Convergent platform for multi-agent data processing in the “Smart Road” system

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Abstract: In the article, the multi-agent platform for convergent sensor data processing in a monitoring system for Smart Road Infrastructure are considered. The platform works with a network of spatially distributed photo-radar complexes, which in real time record road accidents. The paper discusses tools for collection of road accident’s photo and video data fixation, data mining and forecasting of transport incidents, depending on various factors (meteorological, social, operational, etc.). The results of monitoring and analysis of traffic accidents, fixed by an intelligent monitoring system with photo-radar complexes are considered. The connection between the complexes and the data processing center using a heterogeneous wireless network is established. A multi-agent approach developed to address the tasks of sensor data collecting and processing. Convergent approach is the convergence of cloud, fog and mobile data processing technologies. The structure of the neural network is adapted to the diagnosing problems and forecasting. The tasks of intellectual analysis and forecasting traffic accidents solved. The hybrid fuzzy neural network synthesized. Because the comparison of time series of traffic accidents and time series of meteorological factors, it established that the presence of factors to become determinants for an abnormal change in the traffic situation in controlled areas. The monitoring system is a part of Smart Road Infrastructure within the framework of the Smart & Safe City concept.

Keywords: multi-agent platform; convergent data processing; monitoring system; smart road infrastructure; wireless sensor networks; machine learning; convergent model; smart&safe city; big sensor data

1. Introduction

Smart&Safe City means the development and implementation of projects such as Smart Manufacturing, Smart Houses, Smart Light, Smart Energy, Intelligent Transportation System, Smart Road, etc [1, 2]. The goal of Smart Technology Development & Safe City has to ensure the comfort and safety of human life in the urban infrastructure and efficient production in the industrial sector. Smart & Safe City components are integrated into a multimodal smart environment [3]. It provides interaction of cyberphysical devices, cloud computing resources and mobile communication systems. Smart Environment helps the artificial intelligence system to solve problems of automatic control, or to support decision-making based on big data monitoring about the surrounding reality. It is based on the Internet of Things network platform for the collection and processing of sensor data. The platform includes:

Intelligent sensors (sensors, measuring devices, photo and video fixation devices).

Telecommunication networks of broadband data transmission (fiber-optic and wireless) and mobile communication systems.

Satellite navigation systems.

The paradigm of an intelligent multimodal environment includes three basic concepts: ubiquitous (pervasive) computing and networking [4]; intellectual assistant (ambient intelligence) [5]; smart environments [6].

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The creation of Smart Road Environment (SRE) is an important direction in the Smart&Safe City concept [7]. Environment is needed for the interaction of satellite vehicle monitoring systems, intelligent transport systems (ITS) [8], unmanned vehicles, intelligent road infrastructure components and mobile communication users. SRE includes a built-in intelligent functionality in the vehicles, objects of road transport infrastructure and intelligent system for monitoring and traffic management. It is based on methods of monitoring and managing traffic flows [9], provides information and safety to road users. Research in this area relates to the creation of traffic monitoring systems [10], for example, using radio tags [11] or embedded monitoring complexes [12]. Monitoring technology include stream sensor data processing (photos, video streams, telemetry data, user information), data mining, machine learning, forecasting, multi-agent processing [13], the convergence of computing models (clouds, fog and mobile computing) [14]. The monitoring tasks are: monitoring the condition of the pavement, meteorological monitoring, monitoring of traffic flows, monitoring violations of traffic rules.

Modern road transport infrastructure consists of a system of satellite navigation, traffic signal control, regulation of cargo transportation, information boards, detection systems of car numbers, registration of traffic accidents and violations. The intellectualization of the road transport infrastructure is to develop a intelligent systems for monitoring and surveillance, parking management system, decision-making system for traffic flows regulation, intelligent transport systems, etc. The purpose of the SRE elements is to influence the behavior of cars, drivers and pedestrians in terms of optimizing transport routes and passenger flows, reducing security risks by preventing emergency situations. The main elements of the SRE are:

Intelligent real-time monitoring system,

Real-time traffic information system for alerting and warning of road users,

System of accounting and analysis of road users social reactions [15],

Interactive journey planner system,

Intelligent traffic lights systems,

Intelligent signaling system,

Surveillance cameras (CCTV), photoradar complexes,

Satellite systems of transport monitoring,

Parking and loading areas information systems,

Sensor systems for the movement of unmanned vehicles,

Intelligent vehicle transport systems,

Electronic payment systems for road services, etc.

An important element of SRE is an intelligent monitoring system for decision making on the management of the road infrastructure objects. The system works with a network of spatially-distributed photoradar vehicle detectors for road accidents, video surveillance cameras, vehicle information and communication systems (VICS), built-in car navigation equipment and mobile communication equipment. It is designed for the collection and sensor data processing. The monitoring objectives are analysis, assessment and forecast of changes in traffic situations to control the behavior of vehicles and road users and a alert police, emergency services, ambulance, maintenance and other services.[Insert texts here]

2. Materials and Methods

Monitoring of objects and incidents in the road infrastructure is carried out on the basis of the collection and sensor data processing obtained from ground platforms, aerial and space surveillance facilities. The main ground platforms in SRE are CCTV cameras and photoradar vehicle detectors complexes (**Figure 1**).

Figure 1; CCTV cameras and photoradar vehicle detector complexes

Photoradar complexes allow in an automatic mode to fix incidents on objects of a road-transport infrastructure, to collect and accumulate sensor data [16]. A lot of complexes receive a huge amount of data, which can not be processed by a person in real time. Complexes can recognize objects in photos and in a video stream, measure the speed of vehicles in the control zone, automatically capture and save photos of violators, recognize license plates, collect and transfer data to the data center (**Figure 2**). However, the complexes do not have the capabilities of intellectual analysis and forecasting in real-time mode.

Creation of a heterogeneous transport environment is required for the interaction of the complexes and the transfer of sensor data to the data center. The trend in the field of telecommunications consists in replacing wired networks with wireless channels for monitoring distributed objects [17]. A wireless network is necessary for the interaction of mobile and fixed elements of the SRE. It includes a segment of the Internet of Things for the data exchange between complexes, intelligent transport systems, surveillance systems, a segment of the cellular network for data exchange between users and a segment of the satellite navigation system. The heterogeneous network is realized through technologies of wireless sensor networks (WSN) [18], cellular networks, WiFi networks, satellite networks.

Modern approach to distributed computing and storage of sensor data is based on the concept of convergence [19]. Convergence is defined as the interlinking of computing and storage technologies such as media, content and communication networks. Convergence in relation to network technologies means the process of telecommunication technologies convergence with the appearance of similar characteristics in network equipment, communication channels, network standards and protocols, data transfer processes. For example, the technology integration of mobile and cloud computing is the result of the convergence [20]. Another example is the convergence of cloud and fog computing models in a wireless sensor network [21], which is proposed to create an computing platform for distributed sensor data processing in the SRE. The convergent model of cloud, fog and mobile computing (**Figure 2**) is designed for sensor data processing, obtained from spatially-distributed photoradar complexes, a video surveillance camera, navigation equipment, intelligent transport systems and mobile equipment.

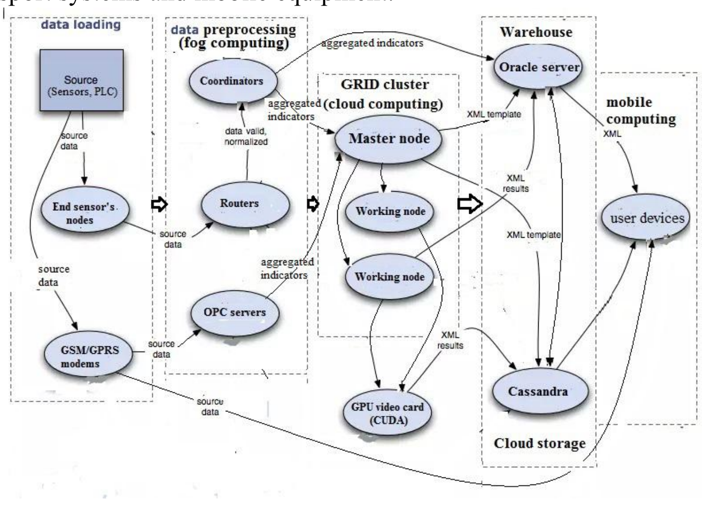

Figure 2; The data flow diagram of convergence model

The convergence networks platform may include some hardware and software levels:

The sensor nodes are associated with industrial controllers and sensors, directly implementing fog computing.

Clusters network segments with coordinators, cellular modems, router, which collects and transfers sensor data into the data warehouse.

Cloud computing clusters.

Warehouse of sensor data and monitoring results.

The user mobile devices for the organization of access to computing and information resources.

The first level of the platform is a fog computing model. It provides the collection and sensor data processing on distributed nodes of the sensor network, in measuring devices and automation devices. Fog computing model also is the platform of data storage services on end-terminal devices and network services for data transmission. Computation are performed terminal devices with limited computing and energy resources - including WSN nodes, controllers, industrial equipment, household appliances with microprocessors equipment, sensor network nodes. Modern WSN nodes have sufficient processing power to organize distributed computing [22]. The fog computing model is the basis of the Internet of things [23]. Fog computing platform is necessary for realization of multi-agent processing of sensor data and consolidated storage of calculation results on sensor network nodes [24, 25].

The second level of the convergent platform is implemented on the basis of the cloud computing model. Cloud platforms are now used in almost all areas of activity [26]. It is used for the ubiquitous network for access to a common pool of configurable resources (software, server, information, platform, etc.) at any time. The user uses the technology of "thin" client as a means of access to applications and data. The infrastructure of the information system is located at the provider of cloud services. The information is stored in cloud storage on the servers of the network. It is temporarily cached by the analytical processing [27]. The trend is the creation of distributed storage for BigData processing [28].

The third level of the convergent platform is related to the data processing on smart phones and tablets for presentation of monitoring results to users with the visualizing events and making decisions to reduce road incidents [29]. Mobile computing model is the platform for human–computer interaction. It involves mobile communication, mobile hardware and software. Communication issues include ad hoc networks and infrastructure networks as well as communication properties, protocols, data formats and mobile technologies. Monitoring of road infrastructure includes procedures:

Vehicles detection and identification in a controlled section of the road with the measurement of its speed;

Photography and video fixation of traffic rules violations;

Collect data on the traffic flows parameters in all monitored areas and transfer to the data processing center via communication channels;

Vehicles detection of on demand and tracking them with visualization of routes of their movements on a cartographic basis;

Photographs and video materials processing about violations;

Accumulation and statistical data processing on offenses for periods of time to identify and analyze the dependencies of changes in violations and road accidents from the influence of various factors (weather conditions, traffic volume, repair work, city events, time of day, seasonal factors, etc.);

Spatial analysis of offenses to identify critical areas and "bottlenecks" in the road transport infrastructure and their dependence on changes in traffic conditions with visualization on the map;

Intellectual data mining and forecasting of road traffic situations for making decisions to improve traffic safety.

Multi-agent approach is advisable to use for the implementation of monitoring procedures. It involves the use of software agents to data collection, data mining and forecasting, as well as to alert road users about road traffic situation via mobile and navigation equipment [30]. The data collection and initial data processing is realized in the fog computing layer by means of agents loaded into sensor nodes. Sensor units are connected to the photoradar complexes. Agents interact with server components of monitoring system.

The hypervisor is used for management of agents. It is consolidated computing resources for distributed data processing. Software agents are interacted with the sensor nodes. Agents responds to requests, decides on the selection of data processing functions, clone and migrate to other network nodes. A feature of the agents is the behavior realization. The behavior is determined by the mathematical function which implements the steps of sensor data processing. Other options determine the agent behavior in case of certain kinds of situations. The model of brokers is offered to agent interaction with server applications at the data center. Broker is an agent that runs on routers and realizing the storage, data protection, transmission and warehouse loading functions.

The multi-agent system includes the following software agents:

Agent for the synthesis and control the photoradar devices queue for inquiry.

Agent for creating threads for asynchronous device polling.

Agents of data polling from devices, separated by geographic zones and by types (devices Cordon-Temp, KrisP, Parkon, etc.). The data polling from device sensors is carried out by agents from different zones using the SNMP protocol.

Agents that keep event logs directly on the complexes. Each complex maintains a local database, recording events in the log files. A lot of local databases represent a distributed hierarchical data warehouse. Agents keep a log file of vehicle passages, a log file of traffic violations, a log file of telemetry parameters for devices diagnostic, etc.

Agents for uploading data from device logs to central storage. Agents work through the web interface and generate a lot of files in XML format. One file contains the data of one violation and is associated with a digital signature file and violation pictures.

Agent for aggregating data about recorded violations for a period of time. This agent generates a Comma Separated Values (CSV) file containing rows with parameters of all violations for a given period. It is an element of a distributed fog database. A lot of CSV files on different devices form a distributed hyper-table of summary data on violations over a period of time.

Agent for aggregating the values of the complex parameters over a period of time. This agent creates a CSV file containing rows with the values of the complex parameters. It is also an element of a distributed database. A lot of CSV files with parameters of different devices form a hyper-table for their diagnosis over a period of time.

Agent for parsing files with violation parameters and parameters of the complexes for loading data into the central cloud storage.

Data mining agents for analysis of violations data. This group of agents analyzes the time series of the uploaded violations data over a time period to identify the dependencies of growth or reduce violations from various factors.

Data mining agents for analysis of device parameter. This group performs analysis of time series of device parameters to detect parameter deviations from the required and reference values (benchmarking). The tools includes data visualization agent, data aggregation agent, data selection agent, data mining agent, data analyze agent [31, 32].

Agents for forecasting violations of traffic rules and agents for forecasting failures and errors in the operation of complexes. Forecasting is performed using the technique of deep machine learning based on the synthesis of a fuzzy neural network, its training and forecasting changes in the operating parameters of the complex.

Agents for data visualization on computers in the data center and on mobile units. A variety of agents form a distributed content management system. Agents are downloadable php and js scripts. They allow in standard browsers to present historical, current and forecast data in the form of graphs, tables and dashboards. The data corresponds to the polling time and geographical coordinates of the complex location.

The data aggregation agent is needed to support the technology of work with database in the aggregation mode for selection and visualization of hyper-table data mart. When the mode is setup, the user should define a set of object properties (columns of values) that will be shown in the hypertable. Available properties can be selected from the drop-down list.

The visualization agent allows to see information in the hypertable data mart. The hypertable is a nonstandard user interface for data visualization. It combines the functionality of a classic table with a tree structure. Elements of the hyper table can be located on distributed sensory nodes. Elements allow to view the dynamic changes of the values changes in real time. The data are grouped according to the parameters and levels of aggregation. A distinctive feature of the hypertable is that the number of rows is not a static value, a row character and functionality are not equal and some of them being the aggregates. The aggregates are nodal and show summary information on the relevant columns of the lower levels aggregation rows. The actual number of the hypertable rows varies dynamically, depending on the grouping of rows. Another feature of the hypertable is the ability to view quickly and analyze changes. User can view hyper-table change of any selected index for the period, as well as the predicted values for the specified forecast horizon. An example of data visualization a photoradar complex parameters is shown in **Figure 3.**

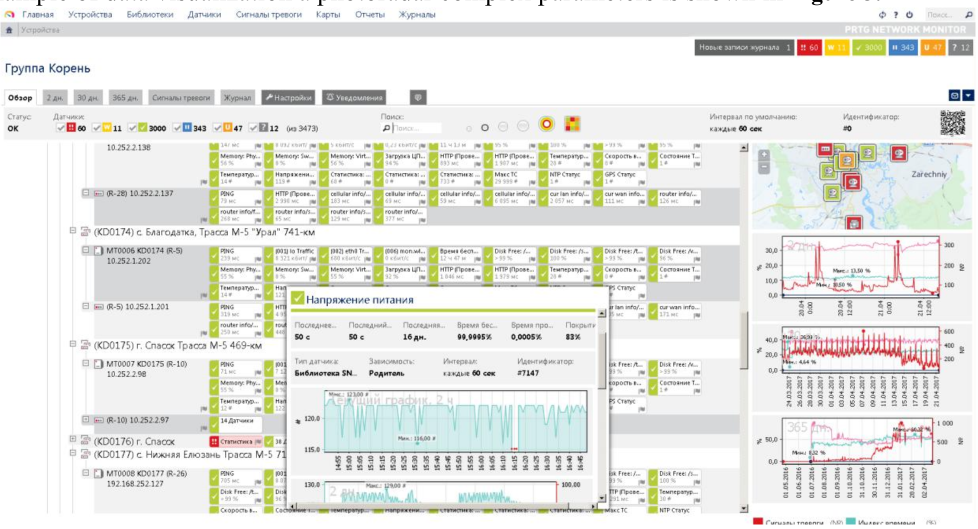

Figure 3; The diagnostic data of the complex

The data analyze agent allows choosing the data needed for the analysis of a concrete situation. The data marts selection criteria can be quite complex. For this purpose, the system uses multi-level queries and filters that limit the data choice. The agent allows the personnel easily create queries to choose the right information.

The diagnostic system is necessary for remote maintenance of photoradar equipment. The system should monitor the complex parameters, transmit telemetric information, predict possible malfunctions and automatically report about failures. The complex has a set of parameters: supply voltage, response time, housing temperature, ambient temperature, etc. Since the complexes are distributed over a large area, a multi-agent remote diagnostic system is being developed to monitor their operation. Key element of a diagnostic system is the mechanism of forecasting of a change, depending on its current parameters, level of external indignations and the influences. The data mining tasks and failures forecasting tasks are solved using deep machine learning and fuzzy neural networks based on the analysis of time series of complex parameters.

We will consider system of forecasting of a qualitative condition of the fotoradar complex on the basis of indistinct implication [33]. In case of N-variables, rules of a conclusion have generally the following appearance: if x_1 is A_1 and x_2 is A_2 and …. and x_N is A_N , then y is B, where A and B are the linguistic values identified in the indistinct way through the corresponding functions. The x_1, x_2,… x_N variables form a N-dimensional entrance vector x the making argument of a condition in which A_1, A_2,…, A_N and B designate sizes of the corresponding function of accessory $\mu_A(x_i)$ (i=1,…,N) and $\mu_B(y)$, the function of Gauss defined in this case:

$$\mu_A(x) = \frac{1}{1 + \left(\frac{x - c}{\sigma} \right)^{2b}}$$

where c, σ, b the parameters of function of Gauss defining its center, width and a form, respectively.

If to consider that is available M-rules (and M-functions of accessory), the matrix of values of functions of accessory of the N×M size is formed:

Rule 1: If $x_1^{(1)}$ it is $A_1^{(1)}$ and $x_2^{(1)}$ it is $A_2^{(1)}$ and …. and $x_N^{(1)}$ it is $A_N^{(1)}$, then $y^{(1)}$ it is $B^{(1)}$,

Rule 2: If $x_1^{(2)}$ it is $A_1^{(2)}$ and $x_2^{(2)}$ it is $A_2^{(2)}$ and …. and $x_N^{(2)}$ it is $A_N^{(2)}$, then $y^{(2)}$ it is $B^{(2)}$

, …………………………………,

Rule M: If $x_1^{(M)}$ it is $A_1^{(M)}$ and $x_2^{(M)}$ it is $A_2^{(M)}$ and …. and $x_N^{(M)}$ it is $A_N^{(M)}$, then $y^{(M)}$ it is $B^{(M)}$.

We will present further sequence of functioning of the diagnostics system of photoradar complexes with a conclusion of Mamdani-Zade in the form of the following stages:

1 stage. Aggregation of the reasons for failures in the systems. The arriving value of function of accessory μ_A(x), where a x – N- dimensional vector, are aggregated in the form of algebraic work:

$$\mu_A(x)=\prod_{i=1}^{N}\mu_A(x_i)$$

2 stage. Aggregation effects of disruption of complexes. Each implication the unique value of function of accessory $\mu_{A\to B}$ is attributed (x, y). This operation is also carried out with use of operation of algebraic work:

$$\mu_{A\to B}=\mu_A(x)\times\mu_B(y)$$

3 stage. Aggregation of results. At this stage the operator of the sum is applied to aggregation of results of implication of many rules.

In final part of a conclusion of Mamdani-Zade the procedure of a defuzzification allowing to receive accurate value of an output variable – the predicted condition of photoradar complex is carried out (**Figure 4**).

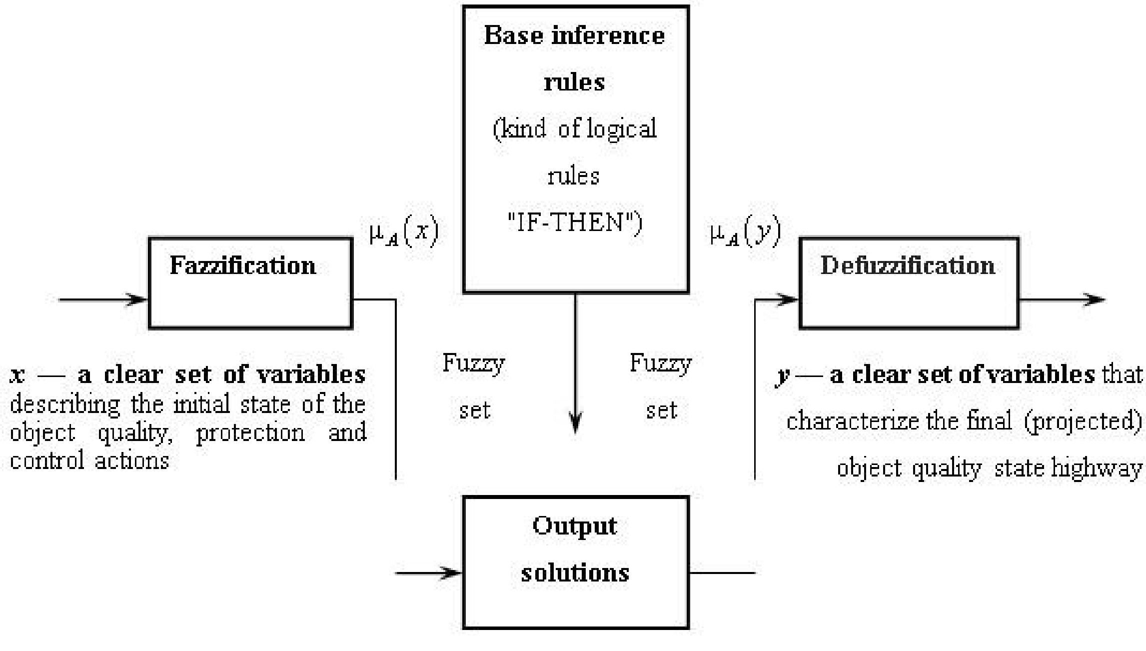

Figure 4; Defuzzifikator transforms an indistinct set to completely determined exact decision y, representing the predicted condition of photoradar complex

Considering that $\mu_A(x)=\prod_{i=1}^{N}\mu_A(x_i)$ for M- rules it can be written down as: $\mu_A^{(k)}(x)=\prod_{i=1}^{N}\mu_A^{(k)}(x_i)$, procedure of a defuzzifikation concerning the center in a discrete form can be written down as:

$$y=\frac{\sum_{k=1}^{M} y^{(k)}\left[\prod_{i=1}^{N}\mu_A^{(k)}(x_i)\right]}{\sum_{k=1}^{M}\left[\prod_{i=1}^{N}\mu_A^{(k)}(x_i)\right]}$$

The main weak spot in an implication method with a conclusion of Mamdani-Zade is subjectivity of creation of a grid of rules and functions of accessory. This defect of a method can be eliminated by creation of the hybrid computing mechanism where implication of Mamdani-Zade is mediated by work of the neural network (NN), with the training mechanism inherent in it. Forecasting is the process of making predictions of the future based on past and present data. Forecasting accuracy is constantly being improved with the continual introduction of machine learning techniques. Time series sensor data is any data set that collects telemetry information regularly over a period of time. The fundamental problem for machine learning and time series is the same: to predict new outcomes based on previously known results. Time series and machine learning can be combined together in order to give the benefits of each approach. Time series does a good job at decomposing data into trended and seasonal elements. This analysis can then be used as an input into a NN model, which can incorporate the trend and seasonal information into its algorithm. The NN represents the parallel computing system consisting of a large number of elementary units of information processing — the neurons, accumulating experimental knowledge and providing them for the subsequent processing. The term "training" is understood as ability of NN to receive reasonable result on the basis of the data which weren't found in the course of training. The sequence of training on the basis of procedure of the return distribution is presented in **Figure 5.**

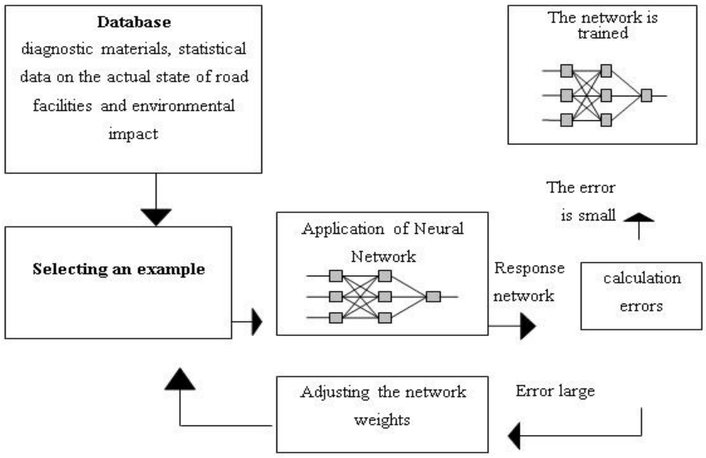

Figure 5; The scheme of HINN training for forecasting of the complex state

This property is used at realization of hybrid indistinct neural network (HINN). We will consider sequence of functioning of HINN (**Figure 6**).

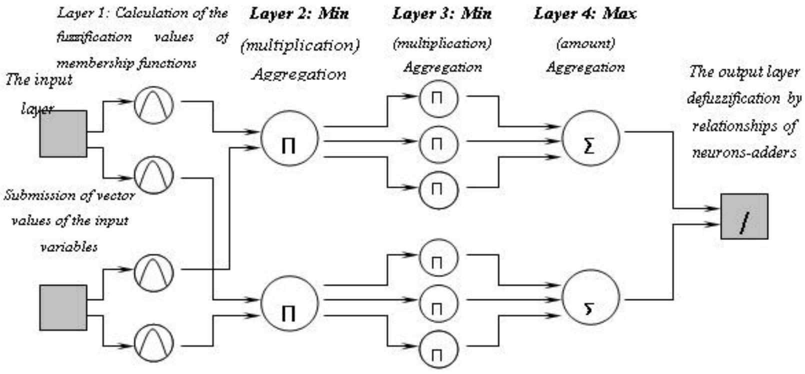

Figure 6; The general structure of NN mediating work of indistinct implication on forecasting with the indication of neurons minimizers and neurons adders.

On the first layer the fuzzifikation is carried out. The formula of a fuzzifikation looks as follows:

$$\mu_A^{(k)}(x_i) = \frac{1}{1 + \left(\frac{x_i - c_j^{(k)}}{\sigma_j^{(k)}} \right)^{2b_j^{(k)}}}$$

where k – quantity of the accessory functions (k=1…M); j – quantity of variables (j=1…N); $c_j^{(k)}$, $\sigma_j^{(k)}$, $b_j^{(k)}$ – parameters of the center, which determine the width and form of the k functions of accessory.

It is necessary to consider that generally the number of functions of accessory doesn't coincide with number of rules. So if each x_i variable has m -functions of accessory, the maximum quantity of rules which can be created at their combination, will make $M = m^N$.

In the second layer aggregation of values of the x_i variables is carried out:

$$w_k = \prod_{j=1}^{N} \left(\frac{1}{1 + \left(\frac{x_i - c_j^{(k)}}{\sigma_j^{(k)}} \right)^{2b_j^{(k)}}} \right)$$

Thus the calculated parameters w_k (k=1…M) at the same time move further in the 3rd layer (for multiplication on weight) and in the fourth layer for calculation of their sum in f_2 neuron.

The third layer when using a conclusion of Mamdani-Zade calculates the centers for k-rules for a formula: $y_k = p_{k0}$, where p_{k0} can be considered as the center of function of accessory of c_k in the Mamdani-Zade model.

After that aggregation of a consequence with use of operation of algebraic work is carried out:

$$w_k \times y_k(x)$$

The fourth layer is presented by two neurons f_1 and f_2, which are carrying out results:

$$f_1 = \sum_{k=1}^{M} w_k \times y_k(x) = \sum_{k=1}^{M} \left[\left(\prod_{j=1}^{N} \mu_A^{(k)}(x_j) \right) \times c_k \right]$$

$$f_2 = \sum_{k=1}^{M} w_k = \sum_{k=1}^{M} \left[\prod_{j=1}^{N} \mu_A^{(k)}(x_j) \right]$$

The fifth layer is presented by the unique neuron which is carrying out a defuzzifikation:

$$y(x) = \frac{f_1}{f_2} = \frac{\sum_{k=1}^{M} w_k \times y_k(x)}{\sum_{k=1}^{M} w_k} = \frac{\sum_{k=1}^{M} \left[\left(\prod_{j=1}^{N} \mu_A^{(k)}(x_j) \right) \times c_k \right]}{\sum_{k=1}^{M} \left[\prod_{j=1}^{N} \mu_A^{(k)}(x_j) \right]}$$

The algorithm of HINN training can conditionally be shared into two stages. At the first stage parameters of the center of output functions of accessory in the third layer are subject to training. For this purpose parameters of scales for the fixing parameters of functions of accessory on the first layer (center, width, form) determine as:

$$y(x) = \sum_{k=1}^{M} w_k^{/} p_{k0}$$

It should be noted that output signals y HINN replace with reference signals d from p of the training selections (the training examples $x^{(l)}$, $d^{(l)}$), where l = 1…p. Then: $wp = d$, where w – the matrix A simplified as a result of replacement of a polynom.

Further the decision of system of the equations is carried out on the basis of pseudo-inversion of matrixes: Ap = d from p = A^+d, where A^+ is the pseudo-return matrix A.

At the second stage after fixing of values of linear parameters $y_k = p_{k0}$ calculated the actual exits of HINN y(i) for i=1…p and a vector of a mistake $\varepsilon = y - d$. Further applying a method of the fastest descent formulas for adjustment of parameters of functions of accessory are used:

$$c_j^{(k)}(n+1) = c_j^{(k)}(n) - \eta \frac{\partial E(n)}{\partial c_j^{(k)}}$$

$$\sigma_j^{(k)}(n+1) = \sigma_j^{(k)}(n) - \eta \frac{\partial E(n)}{\partial \sigma_j^{(k)}}$$

$$b_j^{(k)}(n+1) = b_j^{(k)}(n) - \eta \frac{\partial E(n)}{\partial b_j^{(k)}}$$

where n – number of iteration; η – training speed parameter.

3. Results

A method for forecasting road accidents was implemented depending on three factors: the amount of traffic flow per unit of time, the number of road accidents, the temperature indicators in the control areas. Before we begin to analyze how to do traffic accident inference with location and time information, a proper data structure is needed. When analyzing such spatial and temporal data, the use of matrix is widely accepted as the first choice. For temporal dimension, in order to match the time interval of traffic accident data, we select one hour as the time interval and divided one day into 24-slices. For spatial dimension, we mesh location into Δd latitude and Δd longitude. To guarantee each region is an approximate 500m×500m square, which is a proper area for traffic accident analysis, we select Δd latitude = 0.004 and Δd longitude = 0.005 on a Penza region map (Russia). Therefore, we have a time index t and region index r for each element in the matrix. In this way we have obtained grid data, if traffic accident happened n times in region r at time t, we define risk level. Seventeen area for traffic accident analysis was chosen for the prediction with installed photoradar complexes (**Figure 7**).

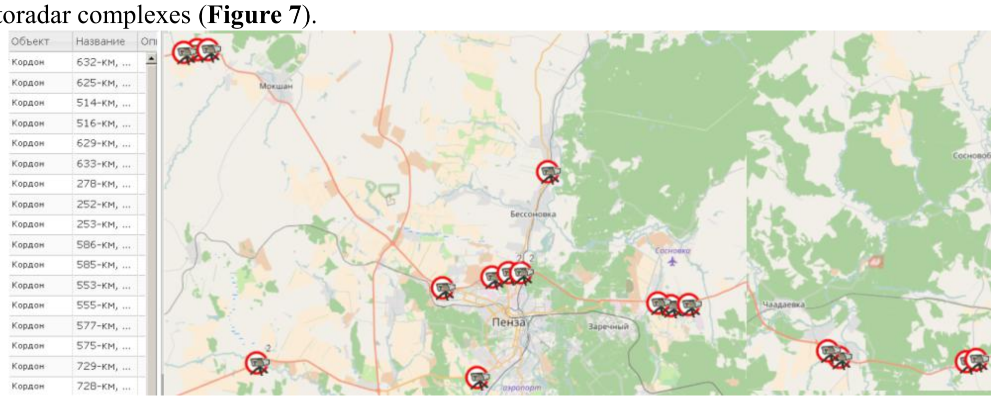

Figure 7; Road area with photo-video fixing complexes

To accumulate statistics, their spatial and intellectual analysis, synthesis of graphs and reports to support decision-making, the system employs a special agent for remote polling of photo-video-fixing complexes and automatic unloading of data on driver offenses and road accidents. Statistical data are presented in the form of time series or function graphs (**Figure 8**) of incidents, changes in speed and density of the flow of vehicles in controlled areas, ambient temperatures and are input parameters for training the neural network.

Figure 8; An example of a graphical representation of the average transport speed

In the process of analyzing time series with the moments of road incidents, time intervals were chosen in which the number of incidents deviated from the average indicators. As an example, we will present graphs of statistics on incidents collected from 6 complexes during the month (**Figure 9**).

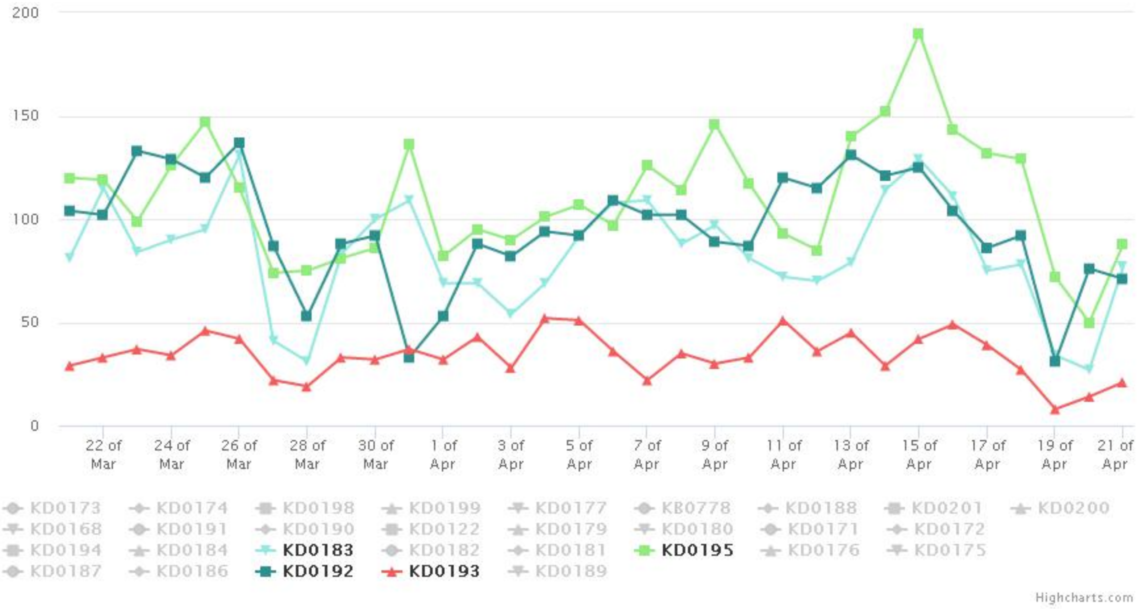

Figure 9; Graphs of the road incidents dynamics at 6 complexes (22 March to 21 April 2018)

Analysis of the data presented in the graphs showed anomalies. It is seen that for a month on 4 complexes (KD0183, KD0192, KD0193, KD0195), the number of road incidents is fixed, which on the average is about 60-70 units. However, after April 18 there is a decrease in the number of road incidents simultaneously on all the complexes. To determine the causes of anomalies and the forecast of incidents, meteorological data (temperatures, atmospheric pressure, precipitation) were collected at anomalous areas at similar time intervals.

Indicators in the form of the number of incidents, temperature values and traffic density values have become input parameters for training the neural network. The number of neurons of the first layer of the network was set to 18, and the number of rules as 9. After training the network, a forecast was made for road accidents (**Figure 10**).

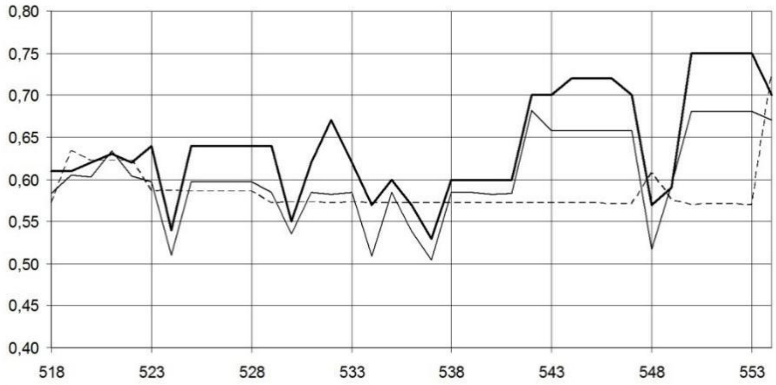

Figure 10; Results of forecasting the number of road accidents (bold line - fact, dashed line - forecast before training, fine line - forecast after training)

The results of the network showed an acceptable error in the forecast of an average of 13%. The model made it possible to determine the dependence of the number of incidents on the changes in traffic and on the temperature regime in the controlled sections of the road. n particular, the prognostic model showed the dependence of the level of incidents recorded by the Kordon-Temp complexes on the M-5 (Ural, Russia) route from changes in temperature and precipitation. It can be concluded that the neural network and the prediction system provide sufficient accuracy for the prediction model.

4. Conclusion

The results of the network showed an acceptable error in the forecast of an average of 13%. The model made it possible to determine the dependence of the number of incidents on the changes in traffic and on the temperature regime in the controlled sections of the road. n particular, the prognostic model showed the dependence of the level of incidents recorded by the Kordon-Temp complexes on the M-5 (Ural, Russia) route from changes in temperature and precipitation. It can be concluded that the neural network and the prediction system provide sufficient accuracy for the prediction model.

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