras. A unified working stage is formed, containing objects of rolling stock observed from various sources of visual data, goods, etc. Next, for each object, its location in three-dimensional space is calculated with reference to some, predetermined reference stationary objects at the marshalling yard. If possible, an estimate of the weight of the car, cargo on the platform and other characteristics is made on the basis of a priori tabular data.

Let's consider the structurally functional organization of the technical vision system, which provides visual data acquisition and situation analysis (Pic. 1).

The technical vision system consists of several intelligent video analysis modules and a computational module. Intelligent modules are located geographically in such a way that they provide simultaneous observation and retrieval of video data at the key nodes of the marshalling yard. Each intelligent module provides analysis of only its section of the marshalling yard and, after processing, transfers the information received to the computational module. The computational module provides a generalization of information on all intelligent modules and the transfer of the received qualitative and quantitative characteristics of the current state and the process of formation / breaking up of the trains.

The intelligent module is a structurally and functionally autonomous device that receives control commands from the computational module, providing, according to the received commands, the calculation of the location parameters of mobile railway objects and their characteristics, as well as the detection of critical situations. The principle of operation of each intelligent module is as follows: an opto-electronic sensor, oriented with the help of an orientation system to a given section of the marshalling yard, continuously receives images coming through the controller into the memory module. The microcontroller reads each frame of the image and produces the actions necessary for calculating the parameters of the railway mobile objects over the images: object detection, preliminary recognition and correlation to a certain class, and calculation of their parameters. The data through the data transmission module and the radio channel at 2,4 GHz are transmitted to the computational module.

The computational module, after receiving the next data from all intelligent modules, performs a comprehensive analysis of the situation at the marshalling yard, and also continuously and in real time transmits the results of the analysis and calculated parameters of the mobile objects (cars, platforms, shunting locomotives) in the process of sorting the train into an automated intellectual subsystem for analysis and forecasting the loading of the marshalling yard, which having an input task formation of a particular train issues recommendations



Pic. 2. Generalized algorithm for functioning of the forecasting system.

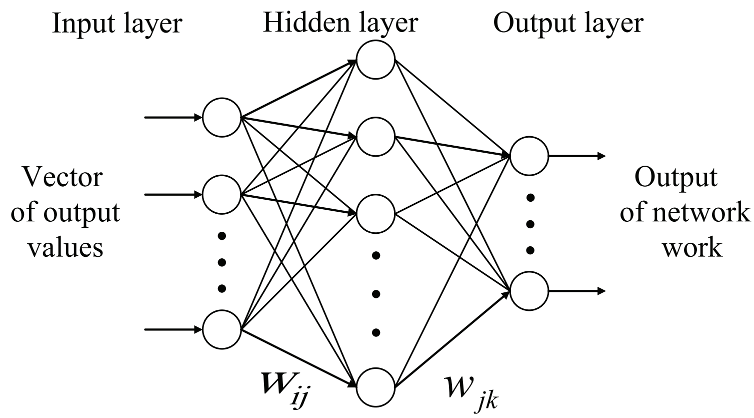
on the movement of cars for the formation of the target train, taking into account the chosen optimality criterion.

In the general case, the structure of the flows of a train's composition at the marshalling yard is represented in the form of a graph G [5, 13].

The capacity of the stations is significantly affected by the processing capacity of the humps, which is the processing of the most probable number of trains (cars) per day with optimal use of track facilities and technical equipment. The processing capacity of the hump, in addition to technical and technological factors, is also influenced by the parameters of the composition to be broken up, in particular the weight of cars, the characteristics of the load, the number of uncouplings in the train, the number of closing groups, etc. No less important is the consideration of weather conditions, which can have a significant impact on the operation of the station.

Movement of cars after uncoupling on a hump is realized in accordance with the following parameters [5, 13]:

– carrying capacity matrix $C = C[c_{ij}]$, where c_{ij} are the carrying capacities of branches of graph G



Pic. 3. The structure of the perceptron with two layers of neurons.

corresponding to tracks connecting node i to node j;

– matrix of distances between nodes, vertices of the graph G L = [l_{ij}];

– cost matrix Q = [q_{ij}], where q_{ij} determines the cost per unit of the track of car coupling movement along the branch ij;

– input matrix of assignments Z_i = [z_{kl}(t)], the elements of which correspond to the train formation plan (number of cars arriving at the input node at time t);

– output matrix of assignments Y_i = [y_{kl}(t)], the elements of which correspond to the predicted load of the tracks of the sorting node (the number of cars located on the exit tracks at time t).

Minimizing the cost of formation of a train is provided by minimizing the functional

$P = \sum\sum P_{ij} = \sum\sum(k_1 \cdot l_{ij} + k_2 \cdot g_{ij} + k_3 \cdot t_{av})$,

where k_i is weighting coefficients determining the influence of distance, time, cost of movement on branches; t_{av} is the average time spent by the trains for formation-breaking up at the node.

At the same time, on the one hand, it is necessary to ensure the maximum flow between nodes, and on the other hand, to have a minimum of costs. The search for correlation of quantities is realized using the approaches [13–16].

The process of formation and breaking up of trains is described using the probability distribution. The distribution functions for each i-th node of the network are given by the matrix H_i = [h_{kl}(t)], where each element is the function of time distribution for formation-breaking up in the i-th node for the composition that came from node k and following to the node l. In the developed system, these functions are calculated using statistical analysis and methods of neural network processing of information [17].

The capacity matrix C = C[c_{ij}], is filled on the basis of a statistical approach, analysis of throughput for several years, taking into account the train's parameters and weather conditions, which requires a predictive neural network.

The distance matrix L = [l_{ij}] is a known quantity and is determined by the existing structure of the location of tracks and switches on the hump.

The cost matrix Q = [q_{ij}] is based on the automated collection of information on delays at the station of locomotives and locomotive brigades in real time. In addition, it is proposed to take into account the forecasting, the analysis of carrying capacity for several years, which also requires a neural network.

The input matrix of assignments in Z_i = [z_{kl}(t)], is also known and determined by the work plan for the hump.

The output matrix of assignments Y_i = [y_{kl}(t)] is calculated using the neural network approach.

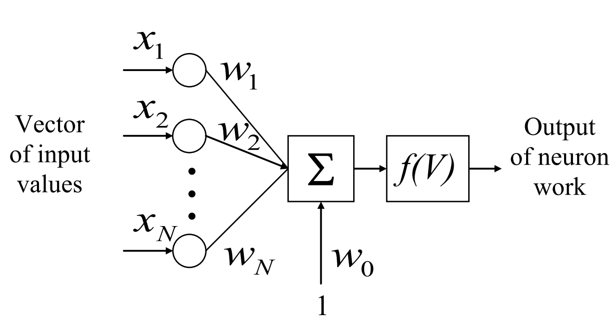
A generalized algorithm for the functioning of the forecasting system is shown in Pic. 2.

III.

The neural network approach is used as the mathematical apparatus of the automated intellectual subsystem of analysis of the loading of the marshaling yard. It implies the need for the following main steps [17]:

1. Preliminary processing of data, identification of characteristic features, the most significant features and their combinations.

2. Preparation of the initial data, consisting in their coding and normalization to increase the informativeness



Pic. 4. Structural diagram of the neuron used in constructing the system of intellectual analysis of the load of the sorting node.

of the examples and bring them to a form that is available for processing by the network.

3. The choice of neural network architecture (paradigm) and its key parameters, such as the number of layers and the number of neurons in each of them.

4. Training, in the process of which the neural network implements the construction of rules that characterize the existing regularities in the data.

5. Using a trained neural network as an expert, submitting to the input new, not yet presented vector of input parameters, and getting the result of its work.

6. Interpretation of the result.

At the first stage, all possible technical and technological characteristics are analyzed, e.g. parameters of the current load, in particular the number of free / occupied tracks and the number of cars in the sorting park, trains awaiting breaking up and planned for the receipt, weight of cars, the presence of dangerous goods, the number of uncouplings in the train, closing groups, and so on. In addition, it is possible to take into account the influence of weather conditions, air temperature, wind speed and direction, the presence of precipitation.

At the second stage, the initial data is coded and normalized, which is associated with the need to work with a large number of different types of parameters. These can be numbers in an arbitrary range, dates, character strings, categorized data, etc. At the same time, the distinctive feature of neural networks is that in them all input and output parameters are represented as floating-point numbers, usually in the range [0 ... 1] or [-1... 1]. An additional purpose of data preprocessing is to increase the informative nature of the examples to increase the speed and effectiveness of training. The more bits of information each sample brings, the better the available data are used.

The average amount of information provided by each example x is equal to the entropy of the distribution of the values of the component H(x). If these values are concentrated in a relatively small region of the unit interval, the information content of such a component is small and when all the values of the variable coincide, it does not carry any information. On the contrary, if the values of the variable x are uniformly distributed in the unit interval, the information is maximal.

The general principle of data preprocessing for neural network analysis is to encode and normalize consistent data in order to maximize the entropy of inputs and outputs.

The next two stages are inextricably linked and are the selection of the neural network paradigm, its key parameters and the adjustment of the weight coefficients. To solve the problem, it is quite possible to use a network of direct propagation, namely, a multilayer perceptron, the structure of which is shown in Pic. 3.

The input values of the neural network are the matrices presented above and converted into a column of input parameters.

At the nodes of the network neurons are located, each of which sequentially carries out the next set of calculations. First, the weighted sum V of the input quantities x_i [18] is calculated:

$$V = \sum_{i=1}^{N} w_i \bullet x_i + w_0.$$

Here N is the dimension of the space of input signals, w_i is the synaptic coefficients or weights, and w_0 is the displacement.

Then the activation function f comes into effect. One of the most commonly used functions is the logistic or sigmoid, which has the form:

$$f(V) = \frac{1}{1 + \exp(-b \bullet V)},$$

where the coefficient b determines the steepness of the sigmoid.

Schematically, the structure of the neuron is shown in Pic. 4.

Applying the above formulas to all neurons of the network, we obtain the resulting formula for the operation of the entire network as a whole:

$$y_k(x_1, \dots x_N) = f\Big(\sum_{j=0}^{m} w_{jk} f\big(\sum_{i=0}^{n} w_{ij} x_i\big)\Big),$$

where y_k – the value of k-th neuron of the output layer [19].

IV.

One of the main problems in using the neural network approach is to select the optimal network topology, parameter values and structural features that would best suit the problem being solved on the available initial data. On the one hand, the number of hidden elements should be sufficient to solve the task, and on the other hand it cannot be too large to provide the expected generalizing ability and avoid retraining. This is due to the fact that the number of hidden elements depends on the complexity of the mapping that the neural network tends to reproduce, and it is not known in advance.

It is obvious that each sorting unit is a unique object and even stations close in their processing capacity can differ greatly in technical and technological features, the degree of influence of individual parameters on the resulting productivity. In this regard the construction of the neural network must be carried out individually for each object, and the selection of data for training the network, too, should be conducted individually. As the initial sample, it is possible to use both real historical data characterizing the parameters of the station operation over a period of time within which its main technical and technological indicators have not changed, as well as data obtained within the framework of simulation modeling, including in developing non-standard scenarios and regimes of critical congestion.

To train networks of the «multilayer perceptron» class, it is possible to use the Backpropagation (BP) algorithm, which is a gradient descent algorithm that minimizes the average quadratic network error:

$$E = \frac{1}{P} \sum_{p=1}^{P} \sum_{k} \left(d_p^k - y_p^k\right)^2,$$

where P is the number of examples in the training set, d^k_p is the desired output of the k-th neuron of the output layer on the p-th training example.

Minimization of the value of E is carried out using gradient methods. The change in weights occurs in the direction opposite to the direction of the greatest steepness for the cost function:

$$w(t+1) = w(t) - \varepsilon \frac{\partial E}{\partial w},$$

where ε is the value of the gradient step or the training coefficient.

The result of the work of the output layer neurons can be taken as values in the range [0, 1], where values close to 0 characterize a small load, and close to 1 values describe critical loading of the sorting node.

Conclusion. In the future, the trained neural network is able to perform the role of an automatic expert for continuous monitoring of the current load *of the marshalling yard, forecasting and early warning on a risk of occurrence of a critical situation. Integration of many such experts with the help of communication technologies into the global system of regulation of traffic flows promises to provide timely warning of risks and optimization of the parameters of the cargo transportation process.*

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