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AN INTELLIGENT NAVIGATOR WITH THE CONTROL OF THE CAR TECHNICAL CONDITION

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ABSTRACT

The paper considers the model of intelligent control systems, means of transport, which provides a higher level of system stability when various nonstationary characteristics and parameters of movement, as well as the destabilizing perturbations. The novelty is based on the fact that the structure and management modules speed and the state of motion of the vehicle built on the basis of the fuzzy system, in the form of neural networks. The use of neural control system will allow modeling the movement of transport in real time considering the optimal calculation of the path, the road map moving car and monitoring of the main parameters of vehicles. The results can be used to increase the level of consumer services of the transport companies on the basis of synthesis of control systems, route and vehicle diagnostics.

Keywords: vehicle, adaptive and intelligent control systems, fuzzy algorithm, optimization, route, movement of car.

1. INTRODUCTION

The speed and safety of delivery of cargo is a priority direction of transport services. Implementation of this direction is currently impossible without further improvement in the technical level of information technologies of the transport system and the application of intellectual and technological systems in the automotive and mechanical engineering.

Currently, for vehicles on-Board diagnostic algorithms, algorithms route, and also the algorithms of control systems by car are developed. Mobile diagnostic scanners aimed at early detection of malfunctions of systems and units of the car and it process the information coming from sensors with the aim of speeding up the process of diagnosis or repair. Such algorithms are: partial or full diagnostics of the engine with preservation of memory errors, constant monitoring of the condition of the brake pads, oil level in the main components of the car, the condition monitoring of electrical and other. For example, the diagnostic system engine determines the following: oil pressure, coolant temperature, air flow, the speed of rotation of the crankshaft, the vehicle voltage, car and current to charge the battery, engine overheating, the higher than recommended maximum speed, the drive with no seat belts, and more.

Algorithms route calculate and display information on parameters of movement of the vehicle, including on the basis of satellite system of navigation. Such information shall include: a choice of online route, the calculation of the average velocity over time or the whole trip, the average fuel consumption depending on the ultimate purpose, time and total mileage of transit, the determination of the distance to the destination, calculating the time of arrival at the destination and more. In some modern models of vehicles on-Board computer include augmented management systems, such as finding the shortest route and promotion in the target position, determination of optimum routes, traffic jams, and autoparking, management of ignition, injectors, automatic climate control, to ensure the efficiency of the transport means and more. Currently, the market of cars produced with integrated multifunction systems, the package which included multimedia, navigation and diagnostic subsystem. In such systems, input data has a complex variable.

Uncertainties in road and traffic conditions, vehicle's state as well as driver's behavior has to be taken into account when developing dynamic navigation system models.

Insufficient precision operational information management objects arising due to the lack of metering and errors of sensors of technological parameters, their unreliability, denial or delay in the transmission of information on levels of control, causing the imprecision in the definition of variables models, initial and boundary conditions.

The inaccuracy of models can occur due to incorrect decomposition of the overall objective of controlling complicated process. At the decision of tasks in a deterministic setting with increasing complexity and dimensions of the model have difficulty sustainability of optimization problems. The optimization implies the withdrawal of certain upper limit. Setting of the task with unclear form [1-3] significantly reduces the possibility of obtaining incompatible solutions for calculation and optimization.

The objective is to create a new algorithm of optimization of the route, for example, reduction of time of search of petrol stations depending on the condition of the tank vehicle road load and the number of gas stations along the prescribed route of the car, through the development of fuzzy control systems of decision making and program management road map [4].

Proceeding from the goals, were set [5] the following tasks: the development of algorithms of decision making; the creation of applied software for the study of convergence of key parameters; the study modules control the direction, speed, and distance from the vehicle to the obstacles; the implementation of a genetic algorithm learning management module direction of vehicles; the development of genetic algorithms training modules control the rate and condition of transport vehicles.

2. PROBLEM STATEMENT AND PRELIMINARIES

2.1. Problem statement

Signals accepted from the external environment are classified by the type of signals, given the information on the state of vehicles, its movement, or about the speed on the radius of the movement. After sorting the signals classes are decides, in what state to switch the operation of transport vehicles i.e. reduce, increase, to keep the rate stable. The decision about the direction of route depends on the basis of individual parts of the vehicles i.e. speed, direction and the state etc.

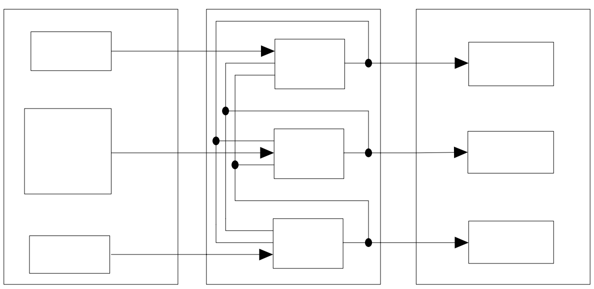

Figure-1. Submission of information and intellectual control system.

To solve the tasks of management of means of transportation with incomplete data [6] adaptive hybrid system can be used consisting of three modules (Figure-1) associated with the use of feedback to ensure a sufficiently complete data set.

Figure 1 presents the low-level description of the proposed system model. It consists of several interacting sub-systems.

The research work [6, 7] defined input parameters in the form of linguistic and fuzzy variables and selecting appropriate functions and facilities with the aim of calculating the basic parameters of control modules vehicles. It gives the possibility to increase the number of input variables to account for all dynamic and mechanical characteristics of the vehicle and its environment functioning and the possibility of increasing the input and output variables, leading to added complexity and mathematical model of the object optimization [8].

2.2. Description of neural fuzzy logic systems

The system will choose an optimal route of the vehicle, where the input data are; the elements of road surface, the condition of the vehicle and the road and the output parameter is the distance to the target, and the result of the calculation of the optimal time depending on the initial specified and expectations of customers.

The first linguistic variable inlet system verbal determines the direction to the obstacle and has a term set T11. Measured technical condition of the vehicle arrives at the second entrance and verbal determined fuzzy variables from the next term-sets $T_{12} = \{t_1^2, t_2^2, t_3^2, ..., t_5^2\}$. Third linguistic variable inlet system verbal determines the distance the technical means to the destination and has a term set $T_{13} = \{t_1^3, t_2^3, t_3^3, ..., t_7^3\}$.

The number of fuzzy neurons of the first layer L1 consists of the sum of all input rules, which equals the number of fuzzy neurons of the first layer:

$L_1 = T_{11}+T_{12}+T_{13}$

The membership function of the fuzzy neurons has the form t - norm, has a triangular shape, and is described by the expression:

$$\mu_{A_i^k} = \begin{cases} 0, & x \quad]- \ , a_i^k], \\ \dfrac{x_i - a_i^k}{b_i^k - a_i^k}, & x \quad [a_i^k, b_i^k], \\ \dfrac{x_i - c_i^k}{b_i^k - c_i^k}, & x \quad [b_i^k, c_i^k], \\ 0, & x \quad [c_i^k, + \ [. \end{cases}$$

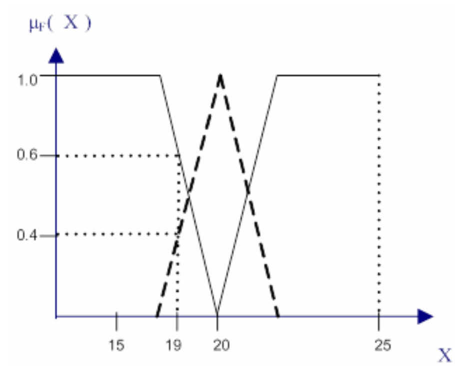

Figure-2. The membership functions of the fuzzy neurons.

The location and the form of such membership function is defined by the following parameters a_i^k , b_i^k и c_i^k , где b_i^k - center; a_i^k и c_i^k - the limits of the membership function.

The number of fuzzy neurons of the second layer, which implements a block of output, determines the degree of conformity.

$$\tau_k = \min_{i=1,...,n} \left\{ \mu_{A_i^k} \left(\overline{x}_i \right) \right\} .$$

The number of cells of the second layer is equal to the number of rules, where they each match one of fuzzy rule. The number of cells of the second layer is determined by the expression

$L_2 = N_1 \times N_2 \times N_3$.

Next, the parameters of the third layer, the number of elements which is determined by the number of fuzzy sets by the formula are define.

$$L_3 = \frac{L_2}{M}.$$

If in the third neural layer is r elements, it is possible to record that

$$y_r = \max_{i=1,\dots,n} \{\tau_k w_{kr}\}$$

Where, r = 1,...,m denotes the number of the item in the third layer, k = 1,...,N is the number of the rule, w_{kr} - weight relationship between the k-th element of the second layer and the r-th element of the third layer.

Thus the task of fuzzification and establishment of fuzzy rules [9-10] are

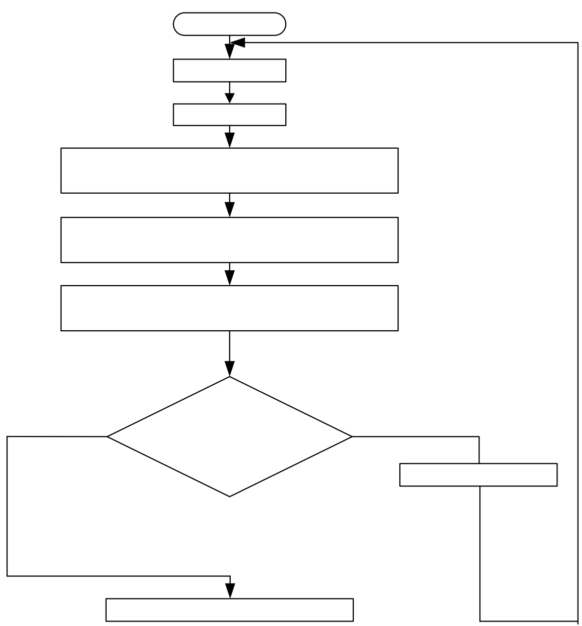

Figure-3. The algorithm of neural fuzzy logic navigation model.

For realization of the unit of defazzification will use the neural network. The input layer of the neural network is associated with the last third layer fuzzy module. The number of elements of this layer is determined by the number of fuzzy rules of the previous layer. Operation defazzification described by expression:

$$\bar{y} = \frac{\sum_{k=1}^{N} \bar{y}^k exp\left(h^k\left(\sum_{i=1}^{n} \bar{x}_i \bar{x}_i^k - 1\right)\right)}{\sum_{k=1}^{N} exp\left(h^k\left(\sum_{i=1}^{n} \bar{x}_i \bar{x}_i^k - 1\right)\right)}.$$

The management system operates in a closed loop, and its work will continue until the information is no longer flow from sensors, describing the trajectory around radius of the vehicle is in motion or when on the system output control is not achieved the desired solution.

Application of models of the composition of fuzzy sets of variables characterizing the state of the object of management, and the elements of the set of decision making about the management will ask lots any reference situations when a significant number of input factors of the control object.

3. SIMULATION RESULTS

In the task of intelligent navigation, the algorithm of control system is constructed with elements of optimization shown in Figure-3. To make the modulation process we must specify the expected input variables and the output variables too. The expected variables are shown in Table-1.

To compute the theoretical mean square error, the optimization fitness function is used [11].

$$Fitness = F_{1,2,3} = min \frac{1}{2}\left(\bar{y}_{1,2,3}(\bar{x}) - d_{1,2,3}\right)^2$$

where

$F_{1,2,3}$ = fitness function of each fuzzy neural network;
$d_{1,2,3}$ = the expected output variables;
$\bar{y}_{1,2,3}(\bar{x})$ = the taken output variables;
$\left(\bar{y}_{1,2,3}(\bar{x}) - d_{1,2,3}\right)$ = the difference between the expected and the taken output variables of each fuzzy neural network.

Table-1. Results of the intelligent navigation model.

The expected (Exp) **and the output** (Out) **results of the model**					
φ [градус]		**V** [км/ч]		**L** [м]	
Exp	**Out**	**Exp**	**Out**	**Exp**	**Out**
20	19, 83	20	0	40	0
25	24, 85	25	24, 90	50	49, 70
35	34, 91	25	25, 16	50	50, 34
10	10, 08	40	39, 93	80	79, 80
5	4, 90	45	44, 70	90	90, 30
5	5	50	49, 76	100	98, 60
10	10, 08	70	79, 80	140	139, 58
5	5, 04	80	80, 17	160	160, 34
5	0	85	84, 76	200	199, 15
5	0	80	80, 13	80	79, 87

The results of the model can be seen approximately with a certain error, the value of which must not exceed 5% of expected output values.

The modeling results are shown in the Table-1 where φ, V, L - are the way, the motion and the distance to the goal.

From Table-1 the obtained results are fully meeting the requirements of the real model of care navigation system, received by the output value. The level of the error is far below the threshold 5%. The error obtained in the results is shown in Table-2.

Table-2. The level of the error for ten examples of the intelligent navigator with the control of car technical condition.

Examples	E_1 (x)	E_2 (x)	E_3 (x)
1	0,014	0	0
2	0,01	0,005	0,09
3	0,004	0,01	0,05
4	0,003	0,002	0,020
5	0,005	0,045	0,045
6	0	0,0280	0,080
7	0,003	0,020	0,088
8	0,001	0,014	0,057
9	0	0,028	0,361
10	0	0,008	0,008

The process of error change of the intelligent navigation model in one segment of the path of car motion is shown in the Figure-4. For the first 10 Examples, the error value is within the range from 0 to 14×10^{-3}, for the second 10 Examples, the range is from 0 to 45×10^{-3}, for the third 10 Examples, the range is from 0 to 0, 3612.

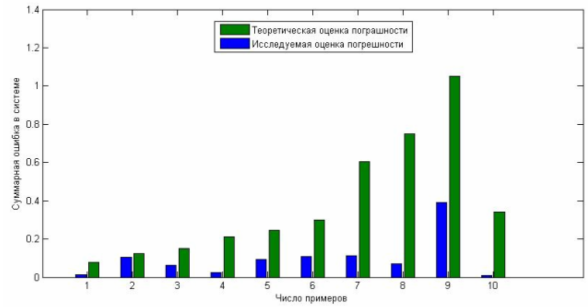

Figure-4. The process of error change of the intelligent navigation model in one segment of the path of car motion.

The results analyze the dynamics of the process of the error change of the intelligent navigation model in one segment of the car motion path. In most cases it is much lower than the theoretical estimates.

3. DISCUSSIONS

The application of the principles of adaptive management, will allow:

- Ensure optimal mode of operation of management systems of vehicles in conditions of incomplete information;
- To ensure proper management of transport means in the context of the dynamic properties of the object in wide range;
- Reduce the time of cargo delivery;
- To reduce the resources and labor costs for transport services, reflecting the level of staff productivity.

Simulation of road and a road map for car travel with the use of neuron-like adaptive control systems of vehicles will allow the use of unmanned control system or switch to a mode of the autopilot, which will lead to increase in the speed of cargo delivery by optimizing driving, and also for unloading and reduces fatigability the driver of a vehicle on certain sections of road and highways.

Thus, adaptive intelligent control system will help in solving the problems of safe operation of transport, monitoring of the condition of vehicles and optimization of traffic.

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