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UNMANNED AERIAL VEHICLES. PERSPECTIVES. MANAGEMENT. POWER SUPPLY

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Multi-authored monograph

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The monograph analyzes the possible options for energy supply and control of unmanned aerial vehicles. Also, the issue of decision-making by the operator of an unmanned aerial vehicle in the management of emergencies is considered.

Recommended for specialists, postgraduate and students in the field of 141 – "Electric power, electrical engineering and electromechanics", 173 – "Avionics" and other related specialties.

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INTRODUCTION

Ukraine possesses a full cycle of aviation engineering and occupies a significant place in the global aviation market in the transport and regional passenger aircraft sector, which allows the development and production of aviation technology in areas such as aircraft engineering, on-board radio-electronic equipment, focused on the use of satellite communication systems, navigation and surveillance, ultralight and light aircraft, helicopter construction, unmanned aerial vehicles. Unmanned aerial vehicles (UAVs) are without exception. Today, this technology is used in many areas of activity and has extremely high prospects for other areas. Unmanned aerial vehicles (UAVs) are currently used to address a wide range of tasks, such as patrolling borders, intelligence, transportation and armed attacks. This diversity is due to the fact that UAVs are very technological, which explains their widespread use. Modern technologies of UAV energy supply have not yet reached the proper level, due to the dynamic development of this technology. Therefore, the purpose of the work is to develop a variant of the power supply system of the UAV using, in addition, alternative power sources and control system of the proposed grid.

The main components of the UAV are: an airplane with a special landing system, a power plant, a power supply for it, a power system, on-board radio electronic equipment (on-board control equipment and electronic elements of the target load).

UAVs are characterized by such advantages over manned aeronautics as: lack of the need for crew and systems for its life support, aerodromes; relatively low cost and low costs for their creation, production and operation; relatively small weight and dimensions in combination with high reliability, long duration and range of flight, maneuverability and a list of target equipment that can be placed on board, etc.

The height of the flight significantly affects the work of the entire complex of electrical equipment and other on-board equipment of the aircraft.

External influences on electrical installations can lead to various damage, for example, to breakage of wires and windings, especially in the places where they are soldered, up to cracks and damage of electrical insulating materials, accelerated wear of axles and bearings in actuators, deviations from normal operation of spring and moving elements of mechanical systems.

The tactical and technical requirements for aircraft equipment, developed taking into account the conditions of operation of the electrical equipment and its purpose, include the following indicators: reliability, requirements for mass and dimensions, strength of electrical equipment, chemical resistance of electrical equipment, ease of operation and repair of electrical equipment, economic requirements.

From the onboard generators all the electronics are emitted on board the aircraft, so the failure of the generators will lead to the discharging of all on-board equipment. In this case, in some types of aircraft, manufacturers install retractable wind power units (RWPUs) that generate current due to the fact that the wind wheel is spinning under the action of the counterflow of air on the blade, which makes it possible at least to monitor the critical technical indicators of the state of airborne equipment and aircraft systems.

At present, Solar batteries (SBs) are another promising alternative power source in the aircraft.Taking into account the fact that the SB were found to be used in space, which occupy a dominant position among other sources of autonomous power supply, we can talk about further active their implementation in the systems of primary emergency power supply of aircraft systems as additional sources of electrical energy. Therefore, in view of the urgency of the problem of increasing the reliability of the operation of the entire complex of aircraft equipment, in order to improve the safety of operation, it is expedient to consider the issues of modernization of the airborne electrical power supply, including the use of renewable energy sources.

CHAPTER 1 ANALYSIS OF THE CURRENT STATE OF UNMANNED AERIAL VEHICLES AND PRINCIPLES OF THEIR CONTROL

1.1 Composition of on-board equipment of modern unmanned aerial vehicles

To provide a monitoring task, the underlying surface in real time during the flight and digital photography in selected areas, including inaccessible areas, and determine the coordinates of the investigated terrain payload of unmanned aerial vehicles (UAV) [3, 4, 5] should be composed of:

– devices for obtaining image information;
– satellite navigation system (GLONASS / GPS);
– radio link device of the image and telemetric data;
– device of command-navigation radio line with an antenna-feeder device;
– device of share team information;
– information exchange device;
– onboard digital computer (OBDC);
– image information storage device.

Modern television (TV) cameras provide the operator a real-time picture of the observed area in the format most similar to the characteristics of the man's visual apparatus, which allows him to navigate freely the terrain and when needed to perform piloting UAV. Opportunities for detection and recognition of objects are determined by the characteristics of the photodetector and the optical system of the television camera. The main disadvantage of the modern TV cameras is their limited sensitivity, which does not provide round-the-clock application. The use of thermal imaging cameras allows ensuring round-the-clock application of UAV. The most promising is the use of combined TV thermal imaging systems. In this case, the operator is provided with a synthesized image that contains the most informative parts, apparently in the infrared wavelength range, which allows significantly increasing of tactical and technical characteristics of the observation system. However, such systems are technically complicated and quite expensive. The use of radar allows getting information round the clock and in adverse weather conditions, when TV and TV channels do not provide information. Application of variable modules allows reducing the cost and reconfigured the composition of on-board equipment to solve the problem in specific conditions of application. Consider the composition of the on-board equipment of the mini-UAV.

The observation course unit is fixed at a certain angle to the launching axis of the aircraft, which provides the required area of seizure on the ground. The composition of heading monitor may include a television camera (TC) with a wide field lens (WFL). Depending on the tasks to be solved, it can be quickly replaced or complemented by a thermal imaging camera (TIC), a digital camera (DC) or a radar.

The detailed inspection device with a rotary device consists of a detailed inspection TC with narrow-gauge lens (NGL) and a three-coordinate rotary device, which provides a reversal of the camera at the rate, roll and pitch according to the instructions of the operator for a detailed analysis of a specific area of the territory. To provide work in conditions of reduced illumination, TC can be supplemented by a thermal imaging camera (TIC) on a microbolometer matrix with a narrow lens. It is also possible to replace the TC with the DC. Such a solution will allow the use of UAVs for aerial photography when the DC optical axis is turned over to the nadir.

Radio link device of the image and telemetric data (transmitter and antenna feeder device) must provide transmission of image and telemetric information in real or close to real time on the control point (CP) within the limits of the radio-visibility.

Devices of command-navigation radio line (receiver and antenna-feeder device) should provide reception within the limits of the radio-visibility of the teams of pilot UAV and control its equipment.

The device for the command information exchange provides the distribution of command and navigation information for consumers on board the UAV.

The device of information exchange provides distribution of image information between on-board sources of the image information, the transmitter of the radio link of the image information and on-board device for storing the image information. This device also provides information exchange between all functional devices that are part of the payload of the UAV on the selected interface (for example, RS-232). Via the external port of this device, before the UAV take off, an introduction of the flight task is made and pre-start automated integrated control of the functioning of the main units and UAV systems is carried out.

The satellite navigation system provides bindings of the coordinates (topographic location) of UAVs and observable objects to the signals of the global satellite navigation system GLONASS (GPS). The satellite navigation system consists of one or two receivers (GLONASS / GPS) with antenna systems. The use of two receivers, antennas which are spaced along the building axis of the UAV, allows determining, in addition to the coordinates of the UAV, the value of its course of the angle.

The on-board digital computer (OBDC) provides control of the UAV aircraft complex.

The device for storing the image information provides the accumulation of the selected information by the operator (or according to the flight task) to the time of landing of the UAV. This device may be removable or stationary. In the latter case, a channel for removing accumulated information in external devices after the UAV landing should be provided. Information, organized from the device for storing the image information, allows more detailed analysis when decoding the information received in the flight UAV.

Built-in power supply unit provides harmonization of voltage and current consumption of on-board power supply and devices included in the payload, as well as operational protection against short circuits and overloads of the power grid. Depending on the UAV class, the payload can be supplemented by various types of radar, environmental sensors, radiation and chemical monitoring. The UAV control complex is a complex, multilevel structure, the main task of which is to ensure the bringing out the UAV in the designated area and the implementation of operations in accordance with the flight task, as well as to ensure the delivery of information received by aircraft UAVs to the control point.

On-board navigation and control unit of UAV

The boarding complex "Leleka" is a full-fledged means of navigation and control of an unmanned aerial vehicle (UAV) of the aircraft scheme. The complex provides: definition of navigational parameters, orientation angles and parameters of movement of UAV (angular velocities and accelerations); navigation and control of the UAV during a flight on a given trajectory; stabilization of the angles of orientation of the UAV in flight; delivery to the channel of telemetric information about navigational parameters, angles of orientation of UAV. The central element of BC "Leleka" is a small inertial navigation system (INS), integrated with the receiver of the satellite navigation system. Built on the basis of microelectromechanical sensors (MEMS gyroscopes and accelerometers), based on the principle of a free platform, the system is a unique high-tech product, which ensures high accuracy of navigation, stabilization and control of any aircraft class. Built-in static pressure sensor provides dynamic height and vertical speed determination. Composition of the onboard complex: block of the inertial navigation system; receiver SNS; autopilot block; flight data storage device; air velocity sensor.

In a basic configuration control is carried out by channels: aileron; elevator; rudder; the engine controller. The complex is compatible with the radio channel PCM (pulse code modulation) and allows to control the UAV manually with the standard remote control and automatic command of the autopilot. Control commands to the autopilot are generated in the form of a standard pulse-width-modulated (PWM) signals, suitable for most types of actuators. Physical characteristics: dimensions,mm: unit autopilot - 80 x 47 x 10; ins - 98 x 70 x 21; the receiver SNA - 30 x 30 x 10; weight, kg: unit autopilot - 0,120; INS - 0,160; receiver SNA - 0,03. Electrical characteristics: supply voltage, V - 10... 27; power consumption (max.), W - 5. Environment: temperature, ° C - from -40 to +70; vibration / shock, g - 20. Control: RS-232 ports (2) - receive / transmit data; ports RS-422 (5) - communication with external devices; PWM channels (12)- control devices; programmable MRP (255) - turning points of the route. Operating range: roll ± 180 °; pitch - ± 90 °; heading (track angle) - 0... 360; acceleration ± 10 g; the angular velocity - ± 150 ° / sec

1.2 Control System of the spatial position of highly directional antenna systems in the complexes of unmanned aerial vehicles

The unmanned aerial vehicle (UAV) itself is only part of a complex, one of the main tasks of which is operative reporting the information to operating personnel of a control point (CP). The possibility of stable communication is one of the most important characteristics determining the performance capabilities of the control system of UAV and provides the bringing of the information received by UAV in real time to operational staff of CP. For communication over long distances and for increasing interference protection at the expense of spatial selection in complexes UAV control are widely used beam antenna systems (AS) as on CP as on UAV. Functional diagram of the spatial position control system of the highly directional antenna system (AS) as for optimization of the process of entering into a contact in the complexes control drones.

Control system of beam antenna system includes:

1. Proper beam antenna system AS, radio parameters of which are selected based on the requirements ensure the required communication range of the radio link.
2. AS servo unit, which provides spatial orientation beam AS in the direction of the expected occurrence of contact object radiation.

3. Automatic tracking system (ATS), which provides stable tracking of the object in the coverage area capture the direction-finding characteristics of the system of ATS.

4. Radio receivers, which ensures the formation of a "Contact" signal indicating the reception of information with the specified quality.

5. Processor of antenna control system, providing analysis of the current state of the AS control system, the formation of signals of servo control to provide AS spatial orientation in accordance with the flight plan and algorithm for spatial scan analysis of correlation, analysis of possibility to transfer the servo AS mode from "External control" to "Automatic tracking", signal transfer servo AC mode to "External control".

The main task performed by the control system of the spatial position of the beam AS is to ensure a stable connection with the object assigned to the flight task.

This task is divided into a number of subtasks:

1. Ensuring the spatial orientation of the beam AS in the direction of the expected emission of the object of contact and its spatial stabilization for the case of the AS location on the aircraft's board.

2. Extension of the zone of stable capture radiation of the object of contact by using a discrete spatial scanning algorithm with a deterministic space-time structure.

3. Switching to the mode of stable automatic tracking of the object of contact by the ATS system when the object of contact is detected.

Ensuring the possibility of re-engagement in case of failure. For a discrete spatial scan algorithm with a deterministic spatial-temporal structure, one can distinguish the following features: beam AS scanning is performed discretely in time and space.

Spatial movement of beam AS during scanning is carried out in such a way that there are no spatial zones that do not overlap with the zone of confident capture of the ATS system for the entire cycle of scanning (see Fig. 1.1).

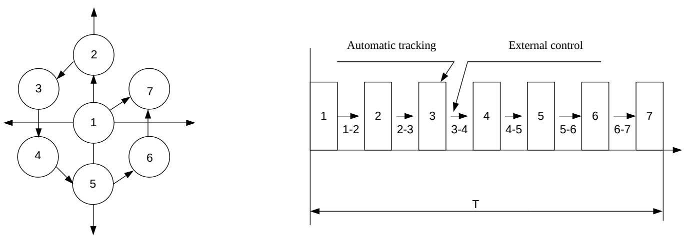

Fig.1.1 An example of the organization of discrete spatial scanning in the azimuthal and elevation planes

For each specific spatial position that is determined by the scanning algorithm, two phases can be identified: "Autotrack" and "External control".

• In the phase "Autotrack" the ATS system evaluates the possibility of receiving the radiation of the contact object for the selected spatial position of the radar.

In the case of a positive evaluation result: Spatial scanning stops. The ATS system continues to autotrack the radiation of the object of contact in its internal algorithm. At the input of the AS servo unit the signals of the spatial orientation of the AS according to the current bearing of the contact object from the ATS system X_{ATS} (t) are received. In the case of a negative evaluation result: The spatial movement of the AS radar is carried out in the next spatial position, which is determined by the scanning algorithm.

In the phase of "External control" at the output of the processor of the antenna control system generates signals AS servo unit control. The components of the servo control signal provide:

X_0 is the initial spatial orientation of the beam AS in the direction of the contact object;

$\Delta X_{aircraft}$ (t) -partitioning the space evolution of the aircraft; X_{alg} (t) is the expansion of the zone of stable capture radiation of the object of contact of the ATS system in accordance with the discrete spatial scan algorithm with the deterministic space-time structure.

In the case of contact failure, from the moment of time $T_{CB} = 0$ (the loss of the signal «CONTACT»), the signal X_{ATS} (T_{CB} = 0) is remembered in the device «Calculate and store», and is used in the subsequent by the processor AS control as the value of the expected bearing of the contact object. The process of contact is repeated as described above. In the "External control" mode the control signal of the beam AS servo unit on the channels "track", "pitch" and "roll" can be recorded

$$\begin{cases}\Psi(1) = [\Psi_0 V \Psi_{ACH}(T_{CB=0})] + \Delta\Psi_{LA}(1) + \Psi_{ALG}(1) - \text{for the channel "track";} \\ \vartheta(\mathrm{t}) = [\vartheta_0 V \vartheta_{ACH}(T_{CB=0})] + \Delta\vartheta_{LA}(\mathrm{t}) + \vartheta_{ALG}(\mathrm{t}) - \text{for the channel "pitch";} \\ \gamma(t) = 0 + \Delta\gamma_{LA}(\mathrm{t}) - \text{for the channel "roll";}\end{cases} \quad (1.1)$$

In the "Autotrack" mode the control signal of the beam AS servo unit can be written

$$\begin{cases}\Psi(\mathrm{t}) = \Psi_{ACH}(t) - \text{for the channel "track" ;} \\ \vartheta(t) = \vartheta_{\mathrm{ACH}}(t) - \text{for the channel "pitch";} \\ \gamma(\mathrm{t}) = 0 + \Delta\gamma_{LA}(t) - \text{for the channel "roll".}\end{cases} \quad (1.2)$$

The specific type of control signals is determined by the design features of the servo unit of the antenna system.

UAV inertial system

The key to this chain is "measuring the state of the system." That is, the coordinates of the location, speed, height, vertical speed, orientation angles, as well as angular velocities and accelerations. In the on-board navigation and control system designed and developed by “TeKnol” Ltd., the small-size inertial integrated system (Sins) performs the function of measuring the state of the system. Having triads of inertial sensors of micromechanical gyroscopes and accelerometers, as well as barometric altimeter and triangular magnetometer, and complexing the data of these sensors with the data of the GPS receiver, the system produces a complete navigational solution for coordinates and orientation angles. The Sins developed by “TeKnol” is a complete Inertial System, in which the algorithm of the free-form INS, integrated with the receiver of the satellite navigation system is implemented. It is in this system that contains the "secret" of the entire complex of UAV control. In essence, at the same time three navigation systems work in the same calculator on the same data. We call them "platforms". Each platform implements its control principles, having its "correct" frequencies (low or high). The master filter chooses the optimal solution with any of the three platforms depending on the nature of the movement. This ensures stability of the system not only in a straightforward motion, but also at bends, uncoordinated turns, lateral impenetrable wind. The system never loses the horizons than providing the correct reactions of the autopilot to external perturbations and the adequate distribution of influences between the control units of the UAV.

On-board control unit of UAV

The UAV navigation and control complex consists of three components (Figure 1).

1. Integrated Navigation System;
2. Receiver of the satellite navigation system
3. Autopilot unit.

Autopilot module produces control commands in the form of PWM (pulse-width-modulated) signals, according to the laws of management, embedded in its calculator. In addition to the UAV control, the autopilot is programmed to control the on-board equipment:

- stabilization of the camcorder,
- synchronized according to the time and coordinates of the shutter operation,
- parachute launch;

- drop of cargo or sampling at a given point and other functions. In autopilot memory can be applied up to 255 turning points of the route. Each point is characterized by coordinates, altitude and speed of flight.

In the flight the autopilot also provides output of telemetric information to the transmission channel for monitoring the UAV flight.

And what then is the quasi-autopilot? Many companies now declare that they provide their systems an automatic flight with the help of "the world's smallest autopilot."

The most illustrative example of this solution is the production of the Canadian firm “Micropilot”. For the formation of control signals here use "raw" data - signals from gyroscopes and accelerometers. Such a decision by definition is not robust (resistant to external influences and sensitive to flight conditions) and in one degree or another is operational only when flying in a stable atmosphere.

Any significant external outrage (wind gusts, ascending stream or air pit) can lead to loss of orientation of the aircraft and an accident. Therefore, everybody who has ever encountered such products sooner or later understands the limitations of such autopilots, which cannot be used in commercial UAV serial system.

More responsible developers, realizing that this navigation solution is necessary, are trying to implement a navigation algorithm using known approaches Kalmanovsky filtering.

Unfortunately, here everything is not so simple too. Kalmanovsky filtering is just an auxiliary mathematical device, not a solution to a problem. Therefore it is impossible to create a robust stable system by simply transferring to the MEMS integrated systems the standard mathematical apparatus. You need fine and proper adjustment of your specific application. In this case for the maneuverable object of the winged circuit. Our system has more than 15 years of experience in the development of inertial systems and algorithms for the development of INS and GPS. By the way, in the world, only a few countries have the know-how of inertial systems. They are Russia, the USA, Germany, France and the United Kingdom. Scientific, design and technological schools are behind this know-how, and at least it is naive to think that such a system can be developed and made "on the knee" in the institute's laboratory or in the hangar of the aerodrome. The dilettant approach here, like in all other cases, can ultimately lead to financial losses and loss of time. Why is such an important automatic flight in relation to the tasks solved by enterprises of the fuel and energy complex? It is clear that air monitoring itself has no alternative. The control of the state of pipelines and other objects, the tasks of protection, monitoring and video surveillance are best resolved with the use of aircraft. But reducing costs, ensuring the regularity of flights, automating the collection and processing of information - here, it is absolutely right to pay attention to unmanned technology, which proves the high interest of specialists to hold the exhibition and forum. However, as we have seen at the exhibition, unmanned systems can also be complex and expensive complexes that need support, maintenance, terrestrial infrastructure and operation services. This applies most of all to the complexes originally created for solving military problems, and now hastily adapted to economic applications. Let's consider separately on the issues of operation. UAV control is a task for a well-trained professional. In the US Army, UAV operators become active air force pilots after an annual studying and training. In many aspects, this is more difficult than piloting an airplane, and as you know, most of the unmanned aerial accidents are caused by pilot-operator errors. Automatic UAV systems equipped with a fully-fledged automatic control system require a minimum level of ground personnel training, while solving tasks at a great distance from the place of base, outside contact with the ground station, in all weather conditions. They are easy to operate, mobile, quickly deployed and do not require terrestrial infrastructure. It can be argued that high performance of UAV systems equipped with high-performance automatic control systems reduces operating costs and personnel requirements.

Systems of automatic UAVs

What are the practical results of using the onboard complex with this inertial system? The company “TeKnol” has developed and offers for customers a system of automatic rapid deployment of UAVs for monitoring and aerial surveillance tasks. These systems are presented on our booth at the exhibition.

The autopilot in the on-board navigation and control complex provides

- automatic flight on a given route;
- automatic take-off and approach;
- support for the specified altitude and flight speed;
- stabilization of the orientation angles;
- software control of on-board systems.

Operative UAV

The system of multipurpose UAV is developed by “Transas” Company and is equipped with the navigation and control complex of “TeKnol”.

Since the control of a small UAV is the most difficult task, let's give examples of the work of the on-board navigation and control system for an operational mini-UAV with a take-off weight of 3.5 kg.

Another important function of the UAV is the camcorder control. In the flight the stabilization of the front view camera is provided by working out the UAV fluctuations on the roll on the signals of the autopilot and data Mins. In this way, the picture of the video image is stable, despite the fluctuations of the aircraft on the roll. In the tasks of aerial photography (for example, when composing an aerial photograph of the proposed area of the work) accurate information on the angles of orientation, coordinates and altitude of the UAV is absolutely necessary for the correction of aerial photographs, automation of cross-linking frames.

Unmanned aerial photography complex is also being developed by “TeKnol” LTD. This is done by refilling the digital camera and its inclusion in the control loop autopilot. The first flights were scheduled for spring 2007. In addition to the above mentioned systems, the UAV is rapidly deployed. The UAV Navigational and Control Complex is operated by SKB “Topaz” (UAV “Voron”), installed on a new UAV developed by “Transas” company (multipurpose UAV complex “Dozor”), tested by Global Teknik (Turkey). Negotiations are held with other Russian and foreign clients. The above information and, the most importantly, the results of flight tests, clearly show that without a full-fledged on-board control complex equipped with this inertial system, it is impossible to construct modern commercial UAV systems that can solve problems safely, expeditiously, in all weather conditions, with minimum maintenance costs. Such complexes are serially manufactured by “TeKnol” Company.

Considered composition of on-board equipment of UAVs can provide a solution to a wide range of tasks for monitoring the terrain and hard-to-reach for human areas in the interests of the national economy. Application to the on-board equipment of television cameras allows in conditions of good weather and light to provide high resolution and detailed monitoring of the underlying surface in real-time. The use of digital cameras allows the use of UAVs for aerial photography in a given area with further detailed decoding. The use of thermal imaging equipment makes it possible to provide round-the-clock UAVs application, although with a lower resolution than with the use of television cameras. The most expedient application of complex systems, for example, TV- thermal imaging cameras, with the formation of a synthesized image. However, such systems are still quite expensive. The presence on board the radar allows to receive information with a lower resolution than TV and thermal imaging cameras, but around the clock and in adverse weather conditions. Application of variable modules of devices for obtaining image information, allows to reduce the cost and reconfigured the composition of on-board equipment to solve the problem in specific conditions of application. The possibility of providing stable contact is one of the most important characteristics that determine the operational capabilities of the UAV control complex. The proposed system for controlling the spatial position of the beam AS in the control systems of the UAV provides optimization of the process of contact and the possibility of its in case of its loss. The system is applicable for use in UAVs, as well as on ground and air control points.

1.3 Basic models of situations and methods of computing technology, using artificial intelligence.

Methods of finding knowledge in the information repository

Consider the main types of methods used to find new knowledge based on the data repository. The purpose of intelligent information technology is to find new knowledge that the user can continue to apply for improving the results of their activities. The result of simulation is the detection of the relation type in the data.

Six methods for identifying and analyzing knowledge can be identified:

- classification,
- regression,
- forecasting of time sequences (rows),
- clustering,
- association,
- consistency.

The first three methods are mainly used for forecasting, while the latter are convenient for describing the existing patterns in the data.

Classification is the most widespread model of intelligent data analysis. With its help, there are signs that characterize the group to which one or another object belongs. This is done by analyzing already classified objects and formulating some set of rules.

In many types of businesses the problem is the loss of steady customers. Classification helps to find the characteristics of "swift" buyers and to create a model of a predictable situation in which the buyer is inclined to go to another seller. Using the model, you can create effective types of discounts, as well as other attractive offers for customer service, which will have a beneficial effect on buyers and keep them from switching to another seller. Once a definite effective classifier is used to classify new entries in a database in existing classes and in this case it acquires the character of the forecast. For example, a classifier that can identify the risk of a loan repayment can be used to decide whether there is a high risk of lending to a particular client. That is, the classifier is used to predict the probability of a loan repayment.

Regression analysis is used when the relation between variables can be expressed quantitatively in the form of some combination of these variables. The resulting combination is used to predict the numerical value that a target (dependent) variable can take, which is calculated on a given set of values of the input (independent) variables. In the simplest case, standard statistical methods such as linear regression are used for this, but most of the real models of the situation do not fall within its scope. For example, sales or stock prices are difficult to predict, since they can depend on the complex of variables relation.

Forecast of time sequences. The basis for any forecasting system is historical information stored in information repositories in the form of time series. If you can build a mathematical model and find prototypes that adequately reflect this dynamics, there is a likelihood that with their help you can predict the behavior of the system in the future. Forecasting of time sequences allows us to estimate the future values of predicted variables based on the analysis of the behavior of time series. These models should contain special signs of time: the hierarchy of periods (month-quarter-year), special time periods (five- six- or seven-day working week), seasonality, holidays, etc.

Clustering differs from the classification by the fact that the classes are not predefined and using the clustering model of the means of intelligent computing independently create homogeneous data groups.

The association promotes the analysis of structures and is used when several events are interconnected. A classic example of the analysis of the purchase structure relates to the representation of the purchase of any number of goods as a single economic transaction. Since a large number of purchases is carried out in supermarkets and buyers use shopping baskets for convenience, and where they make up the purchased product, the search for the associations is the results of the analysis of the contents of the basket. The purpose of using this approach is to search for trends (identical sites) among a large number of transactions that can be used to explain the behavior of buyers. Such information can be used to regulate stocks, change the placement of goods in the store and decision making on an advertising campaign to increase sales or to promote a specific type of product. For example, a study conducted in a supermarket can show that 65% of buyers of potato chips, take also "Coca-Cola", and in the presence of discounts for such a set of "Coca-Cola" in 85% of cases. With such data, managers are easy to judge how effective the discount is. Although this approach came from retail, it can also be applied in the financial sector to analyze the portfolio of securities and to search for financial services sets that customers often take together. This can be used to create some set of services as part of a sales promotion campaign.

The sequence takes place if there is a chain of events connected in time. Traditional analysis of the structure of purchases deals with a set of goods representing one transaction. The variant of such an analysis occurs if there is additional information (the number of the customer's credit card or his bank account number) to link different purchases to a single temporary series. In this situation, it's important not only data coexistence within a single transaction, but also the order in which these data appear in different transactions and the time between those transactions. The rules setting these relations can be used to determine the typical set of previous sales that may lead to subsequent sales of the specified product. It was established that after buying a home in 45% of cases, a new cooker is bought within a month, and in the next two weeks, 60% of new occupants will be acquired by a refrigerator.

Methods (algorithms) of intellectual calculations

- network neurons;
- solutions trees;
- systems of reasoning based on similar cases;
- algorithms for determining associations and sequences;
- fuzzy logic;
- genetic algorithms;
- evolutionary programming;
- data visualization.

Neurons of the network are systems that have such an architecture, the use of which can simulate the work of neurons conventionally. The mathematical model of the neuron is a universal nonlinear element with the possibility of wide change and adjustment of its characteristics (parameters). Neurons of the network represent a set of interconnected layers of neurons that receive input data, perform their processing, and generate the result that is issued at the output. Between the nodes of the visible input and output layers may be a certain number of hidden layers. Neurons of the network implement a non-transparent process. This means that the constructed model, as a rule, does not have a clear interpretation. Many packages of computer programs that implement algorithms of neural networks, used in the processing of commercial information, in the recognition of images, decoding of handwritten text, interpretation of cardiograms.

Hardware and software for implementing algorithms of neural networks are called neurocomputer.

Neurocomputers provide the use of existing methods to solve many of the original tasks. And it does not matter that a specialized computer allows solving better one class of tasks. More important is that one neurocomputer will solve both this task and the other, and the third, and it is not necessary to design and create a specialized computer every day, a neurocomputer will do everything itself and not even worse.

Instead of programming - learning. Neurocomputer studies, you only need to form training sets. The work of the programmer is replaced by the new work of the teacher. Is it better or worse? Not one, not another. The programmer points the machine to all the sequences of the work and the teacher creates a "learning environment" to which the neurocomputer adapts. There are new opportunities for work.

Neurocomputers are effective where an analogue of the human way of thinking (intuition) is needed, in particular, for pattern recognition, reading of handwritten texts, preparation of analytical forecasts, translation from one language to another, etc. Of course it is difficult to develop an explicit algorithm for these purposes.

Neural networks allow to create effective software and mathematical support for computers with a high degree of parallel processing (calculations).

Neurocomputers are "democratic", they are simple as word processors, so a low-skilled user can work with them.

Solutions trees - this method is widely used in various fields of production, finance and business, which often encounter problems of numerical prediction. As a result of the application of this method, a hierarchical structure of the classification rules of the type, "IF... THEN...", having the form of a tree, is created for the data sample training. In order to decide which class to refer to some object or situation, one must answer the question that is at the nodes of this tree, starting with its root. The questions may look like "The value of A is greater than X?" or the form "The value of the variable B belongs to a subset of C?". If the answer is positive, go to the right node of the next level, if negative - then to the left node; then the procedure of answering a question that is linked to the corresponding node is again performed. Thus, in the end, one can reach one of the finite nodes where the class of the object is defined. This method is a good visual representation of the rules and is easy to understand. At the present time, there is an increasing interest in the tasks that are used to solve a solutions tree. This is mainly due to the fact that most of the production and economic problems are solved by them faster than algorithms of neural networks; they are simpler and clearer for users. At the same time, it cannot be said that solutions trees always work smoothly: for certain types of data, they may not be acceptable. The fact that the individual nodes in each industry are given less number of data records - the tree can segment the data for a large number of individual cases. The greater the numbers of such individual cases, the less study examples fall into each such individual case, and their classification becomes less reliable. If the tree is too "branchy" - it consists of a large number of small branches - it will not give statistically substantiated answers. As practice shows, in most systems that use solutions trees, this problem does not find a satisfactory solution.

Systems of reasoning based on similar cases. The idea of the algorithm is quite simple. In order to make a forecast for the future or to choose the right solution, the systems find in the past similar analogues of the current situation and choose the same answer that was right for them. Therefore, this method is also called the "closest neighbor" method. Systems of reasoning on the basis of similar cases give good results in various tasks. Their main disadvantage is that they do not create any models or rules that generalize previous experience - in choosing a solution they are based on an array of available historical data, so it is impossible to say on the basis of which specific factors these systems build their answers.

The algorithms for determining associations find rules about individual items that appear together in one transaction, for example, in one purchase.

Consistency is also an association, but time-dependent. The association is written as A>B, where A is a prerequisite, and B is a consequence. The frequency of the appearance of each individual object or group of objects is determined as follows: the amount of the occurrence of this object in all events (purchases) is calculated and divided by the total number of events. This value is measured as a percentage and is called "prevalence". The low prevalence (less than one thousandth of a percent) suggests the non-essential association. To determine the importance of each associative rule obtained, it is necessary to obtain a value called "trust A to B" (interconnection A and B). This value shows how often with the appearance of A appears B and is calculated as the ratio of the incidence (prevalence) of the occurrence (prevalence) of A and B together with the prevalence of A. That is, if the confidence A to B is 20%, this means that when buying goods A in every fifth case product B is bought as well. If the prevalence of A is not equal to the prevalence B, then the confidence A to B does not equal the confidence B to A. In fact, buying a computer more often leads to the purchase of floppies than buying a floppy disk before buying a computer. Another important characteristic of the association is the power of the association. The greater the power, the greater the effect that the appearance of A makes on the appearance of B. Power is calculated by the formula: (confidence A to B) / (prevalence B).

Some association search algorithms first sort data and only then determine the relationship and prevalence. The only difference between such algorithms is the speed or efficiency of associations staying. This is important because of the huge number of combinations you need to take to find more meaningful rules. Association search algorithms can create their own databases of prevalence, trust, and power, which can be accessed upon request. For example: "Find all associations in which for the product X the trust is more than 50% and the prevalence is not less than 2.5%." When you find sequences, a time variable is added that allows you to work with a series of events to find successive associations over a period of time.

Summing up this analysis method, it is necessary to say that there may be a situation where the goods in a supermarket will be grouped using the found models, but this, instead of the expected profit, will have the opposite effect. This can happen because the client will not go shopping for a long searching the desired product, while buying something else that falls into the eye, and that what he never planned to buy.

Fuzzy logic is used for data arrays in which the membership of data to any group is a probability in the range from 0 to 1. Clear logic manipulates the results, which may be either true or false. Fuzzy logic is used in cases where there exists "maybe" in addition to "yes" or "no".

The scope of using fuzzy logic algorithms is any kind of analytical system, including:

- nonlinear control over processes (production);
- improving management and coordination strategies, for example, complex industrial production;
- self-learning systems (or classifiers);
- research of risky and critical situations;
- pattern recognition;
- financial analysis (securities markets);
- data research (corporate repositories).

In Japan, this trend is going through a boom. There is a specially created Laboratory for International Fuzzy Engineering Research (LIFE). The program of the organization is the creation of more close to human computing devices. LIFE combines 48 companies including Hitachi, Mitsubishi, NEC, Sharp, Sony, Honda, Mazda and Toyota. From foreign LIFE participants, the following can be distinguished: IBM, Fuji Xerox, and NASA is also interested in LIFE activity.

The power and intuitive simplicity of fuzzy logic as a methodology for solving emerging problems ensures its successful use in embedded control and information analysis systems. At the same time there is a connection of human intuition and the operator's experience. Unlike traditional mathematics, which requires at each step the simulation of precise and unambiguous formulations of patterns, fuzzy logic offers a completely different level of thinking, which makes the creative process of simulation happen at a high level of abstractions, in which only a minimal set of regularities is postulated.

Genetic algorithms are a powerful tool for solving various combinatorial problems and optimization tasks. However, genetic algorithms are now included in the standard toolkit methods of intelligent computing. This method is called so because it imitates in a certain degree the process of natural selection in nature. Let us have to find a solution to the problem, the most optimal in terms of some criterion, where each solution is fully described by a certain set of numbers or values of non-numerical nature. For example, if we need to choose a set of fixed number of market parameters that significantly affect its dynamics, it will be an array of names of these parameters. About this array we can speak as about a set of chromosomes that determine the quality of the individual - this is the solution for the problem. The values of the parameters that determine the solution are called genes. Finding the optimal solution is similar to the evolution of the population of individuals represented by sets of chromosomes. There are three mechanisms in evolution: first, the selection of the strongest - sets of chromosomes, which correspond most optimal solutions; and secondly, crossing - the production of new individuals by mixing the chromosome arrays of selected individuals; and, thirdly, mutations - random changes in genes in some individuals in the population. As a result of generational change, a solution to the problem is being made, which can no longer be further improved.

Evolutionary programming is the youngest area of intellectual computing. Hypotheses about the type of dependence of the target variable on other variables are formulated by the system in the form of programs in some internal programming language. If this is a universal language, theoretically it can express dependence of any kind. The process of constructing such programs is based on evolution in the world of programs (this method is a bit similar to genetic algorithms). If the system finds a program that accurately expresses the desired dependence, it starts to make small modifications to it and selects among the child programs that are built in this way those that increase the accuracy of its functioning. The system "grows" several genetic lines of programs that compete with each other in the exact finding of the desired dependence. The special broadcasting module translates the found dependencies from the internal language of the system into the user's language (mathematical formulas, tables, etc.), making them readily available. In order to make the obtained results more understandable to the user of mathematics, there is a large arsenal of various means of visualization of the detected dependencies. The search for the dependence of the target variables on the other is carried out in the form of functions of a certain type. For example, in one of the most successful algorithms of this type - the method of group accounting of arguments (MGAA) dependence is sought in the form of polynomials. Moreover complex polynomials are replaced by several simple ones, taking into account only some of the signs (groups of arguments). Pair wise association of attributes is usually used. This method has no great advantages compared with neural networks with a ready set of standard nonlinear functions, but the resulting dependency formulas, in principle, are subject to analysis and interpretation.

Data visualization programs in defined content are not a means of analyzing information because they only represent it to the user. However, the visual representation, say, of just four variables clearly summarizes the vast amount of data.

Combined methods. Manufacturers often combine these approaches. Combining algorithms of neurons of the network and technology of solutions trees helps to build a more accurate model and increase the speed. For the solution of each problem it is necessary to look for the optimal method.

1.4 Neurons of the network

An artificial neural network (ANN) is a mathematical model, as well as a parallel computing device that is a system of connected and interacting simple processors (artificial neurons). As a mathematical model, an artificial neural network is a separate case of methods for pattern recognition or discriminate analysis. Such processors are usually quite simple, especially compared to processors used in personal computers. Each processor of such a network only deals with signals that it receives from time to time, and signals that it periodically sends to other processors. However, being connected to a fairly large network with managed interaction, such locally simple processors are able to perform quite complex tasks. The concept arose in the study of processes occurring in the brain during thinking and when trying to simulate these processes. The resulting models are called artificial neural networks (SNNs), which use a large number of bonds that bind separate neurons. Grouping in the human brain occurs in such a way that information is processed dynamically, interactive and self-organizing way. Biological neurons of the network are created in a three-dimensional space of microscopic components and are capable of various connections, and for the human-made network there are physical constraints.

On the other hand, the artificial neural network is a set of artificial neurons interconnected. As a rule, transfer functions of all neurons in the network are fixed, and weights are network parameters and may change. Some neuron inputs are labeled as external network inputs. Some outputs - like external outputs of the network. By giving any number to the network inputs, we receive a set of numbers on the outputs of the network. Thus, the work of the neural network consists in the transformation of the input vector into the output vector, and this conversion is determined by the weights of the network.

The simplest models of artificial neural networks

The McCulloch-Pitts model was the starting point for building a simple unidirectional neuron network called the perceptron. Such a network was proposed and studied by Rosenblatt in the late fifties - early sixties of the XX century.

The signal x at the output of the linear part of the perceptron is given by the expression

$$x = \sum_{i=1}^{N} w_i u_i - v = \sum_{i=0}^{N} w_i u_i \, , \tag{1.3}$$

where $w_0 = v$, $u_0 = -1$.

The task of the perceptron is to classify the vector i=[$и_{:}$.....u_N]^T in the content of assigning it to one of the two classes, denoted by the symbols L_1 and L_2. The perceptron assigns the vector i to the class L_1, if the output signal y receives the value 1, i to the class L_2, if the output signal y takes the value -1. After this, the perceptron divides the N-dimensional space of the input vectors i into two half-spaces divisible by (N-1) -dimensional hyper plane given by the equation

$$\sum_{i=1}^{N} w_i u_i - v = \sum_{i=0}^{N} w_i u_i = 0, \tag{1.4}$$

Hyperplane is called the decision boundary. If N = 2, then the decision boundary is the straight line given by the equation

$$w_1 u_1 + w_2 u_2 - v = 0. \tag{1.5}$$

The point (i_1, i_2) lying above this line refers to class L_1, whereas the point (i_1, i_2) lying under this line refers to the class L_2. Points lying on the boundary of a solution can be arbitrarily attributed to class L_1 and to class L_2.

For further reason we assume that the weights w_i, i = 0, 1,..., N in the hyperplane equation are unknown, whereas the so-called training signals u (n), n = 1, 2… are sequentially fed to the input of the perceptron, where u (n) = [i_1 (n),.... u_N] T.

Unknown values of weight will be determined in the learning process of the perceptron. This approach is called "learning with a teacher" or "supervised learning". The role of the "teacher" is to assign correctly the signals u (n) to classes L_1 or L_2, despite of the weight uncertainly of the equation of the decision boundary. Upon completion of the learning process, the perceptron must correctly classify the signals that arrive at its input, including those that were missing in the learning sequence u (n), n = 1, 2..... In addition, we assume that the plural of the vectors u (n), n = 1, 2,..., for which the output of the perceptron takes respectively values 1 and -1, are linearly separated, that is, they lie in two distinct half-spaces separated by a hyperplane. In other words, it is possible to divide the learning sequence {u (n)} into two sequences {u_1(n)} і {u_2(n)} так, що {u_1(n)} $\in L_1$ і {u_2(n)} $\in L_2$.

At the n-th moment of time, the signal at the output of the linear part of the perceptron is determined by the expression

$$x(n) = \sum_{i=0}^{N} w_i(n) u_i(n) = w^T(n) u(n), \tag{1.6}$$

where

$$u(n) = [-1, u_1(n), u_2(n).....u_N(n)]^T, \tag{1.7}$$

$$w(n) = [v(n), w_1(n), w_2(n).....w_N(n)]^T. \tag{1.8}$$

The training of the perceptron is in the recurrent correction of the weight vector w(n) according to the formulas

$$w(n+1) = \begin{cases} w(n), & if\ \ w^T(n)u(n) \geq 0\ i\ u(n) \in L_1, \\ w(n), & if\ \ w^T(n)u(n) < 0\ i\ u(n) \in L_2, \end{cases} \tag{1.9}$$

and

$$w(n+1)=\begin{cases} w(n)-\eta u(n), & if \;\; w^T(n)u(n)\geq 0 \; i \; u(n)\in L_1, \\ w(n)+\eta u(n), & if \;\; w^T(n)u(n)<0 \; i \; u(n)\in L_2, \end{cases} \quad (1.10)$$

where the parameter η for 0 <η <1 is the correction step, while the initial values of the components of the vector of weights are set to zero, that is,

$$w\,(0) = 0. \quad (1.11)$$

Dependences (1.9) and (1.10) can be represented in a more concise form. To do this, we define the so-called reference (given) signal d(n) in the form

$$d(n)=\begin{cases} +1, & if \;\; u(n)\in L_1, \\ -1, & if \;\; u(n)\in L_2. \end{cases} \quad (1.12)$$

In addition, note that the output signal of the perceptron can be described by expression

$$y(n) = sgn(w(n)u(n)). \quad (1.13)$$

Taking into account the entered notation, recursion (1.10) and (1.11) take the form

$$w\,(n + 1) = w\,(n) + [d\,(n) - y\,(n)]\,u\,(n). \quad (1.14)$$

The difference d(n) -u(n) can be interpreted as the error between the reference (given) signal d(n) and the actual output signal y(n).

The convergence of the algorithm (1.12) was researched by Rosenblatt, as well as by other authors. Taking into account the above condition for the linear separability of the input signals, the algorithm (1.12) converges, that is,

$$w(n_0) = w(n_0 + 1) = w(n_0 + 2) \quad (1.15)$$

Upon completion of training, the decisive boundary of the perceptron is determined by the expression

$$\sum_{i=0}^{N} w_i(\,n_0\,)u_i = 0, \quad (1.16)$$

and the perceptron correctly classifies as signals belonging to the learning sample {u(n)}, which are not included in this set, but fulfill the condition of linear separability. Recall that the condition of linear separability does not correspond to the logical function XOR.

Systems like Adaline

Adaline Systems (Adaptive Linear Neuron) were proposed in 1960 by Wadrou and Hoff. Bernard Wadrou and Ted Hoff described a whole family of systems like Adaline. Before moving on to a detailed discussion of Adaline systems, let's look at the model of the so-called linear weighted adder.

Adaptive Linear Weighted Adder

The application of the algorithm (1.17) involves knowledge of the matrix R and the vector ∂. In the case when these quantities are unknown, it is worth replacing the gradient with its approximation. Let's write the recursive expression in the form

$$\text{w(n + 1) = w(n)-}\frac{1}{2}\eta\frac{\partial E[\varepsilon^2(n)]}{\partial w(n)}. \qquad (1.17)$$

If in this formula replace the gradient with its approximate local value (instantaneous estimate), ie

$$\frac{\partial E[\varepsilon^2(n)]}{\partial w(n)} \rightarrow \frac{\partial \varepsilon^2(n)}{\partial w(n)} \qquad (1.18)$$

then get a recursive look

$$\hat{w}\text{ (n + 1) = }\hat{w}\text{ (n)-}\frac{1}{2}\eta\frac{\partial \varepsilon^2(n)}{\partial w(n)}. \qquad (1.19)$$

From the expressions (1.18) and (1.19) it follows that

$$\frac{\partial \varepsilon^2(n)}{\partial w(n)} = 2\varepsilon(n)\frac{\partial \varepsilon(n)}{\partial w(n)} - 2\varepsilon(n)u(n). \qquad (1.20)$$

When substituting dependence (1.19) in the formula (1.20) we obtain the so-called algorithm LMS (Least Mean Square) in vector form

$$w(n + 1) = w(n) + u(n)[d(n) - w(n)u(n)] \qquad (1.21)$$

or in a scalar form

$$\hat{w}_k(n + 1) = \hat{w}_k(n)-u_k(n)[\,d(n)-\sum_{k=1}^{N} w_k(n)u_k(n)] \qquad (1.22)$$

for k = 1..... N.

Presents adaptive linear weighted adder known in the literature by name Adaline (Adaptive Linear Neuron). It consists of two main parts:

1) a linear weighted adder with adaptive weights that are corrected

$$\hat{w}_1(n)\text{.....}\ \hat{w}_N(n),$$

2) a subsystem designed for adaptive correction of these weights and implementing the LMS algorithm.

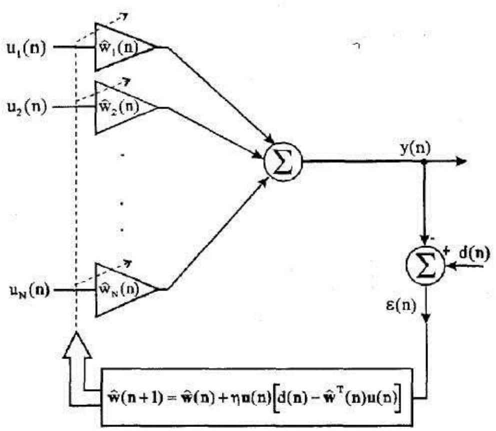

Fig. 1.2 Adaptive Linear Weighted Adder.

The parameter η in the algorithm (1.23) is selected so that the condition is fulfilled

$$0 < \mu < \frac{2}{TrR} = \frac{2}{\sum_{k=1}^{N} E[(u_k(n))^2]} \tag{1.23}$$

where Tr denotes the matrix R.

Adaptive Linear Weighted Adder with Sigmoid at the Outlet

The output signal of an adaptive linear adder with a sigmoid on the output can be described by the expression

$$y(n) = f(\sum_{k=1}^{N} w_k(n)u_k(n)), \tag{1.24}$$

where the function f is determined by the formula (1.25). The error of implementation (1.25) is equal to

$$\varepsilon(n) = d(n) - f(\sum_{k=1}^{N} \hat{w}_k(n)u_k(n)), \tag{1.25}$$

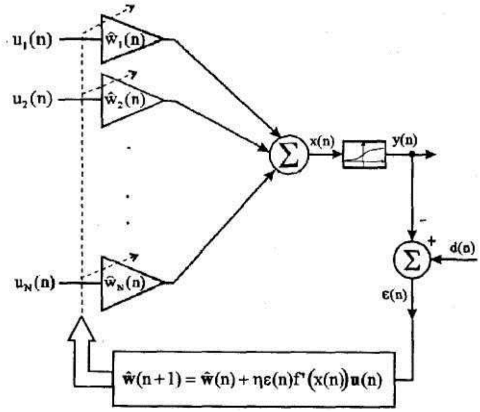

Fig. 1.3 Adaptive Linear Weighted Adder with Sigmoid at the Outlet.

To correct the weights k (k), k = 1..... N, we apply the LMS algorithm in the recursive form (1.25). In this case, obvious equality

$$\frac{\partial \varepsilon^2(n)}{\partial \hat{w}(n)} = 2\varepsilon(n)\frac{\partial \varepsilon(n)}{\partial \hat{w}(n)}, \tag{1.26}$$

and

$$\frac{\partial \varepsilon(n)}{\partial \hat{w}(n)} = -\frac{\partial f(x(n))}{\partial \hat{w}(n)} = -f(x(n))\frac{\partial x(n)}{\partial \hat{w}(n)}, \tag{1.27}$$

where

$$x(n) = \sum_{k=1}^{N} \hat{w}_k(n)u_k(n)) = \hat{w}^T(n)u(n). \tag{1.28}$$

As

$$\frac{\partial x(n)}{\partial \hat{w}(n)} = u(n), \tag{1.29}$$

so

$$\frac{\partial \varepsilon(n)}{\partial \hat{w}(n)} = -f'(x(n))i(n). \tag{2.59}$$

With the substitution of equations (2.55) and (2.59) in the recursive expression (2.48) we obtain the following algorithm for adaptive weight correction:

$$\hat{w}(n + 1) = \hat{w}(n) + \eta\varepsilon(n)f'(x(n))u(n), \tag{1.30}$$

or in a scalar form

$$\hat{w}_k(n + 1) = \hat{w}_k(n) + (n)f'(x(n))u_k(n), \tag{1.31}$$

for k = 1..... N. If ε (n) = 1, then the function (2.6) corresponds to the condition

$$f'(x) = f(x)(1 - f(x)). \tag{1.32}$$

Therefore, the algorithm (2.60) can be written in the form

$$\hat{w}_k(n + 1) = \hat{w}_k(n) + (n)f(x(n))(1 - f(x(n))u_k(n) \tag{1.33}$$

for k = 1..... N, where the error ε (n) is determined by the expression (1.30).

Algorithms (1.31) and (1.32) are the basis of the method for the back propagation of error which is described below.

1.5 Classification of artificial neural networks

Classification by type of incoming information:

– analogue neurons of the network (use information in the form of real numbers);

– dual neuron networks (operate with information presented in dual-type).

Classification by the nature of training:

– with a teacher (the source space for neural network solutions is known);

– without a teacher (the neural network forms the output space of solutions only on the basis of input impacts). Such networks are called self-organizing;

– with a critic (penalty system and incentive).

Classification by the nature of the synapse tuning

Fixed-line networks (weight ratios of the neural network are selected immediately, based on the conditions of the task, while: d/dt = 0, where W is the weighting of the network); networks with dynamic connections (for them, in the learning process, the adjustment of synaptic connections is made, that is, d/dt ≠ 0, where W is the weighting coefficients of the network).

Classification by the nature of connections

Direct Broadcast Networks (Feedforward)

All communications are directed strictly from the input neurons to the original. Examples of such networks are single-layer and multi-layer perceptrons, Ward networks.

Recurrent Networks

The signal from the source neurons or neurons of the hidden layer is partially transmitted back to the inputs of the neurons of the input layer. Like any system that has feedback, the recurrent network is striving for a steady state. As is known, the most stable state is provided by minimizing the energy of the system. The recurrent network "filters" the input data, returning to a steady state and, thus, allows solving tasks of data compression and associative memory construction. A striking example of such networks is the Hopfield network.

Bidirectional networks

In such networks between layers there are bonds both in the direction from the input layer to the output, and in the reverse.

Radial-basic functions

Artificial neural networks that use radial-based activation functions (such networks are abbreviated as RBF networks). General view of the radial-basic function:

$$f(x)=e^{-\frac{x^2}{\sigma^2}}$$

where σ is the width of the function window.

The radial-basic network is characterized by three peculiarities:

1. The single hidden layer
2. Only the hidden layer neurons have a nonlinear activation function
3. The synaptic weights of the links of the input and the hidden layers are equal to one

Self-organizing cards

Such networks are, as a rule, two-dimensional structure of neurons. Before learning the structure is random, the neurons are distributed approximately equal. In training, for each training record, a point is calculated that corresponds to it in the structure of the network. The neuron, located closest to the desired point, is called the neuron-winner. The weights of the links that connect this neuron with others increase, thereby reducing the structure slightly. The weights of the neurons, which are "neighbors" of the neuron-winner, to other neurons also increase, but weaker, etc. Thus, the more often the neuron "wins" when compared with the sign, the more "denser" to it are the other neurons. At the end of the training, the network represents several zones of neuronal concentration, called clusters.

1.6 Learning Neural Network

Like their biological prototypes, ANN can learn, that is to improve their work under the influence of the environment, which changes its parameters. There are many definitions of the term "learning," but the following is best suited to the ANN: given by Mendel and McLaren:

Training is a process in which the free parameters of the neural network are adapted as a result of its continuous stimulation of the external environment. The type of learning is determined by that way in which changes are made.

In modern literature, in addition to the term "learning", equally, the concepts of "network training" and "network settings" are also used. In general, two main types of learning can be distinguished: supervised learning and self-organized learning. The first type implies the presence of a "teacher" that observes the response of the network and directs changes to its parameters. In the second case, the network itself is organized under the influence of the external environment and studies it independently, without the help of the "teacher". Self-education is inherent in problems of pattern recognition and classification. In controlling the management tasks, the controlled learning of ANN is usually used.

There are two varieties of controlled learning: direct controlled learning and reinforcement learning. Since the first kind appeared before the second and more widespread, it is usually referred to it simply as a controlled learning.

Neurons of the network are not programmed in the usual sense of the word, they are learning. Ability to study is one of the main advantages of neural networks in the traditional algorithms. Technically, the training is to find the coefficients of the relation between neurons. In the learning process of a neuron, the network is able to detect complex interdependencies between incoming data and output, as well as perform generalization. This means that, in the case of successful training, the network will be able to return the correct result based on data that was missing from the training sample. Teaching a neural network means to tell it what we are requiring from it. This process is very similar to learning a child alphabetically. Showing a letter "A" to a child, we ask: "What is this letter?" If the answer is incorrect, we inform the child that answer which we would like to receive: "This is the letter A". The child remembers this example with the correct answer, that is, in memory some changes are made in the right direction. We will repeat the process of presenting the letters again and again until all 33 letters are firmly remembered. Such a process is called "learning with a teacher".

When learning the network, we are acting similar. We have some database containing examples (a set of handwritten images of letters). Presenting an image of the letter "A" to the network input, we get some answer from it, not necessarily correct one. We know the correct (desirable) answer - in this case, we would like to see the signal level at the output marking "A" maximum. Usually, as a desirable output in the classification task take a set (1, 0, 0,...), where 1 stays on the output with the label "A", and 0 - on all other outputs. By calculating the difference between the desired response and the actual response of the network, we get 33 numbers - an error vector. The algorithm for the reciprocal distribution of errors is a set of formulas that allows to calculate the necessary corrections for the network weights in the error vector. The same letter (as well as different images of the same letter), we can present for the network many times. In this sense, learning is more like a repetition of exercise in sports - training. In fig. is a diagram of the network learning process.

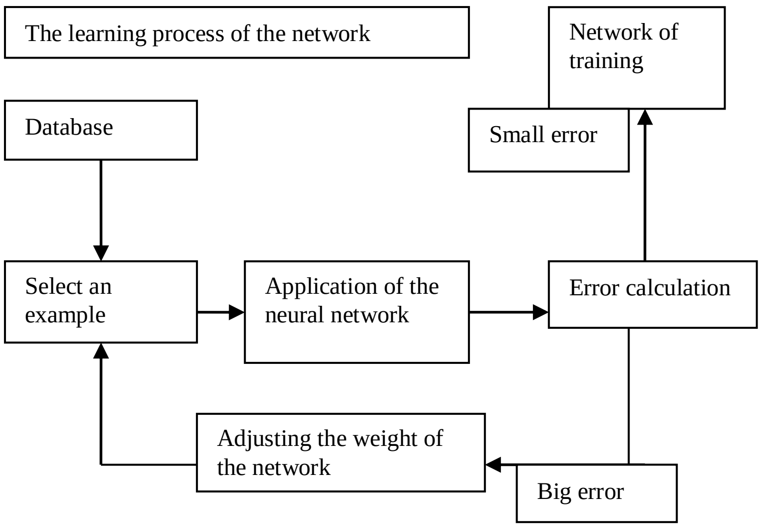

Fig 1.4 Scheme of network learning process

After repeatedly presenting examples the network weight is stabilized, with the network giving correct answers to all (or almost all) examples from the database. In this case, they say that "the network has studied all the examples", "network trained", or "network is trained." In software implementations one can see that in the learning process the magnitude of the error (the sum of the squares of errors on all outputs) gradually decreases. When the magnitude of the error reaches zero or an acceptable low level, the workout is stopped, and the received network is considered trained and ready for use on new data.

It is important to note that all the information that network has about the task is contained in the set of examples. Therefore, the quality of training network depends on the number of examples in the training sample and how full these examples describe this task. For example, it is senseless to use the network to predict the financial crisis, if there are no crises in the training sample. It is believed that for a full-time training, at least several dozen (or better hundreds) of examples are required. As we have already said, learning a network is a complex and knowledge-intensive process. Learning algorithms have different parameters and settings, for managing which requires an understanding of their impact.

1.7 Application of Neural Network

Neural networks cannot be considered universal to solve all computational problems. Computers and computing methods are ideal for many applications. Computers surpass a person's ability to do numerical and symbolic calculations.

Table 1.1 The characteristics of a computer with the von Neumann architecture compared with the neural network.

	Computer	Neuron Network
Processor	Complex High speed One or more	Simple Low speed A large number of
Memory	Separately from the processor Localized Address to the address	In the processor Parallel Content addressing
Calculations	Centralized Sequential Saved programs	Parallel Programs Parallel Self-study
Reliability	Vulnerability	Viability
Specialization	Numerical Operations	Problems of Perception
Operation environment	Strictly defined Strictly limited	Poorly defined Without limits

Functions	Logically, through the rules concept, computation	Through the image, drawings, management
Method of training	By rules	By example
Application	Numerical processing Information	Recognition, speech recognition, text recognition

However, a person can easily solve complex problems of external data perception (recognition of man in the crowd on its identity) with such speed and precision that the most powerful computer seems being a slowcoach. The table shows the characteristics of a computer with the von Neumann architecture compared with the neural network.

We will consider in details the use of neural networks for solving practical problems.

Clustering

In addition to the classification tasks neural networks are widely used to find dependencies in data and clustering.

For example, a neural network based on the method of group accounting of arguments allows to build on the basis of the training sample the dependence of one parameter on the other in the form of a polynomial $y= x_1^3 - 4x_3{}^2x_8^5 + x_3^2$. Such a network can not only instantly examine the multiplication table, but also find complicated hidden dependencies in data (for example, financial) that are not detected by standard statistical methods. Clusterization is the breakdown the set of input signals into classes, with the fact that neither quantity nor attributes of classes are known in advance. After training such a network is able to determine which class is the input signal. The network may also signal that the input signal does not belong to any of the selected classes - this is a sign of the new, missing data in the training sample. Thus, such a network can detect new, previously unknown classes of signals. The correspondence between the classes, the allocated network, and the classes that exist in the subject area, is established by man. When solving a clustering problem, the trained set does not have class labels. The clustering algorithm is based on similarity of images and places similar images in one cluster. Known cases of clustering for knowledge production, data compression and data properties research.

Prediction and approximation

The ability of the neural network to predict directly derives from its ability to generalize and to allocate hidden dependencies between input and output data. After learning the network is able to predict the future value of a sequence based on several previous values and / or some existing factors at the moment. It should be noted that forecasting is possible only when the previous changes really determine the future in a certain degree. For example, predicting stock quotes based on quotations over the past week could prove to be successful (or maybe not), while forecasting the results of tomorrow's lottery based on data over the past 50 years will almost certainly not bring any results. The tasks of forecasting are especially important for practice, in particular for financial applications, so we will explain the ways of using neural networks in this area in details.

Decision making and management

This problem is close to the classification problem. Classifications are subject to a situation, the characteristics of which are received on the input of the neural network. At the exit of the network at the same time there should be a sign of the decision, which it accepted. In this case, as input signals, various criteria for describing the status of a controlled system are used. Consider the dynamical system given by the set {u (t), y (t)}, where u(t) is the input control influence, and y(t) is the output of the system at the time t. In control systems with a reference model for the purpose of control is the calculation of such input influence u(t), in which the system operates on the desired trajectory, which is specified by the reference model. An example is optimal engine control.

Data compression and associative memory

The ability of the neural network to detect interconnections between different parameters makes it possible to express large-dimensional data more compactly, if the data are closely interrelated with one another. The reverse process - the recovery of the initial set of data from a piece of information - is called (auto) associative memory. Associative memory also allows restoring the output signal / image from noisy / damaged input data. Solving the problem of heterosocial memory allows realizing the memory that is addressed by the content.

In traditional computers, memory access is available only with an address that does not depend on the memory. Moreover, if there is an error in the calculation of the address, then there can be found completely different information. Associated memory or memory, which is addressed by the content, is accessible by the indication of the given content. Memory contents can be caused even by partial input or damaged content. Associative memory can be used in multimedia information databases.

Optimization

Numerous problems in mathematics, statistics, technology, science, medicine and economics can be considered as problems of optimization.

The task of the optimization algorithm is to find such a solution that satisfies the system of constraints and maximizes or minimizes the target function.

Despite the advantages of neural networks in certain areas over existing traditional calculations, neural networks are not perfect solutions. They learn and can make "mistakes". In addition, it cannot be guaranteed that the developed network will be the optimal network. The use of neural networks requires the developer to fulfill a number of conditions:

- a set of data containing information that characterizes the problem;
- a properly sized data set for training and testing of the network;
- understanding of the basic nature of the problem to be solved;
- choice of the adder function, transfer function and teaching methods;
- understanding tools of the developer;
- appropriate processing power.

New computing capabilities require developer skills beyond the boundaries of traditional computing. Initially, the calculations were only hardware and engineers made them work. Then, there were software specialists: programmers, system engineers, database specialists and designers. Now there are neuron architects. A new professional must have a qualification higher than his predecessors. For example, he should know the statistics to select and evaluate the training and test sets.

When creating effective neural networks, important for modern software engineers are logical thinking, empirical skills and intuition.

1.8 Recent trends in the development of neurocomputer technologies

A detailed analysis of neurocomputer developments allows highlighting the main promising directions of the modern development of neurocomputer technologies: neuropackets, neural network expert systems, databases with the inclusion of neural network algorithms, image processing, control of dynamic systems and signal processing, financial management, optical neurocomputers, virtual reality. Developments in this area are engaged in more than 300 foreign companies, and their number is constantly increasing. Among them are such giants as Intel, IBM and Motorolla. Today there is a tendency of transition from software implementations to software and hardware implementation of neural network algorithms with a sharp increase in the number development of neurocircuits with neural network architecture. The number of military developments sharply increased, mainly aimed at creating super-fast, "smart" supercomputers.

If we talk about the main direction - the intellectualization of computing systems, giving them the properties of human thinking and perception, then neurocomputers - almost the only way of development of computer technology. Most of the failures on the way to improving artificial intelligence over the past 30 years has been linked to the fact that for computing the important and difficult task of setting tasks, which were inadequate in terms of possibilities of the problem to be solved, mostly from traditional computers. At the same time, as a rule, the task was not solved, but the principled possibility of its solution was shown. Today, the active development of computer technology creates objective conditions for the construction of computing systems that are adequate in terms of capabilities and architecture for virtually any task of artificial intelligence.

In Japan, since 1993, the program "Real world computing program" has been adopted. Its main goal is to create an evolving adaptive computer. The project is designed for 30 years. The basis of development is neurotechnology used to recognize images, processing semantic information, managing information flows and robots that can adapt to the environment. Only in 1996 was held about hundreds of international conferences on neurocomputers and related issues. Developments of neurocomputers are carried out in many countries around the world, in particular, in Australia; a model of commercial super neurocomputer was created.

For what class of tasks is an efficient use of a computing device built on the new technology? With regard to neurocomputers, the answer to this question is constantly changing during 50 years.

In the history of computer technology, there have always been tasks that are not solved by traditional computers with the von Neumann architecture and for them the transition to neural network technologies is logical in the case of increasing the dimension of space or reducing the processing time. You can distinguish three areas of application of neural network technologies: general, applied and special.

General tasks

These tasks are reduced to the neural network processing of multidimensional array variables, for example:

- control of credit cards. Today, 80% of credit cards in the US are processed using neural network technology;

- a system for detecting hidden substances using a system based on thermal neurons and using a neurocomputer on custom digital neurons. A similar system of the SAIC company is operated at many US airports for baggage screening for the detection of drugs, explosives, nuclear and other materials;

- automated Control System for Safe Storage of Nuclear Products.

Applied tasks

Image processing

The promising tasks of processing images of neurocomputers are the processing of aerospace images (compression with reconstruction, segmentation, image processing), search, selection and recognition moving object of a given form on the image, processing of image streams, processing information in high-performance scanners.

Signals processing

First and foremost, this is a class of tasks associated with the prediction of temporal dependencies:

- forecasting of financial indicators;
- prediction of reliability of elements and systems;
- prediction of NPP power and prediction of reliability of power supply systems on planes.

When solving these tasks, there has been a shift from simple regression and other statistical models to forecast extrapolated nonlinear adaptive filters realized in the form of a complex of neuronic networks.

System of control of dynamic objects

This is one of the most promising applications of neural computers. In the United States and Finland works are performed on the use of neural computers for the control of chemical reactors. Promising is the development of a neurocomputer for a control of the movable installation of hypersonic aircraft. Relevant to the decision using a neurocomputer is the task of the neural network learning making accurate maneuver of the fighter, the task of robot control: direct, inverse kinematic and dynamic problem, route planning robot motion. The transition to such linked primarily with the limited volumes of host computing systems, as well as the necessity of implementing effective management in real time.

Neural network expert system

The necessity of realization of expert systems with the algorithm of neural networks occurs with a significant increase in the number of rules and conclusions. Examples of specific implementation of the neural network expert systems may be the system of choice of aircraft maneuvers during air combat and medical diagnostic expert system for the assessment of the pilot.

The neural chips and neural computers

Main result of the development of neural network algorithms for solving the problem is the ability to create neurochip architecture adequate to the task. To implement neural network algorithms with the use of universal microprocessor means effective to create an architecture oriented to the implementation of neuromedin operations than to use the standard algorithms aimed at modification of the solution. Unlike other areas of development surproduction of computers, neurocomputers provide an opportunity to develop using the available capacity of the electronics industry. It should be noted a number of important features of these works:

- this allows to create unique supercomputers using existing components in the database;
- development of neural chips and neural computers are characterized by the transition from digital processing to analog-to-digital and analog;
- neural network architecture compared with other enhance use of new technological ways of implementation: nanosistemy on plastic, optoelectronic, and optical neurocomputers, molecular neurocomputers and nanoneuroscience; there is a need for universalization CAPR neural chips.
- technologies for systems on plastic and nanotechnology may lead to new sverhpredelna architectures. Since nanoneuroscience, we come to a fundamentally new architectural elements forming superparallel high-performance computing systems.

Some conclusions

Neurocomputers are a promising direction of development of modern high-performance computing, and the theory of neuronic networks and neuromathematics represent priority areas of computational science, and with appropriate support develop rapidly. The basis for the active development of neural computers is the fundamental difference between the neural network algorithms of the solution of tasks on uniprocessor and metaproteomic. Neurocomputers are the subject of research from several disciplines; therefore, a common definition of neurocomputer can be given only taking into account the different points of view, adequate different areas of science.

Mathematical statistics

Neurocomputers are systems that allow to formulate a description of the characteristics of random processes and a set of random processes with complex, multimodal or unknown distribution functions.

Mathematical logic and automata theory

Neurocomputers are systems in which the algorithm for solving the problem is represented by a logical network of elements of a particular type - neurons, with a complete rejection of Boolean elements of type I, OR, NO, resulting in the introduction of specific links between the elements that are the subject of a separate consideration.

Theory of management

As a control object, a well-formalized object is chosen - a multilayer neural network, and the dynamic process of its configuration represents the process of solving the problem. In this case, virtually the whole apparatus for the synthesis of adaptive control systems is transferred to the neuron network as a separate type of control object.

Computational Mathematics

Neurocomputers implement algorithms for solving problems presented in the form of neuronal networks. This restriction allows to develop algorithms that are potentially more parallel than their other physical implementation. The set of neural network algorithms for solving problems is a perspective section of computational mathematics, conventionally called neuralmathematics.

Computers

Neurocomputer is a computing system in which two fundamental technical solutions are realized:

- simplified to the level of the neuron processor element of a homogeneous structure and complex connections between the elements;

- the programming of the computing structure is transferred to change the weighting coefficients of the links between the processor elements.

The general definition of a neurocomputer can be presented in the following way.

Neurocomputer is a computing system with hardware and software architecture adequate to the execution of algorithms presented in a neural network logical basis.

1. Neurocomputers provide a standard way to solve many non-standard tasks. And it does not matter that a specialized machine better solves one class of tasks. More importantly, one neurocomputer will solve both this task and the second and third, and it is not necessary to design a specialized computer every day, a neurocomputer will do everything itself and almost no worse.

2. Instead of teaching programming. Neurocomputer learns, you only need to form training sets. The work of the programmer is replaced by

the new work of the teacher. Is it better or worse? Neither one nor the other. The programmer indicates the machine with all the details of the work, the teacher creates a learning environment, which adapts to the neurocomputer. There are new opportunities for work.

3. Neurocomputers are effective where they require an analogue of human intuition, in particular, for pattern recognition, reading handwritten texts, preparation of analytical forecasts, translation from one language to another, etc. It is usually difficult to make an explicit algorithm for such tasks.

1.9 Problems of optimization and application of algorithms

Genetic algorithms are currently very popular ways of solving optimization problems. They are based on the use of evolutionary principles to find the optimal solution. The idea itself seems rather intriguing and interesting to make it into life, and many positive results only stir the interest of researchers. Here will not be considered the history of the formation and recognition of evolutionary calculations in general and genetic algorithms in particular. Instead, we will immediately go over to the algorithms themselves. As we have already said, genetic algorithms are mainly used to solve optimization problems, that is, tasks that have some function of several variables F (x_1, x_2,..., x_n) and need to find either its maximum, or its minimum. Function F is called the target function, and the variables are the function parameters. The genetic algorithms are "sewn" to this task in the following way. The parameters of the task are genetic material - genes. The set of genes forms the chromosome. Each person has its own chromosome, and, consequently, its set of parameters. Substituting the parameters for the target function, you can get some meaning. The extent to which this value satisfies the set conditions determines the characteristics of the person called fitness. The function that determines the fitness must satisfy the following condition: the "better" person, the higher the fitness. Genetic algorithms work with a generally fixed size population, consisting of individuals specified using the method described above. Individuals "cross" with each other with the help of genetic operators (about how this process is going to happen - will be described separately), and thus the descendants are leaving, with some of the descendants replacing representatives of the older generation in accordance with the strategy of the formation of a new generation. Selection of individuals for crossing is carried out in accordance with a selection strategy. The newly formed population is re-evaluated, and then the most worthy to cross the person crossing, the "children" and take the place of "old" individuals, etc. are chosen. All this continues until there is a person whose genes represent the optimal set of parameters in which the target function is close to or at least equal to or equal to the maximum. The shutdown of GA may also occur if the population is degenerate, that is, if there is virtually no diversity in the genes of the individuals of the population, or if the time limit has just expired. The degeneration of the population is called premature convergence.

It might seems that GA is just a distorted random search option. But the fitness was introduced at all in vain. The fact is that it directly affects the person's chance to participate in intercourse with the subsequent "birth of children". Choosing each time to cross the most adapted individuals, it is possible with a certain degree of confidence to assert that the descendants will be either not much worse than the parents, or better. Approximately this confidence value can be estimated using the Template Theorems (Theorems Shim)

Theoretical aspects of GA follow:

- Representation of data in the genes
- Genetic operators
- Models of GA
- Functions
- Strategies for selection and formation of a new generation

Where do GAs apply? There are a lot of applications in total, so the listed list is not exhaustive.

- extreme tasks (search for minimum points and minimum);
- tasks about the shortest path;
- layout tasks;
- scheduling;
- approximation of functions;
- selection (filtering) of input data;
- adjustment of artificial neural network;
- modeling artificial life (Artificial life systems);
- bioinformatics (coagulation of proteins and RNA);
- game strategies;
- nonlinear filtration;
- developing Agents / Machinery (Evolvable agents / machines);
- optimization of queries in databases;
- various tasks in graphs (the task of traveling salesman, coloring, finding pairing);
- training of the artificial neural network;

- artificial life.

Some sections may contain sub sections. For example, extreme tasks include a whole class of problems of linear and nonlinear programming.

1.10 Evolutionary algorithms in neural networks

Combining genetic algorithms and neural networks is known in the literature under the acronym COGANN (Combinations of Genetic Algorithms and Neural Networks).

Table 1.2 Combining Genetic Algorithms and Neural Networks

Type of combination	**Combination characteristic**	**Examples of using**
	Genetic algorithms and neural networks are independently used to solve the same problem	Unidirectional neural networks, Kohonen networks with self-organization and genetic algorithms in classification problems
Auxiliary	Neural networks for providing genetic algorithms	Formation of the initial population for the genetic algorithm
	Genetic algorithms for providing neural networks	Neural network analysis
		Parameter selection or parameter space conversion
		Selection of parameters or learning rules (evolution of learning rules)
Equal	Genetic algorithms for learning neural networks	Network learning evolution (evolution of link weights)
	Genetic algorithms for choosing the topology of the neural network	Evolutionary selection of network topology (evolution of network architecture)
	Systems combining adaptive strategies of genetic algorithms and neural networks	Neural networks for solving optimization problems using a genetic algorithm for selecting weights of a network
		Implementation of a genetic algorithm using a neural network
		The use of a neural network for the implementation of the crossing operator in the genetic algorithm

This association can be supportive or collaborative. The subsidiary combination of the two methods means that they are applied sequentially one after the other, one of which serves to prepare the data used in the implementation of the second method. If you combine equally, both methods are applied simultaneously. The classification of these types of associations of genetic algorithms and neural networks is presented in Table 1.2.

The next part of this section will discuss the specific combinations that are reflected in the table. Figures illustrate various approaches to solving problems that are considered as auxiliary combinations of genetic algorithms and neural networks.

It should be noted that, according to the remarks made in clause 1.18, the term "genetic algorithms" is used here in a broader sense than the classic genetic algorithm.

Independent application of genetic algorithms and neural networks

Genetic algorithms and neural networks can be independently used to solve the same problem. This approach is illustrated in Fig. 1.5.

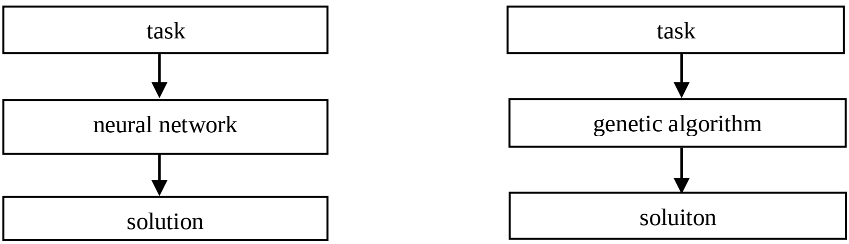

Fig. 1.5 The genetic algorithm and the neural network are independently used to solve the same problem.

For example, the independent application of neural networks, genetic algorithms, and the KNN algorithm "nearest neighbor" (K - means nearest neighbor) are described for solving classification problems. The literature compares the three-layer unidirectional neural network with reverse error propagation (teaching with a teacher), Kohonen's network with self-organization (learning without a teacher), a classification system based on a genetic algorithm, and the KNN algorithm, the "closest neighbor". The authors of a number of papers consider the independent application of these methods for solving the problem of automatic classification of EMG results (electromyography - registration of electrical activity of muscles) by auxiliary association. There are also other works that compare the possibilities of using different methods (in particular, genetic algorithms and neural networks) for solving the same problems. An example of a problem that can be solved with the help of both a neural network and a genetic algorithm can serve as a salesman problem.

Most researchers have studied the possibility of using genetic algorithms to ensure the operation of neural networks. To a few reverse cases is a hybrid system designed to solve a trace problem, which is classified as an example of an auxiliary association of neural networks and genetic algorithms. In this system, the genetic algorithm is used as an optimization procedure designed to find the shortest path. The neural network is used in the formation of the initial population for the genetic algorithm. This approach is schematically illustrated in Fig. 1.6.

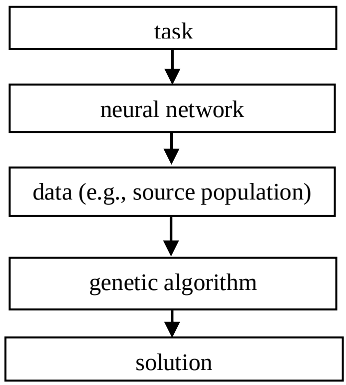

Fig. 1.6 Auxiliary neural network association with genetic algorithm

Genetic algorithms to support neural networks

An approach based on the use of a genetic algorithm for the operation of the neural network is schematically presented in Fig. 1.7.

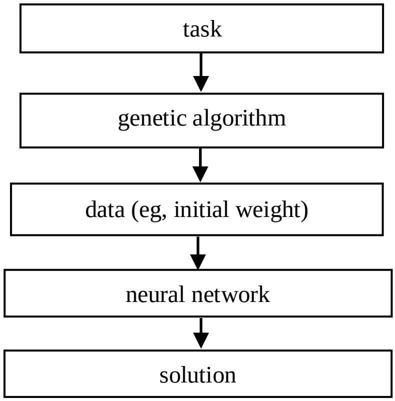

Fig. 1.7 An ancillary combination of a genetic algorithm with a neural network.

We know a lot of works devoted to such an association of considered methods. There are three areas of problem:

- application of a genetic algorithm for selecting parameters or transforming the space of parameters used by the neural network for classification;
- application of the genetic algorithm for selecting the training rules or parameters governing the training of the neural network;
- application of the genetic algorithm for analysis of the neural network.

Generally speaking, the first two areas of the complement of genetic algorithms in neural networks can improve the functioning of the networks (that is, they solve the problem of synthesis), while the third one serves to analyze their functioning. Let's start with the discussion from the last position.

Neural Network Analysis. Some researchers used genetic algorithms as an auxiliary tool to find out the regularities of the functioning of neural networks or to analyze the effectiveness of their work. The genetic algorithm was used to construct an "instrumental system" that facilitates understanding of the functioning of the network - simply speaking, to find out what and why the network does. This understanding is necessary in order for the neurosite classifier not to be perceived as a "black drawer" that forms an answer in some mysterious way, and that decisions on the classification of objects should be explained. A similar "explanation facilities" is used in most expert systems. The construction of these tools for their application in neural networks is considered a more extensive problem related to network analysis. The genetic algorithm was used to construct the so-called vectors codebook, representing the input signals, in which the activation function of a specific output neuron of the network takes the maximum or close to it value. Input vectors were represented in chromosomes by a plurality of real numbers from 0.0 to 1.0. The neural network, which is intended for the decision of the classification problem, was analyzed. A similar approach was applied to the ART1 network (a partial ART case with binary inputs). The genetic algorithm also analyzed the neural network used as a model of associative storage device. The examples presented describe the auxiliary combination of genetic algorithms and neural networks, although they can not be considered typical of the scheme presented in Fig. 1.4.

Selection of parameters or transformation of space parameters.

The genetic algorithm is used in the preparation of data for the neural network, which plays the role of a classifier. This training can be accomplished by converting the space of parameters or by allocating some subspace containing the necessary parameters.

The first of these methods, the so-called parameter transformation, is most often used in algorithms such as the "closest neighbor", although known are its terms in the neural network classifiers. The second approach is to allocate a subset of the parameters that are taken into account. It turns out that limiting the set of parameters often improves the functioning of the neural network as a classifier and, in addition, reduces the volume of computations. Such a plural constraint that is taken into account by the neural network of parameters was used, in particular, to control the scenarios of events on nuclear objects, as well as to recognize Chinese hieroglyphs. There are other examples of data preparation for neural networks using genetic algorithms.

Selection of the parameters and rules of training. The genetic algorithm is also used to select the learning parameters - most often the learning rate and the so-called moment for the algorithm of the propagation error. Such an adaptive refinement of the parameters of the algorithm of reciprocal distribution (they are encoded in the chromosomes) as a result of evolution can be considered as the first attempt to evolutionary modification of the training rules. Instead of the direct application of the genetic algorithm for the selection of training parameters, an evolutionary approach is developed, aimed at constructing the optimal training (learning algorithm).

Note that the evolutionary concept can already be considered as a transition from an auxiliary to an equal integration of the genetic algorithm and neural networks.

Application of genetic algorithms for training neural networks

The idea that neural networks can be trained using a genetic algorithm was spoken by different researchers. The first work on this topic concerned the application of the genetic algorithm as a method for teaching small unidirectional neural networks, but the following application of this algorithm was implemented for networks with greater dimensionality.

As a rule, the task is to optimize the weight of the neural network, which has given topology. Weights are encoded in the form of binary sequences (chromosomes). Each person in the population is characterized by a complete set of neural network weights. The assessment of the fitness of individuals is determined by the function of fitness, which is given in the form of the sum of squares of errors, that is, the differences between the expected (reference) and the actual values obtained at the output of the network for various inputs.

Here are two important arguments in favor of using genetic algorithms to optimize the weight of the neural network. First of all, genetic algorithms provide a global view of the space of weights and allow to avoid local minima. In addition, they can be used in tasks for which information about gradients is very difficult or it is too expensive.

Genetic algorithms for choosing the topology of neural networks

As the most obvious way of combining a genetic algorithm with a neural network, an attempt is made to encode in a genotype the topology of an object (in this case, a neural network) with an indication of the number of neurons and bonds between them in the next determination of the weight of the network using any known method.

Designing the optimal topology of a neural network can be presented in the form of searching for such an architecture that provides the best (relative to the chosen criterion) solution to a specific task. This approach involves overcoming the architectural space, compiled from all possible options, and the choice of the point of this space, the best of the given optimality criterion.

Given the advantages of evolutionary design of architecture in recent years, a large number of studies have been carried out, in which the focus was on the evolution of the neural network connections, that is, the number of neurons and the topology of the links between them. Only in some papers was considered the evolution of the functions of transitions, although these functions are considered an important element of architecture and affect the functioning of the neural network. Also, as in the case of evolutionary learning, the first step in the evolutionary design of architecture is to form the initial set of considered variants.

Adaptive interacting systems

To equate combination of genetic algorithms and neural networks, it is worthwhile to attribute a combination of adaptive strategies of both methods, which is a single adaptive system. You can give three examples of systems of this type.

The first of these is a neural network for an optimization problem with a genetic algorithm for determining the weight of the network.

The second example relates to the implementation of the genetic algorithm using a neural network. In this case, the neural subsystems are used to perform genetic reproduction and cross-breeding operations.

In the third example, somewhat similar to the previous one, the neural network is also used as an interrupt operator in a genetic algorithm designed to solve optimization problems.

The examples presented relate to such an equitable combination of genetic algorithms and neural networks, which ultimately allows to obtain a more efficient algorithm that combines the best of both methods.

A typical cycle of evolution

Once a certain type of evolution is introduced into the artificial neural network, there is an immediate need for a corresponding chromosomal representation of the data, that is, a method of genetic population coding of individuals must be created. The development of the coding method is considered the first stage of such an evolutionary approach, along with which the typical process of evolution involves the following steps:

- decoding;
- training;
- fitness estimation;
- reproduction;
- formation of a new generation.

The block diagram retains its relevance, since it reflects both the classic genetic algorithm and the so-called evolutionary programs that are based on the genetic approach and generalize its principles. Consequently, this universal block diagram corresponds to different evolutionary algorithms, and in each of them, the initial population of the chromosomes must first be generated. By analogy with the classic genetic algorithm, initialization (that is, the formation of this initial population) consists in random selection of the required amount of chromosomes that are included in it, which implies the corresponding genetic encoding of each person. In the classical genetic algorithm, the chromosomes are represented only by binary sequences. In an evolutionary approach, choosing a coding method is an important and topical task.

Further, in accordance with the typical evolution cycle, it is necessary to decode each person (chromosome) of the initial or current population in order to obtain a plurality of solutions (phenotypes) of this task. In the case of the evolution of weights, architectures and / or training rules, the phenotypes represent, respectively, the plurality of weights, architectures and training rules.

Subsequently, in accordance with the genetic algorithm, the values of the fitness function of the individuals of the initial (or current) population are calculated. In the neural network approach, after decoding the chromosomes, a set of neural networks is obtained, for which the degree of adaptability is determined by the results of learning these networks.

When implementing a typical cycle of evolution, it is necessary to construct a set of corresponding neural networks (phenotypes):

- networks with fixed architecture and a set of scales encoded by chromosomes - in the case of the evolution of weights;
- networks with encoded chromosomes architecture - in the case of the evolution of architecture;
- networks with randomly generated architectures and initial scales - in the case of the evolution of training rules.

After training, the suitability of each person in the current population is assessed. Note that, as well as in the example of maximizing the function, to evaluate the adaptability of the chromosomes it is necessary to decode them first and then calculate the values of the fitness function of the individuals according to their phenotypes.

The next step in the genetic algorithm is the selection of chromosomes. Chromosomes that are subject to reproduction are selected, that is, a parent pool formed, whose individuals, as a result of the application of genetic operators, will form a population of descendants. Selection can be based on the roulette method or any other, for example, using the Whitley algorithm. According to these methods, selection is performed with the probability proportional to the suitability of the chromosomes, or according to their rank (using the rank method). Under the reproduction in this case, the process of selection (selection) and copying (propagation) of a chromosome for the formation of a transitional population (parent pool) is to be understood, the person of which will be exposed to the influence of genetic operators of crossing, mutation and, possibly, inversion.

The use of genetic operators by the selected chromosome selection method is analogous to the classical genetic algorithm, and these operators may differ from the crossing and mutation of the basic algorithm. As noted, for a specific task, genetic operators can be determined individually.

As well as in the classic genetic algorithm, as a result of the application of genetic operators with the selected selection method of chromosomes, a new population of individuals (descendants) is formed. The following steps of the algorithm are repeated for the regular population up to the completion of the condition of the completion of the genetic algorithm. At each iteration a new generation of descendants is formed.

The best person from the last generation is considered a sought-after solution to this task.In this way, you get the best scales, the best architecture, or the best training rule.

Evolution of the rules of learning

It is known that different training algorithms are needed for different architectures and learning tasks. The search for an optimal (or almost optimal) learning rule, as a rule, takes place taking into account expert knowledge and often - by trial and error. Therefore, the development of automatic methods for optimizing the rules of training neural networks is considered promising. The development of human learning abilities from relatively weak to very strong indicates the potential for the application of an evolutionary approach in the process of training artificial neural networks.

The scheme of the chromosomal representation in the case of the evolution of the rules of training should reflect the dynamic characteristics. Static settings (such as architecture or network weight values) are much easier to code. The attempt to create a universal representation scheme that would allow describing arbitrary types of dynamic characteristics of the neural network is deliberately doomed to failure, since it involves unnecessarily large amounts of computations necessary for viewing the entire space of training rules. For this reason, the type of dynamic characteristics is usually subject to certain restrictions, which allows to choose the general structure of the rules of learning. Most often it is established that for all links of a neural network, the same teaching rule that can be given by the function of the form should be used.

$$\Delta w(t)=\sum_{k=1}^{n}\sum_{i_1,i_2\cdots i_k=1}^{n}[\theta_{i_1,i_2\cdots i_k}\prod_{j=1}^{k}x_{i_j}(t-1)], \tag{1.34}$$

where t - time, Δ_w - weight gain, x_{i_j} - so-called local variables, $\theta_{i_1,i_2,\cdots,i_k}$ - actual coefficients.

The main purpose of the evolution of the rules of learning is to select the corresponding values of the coefficients $\theta_{i_1, i_2, \cdots, i_k}$.

Given the large number of components of the equation (1.34), which can make the evolution too slow and practically ineffective, additional restrictions are often introduced based on heuristic assumptions.

Imagine a typical cycle of evolution of the rules of learning.

1) Decode each person of the current population to describe the training rule to be used as a training algorithm for neural networks.

2) Formation of a plurality of neural networks with randomly generated architectures and initial values of weights, as well as evaluation of these networks, taking into account their training according to the rule obtained in step 1, in the categories of accuracy of training or testing, duration of training, complexity of architecture, etc.

3) Calculation of the suitability of each person (coded training rule) based on the evaluation of each neural network in step 2, which is a kind of balanced averaging.

4) Reproduction of individuals with a probability corresponding to their fitness or rank depending on the method of selection used.

5) Formation of a new generation as a result of application of such genetic operators as cross-linking, mutation and / or inversion.

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CHAPTER 2 COMPLEX OF UNMANNED AERIAL VEHICLES POWER SUPPLY USING ALTERNATIVE ENERGY SOURCES

2.1 Review of the current state of development of power systems for unmanned aerial vehicles

Ukraine possesses a full cycle of aviation engineering and occupies a significant place in the global aviation market in the transport and regional passenger aircraft sector, which allows the development and production of aviation technology in areas such as aircraft engineering, on-board radio equipment, focused on the use of satellite communication systems, navigation and observation, ultralight and light aircraft, helicopter construction, unmanned aerial vehicles. Unmanned aerial vehicles (UAVs) are no exception. Today, this technology is applied in many areas of activity and has extremely high prospects for other areas. Unmanned aerial vehicles (UAVs) are currently used to address a wide range of tasks, such as border patrols, reconnaissance, transportation and armed attacks. This diversity is due to the fact that UAVs are very technological, which explains their widespread use. Modern technologies of UAV energy supply have not yet reached the proper level, due to the dynamic development of this technology. Therefore, the purpose of the work is to develop a variant of the power supply system of the UAV using, in addition, alternative power sources and control system of the proposed grid.

The main components of the UAV are: an airplane with a special landing system, a power plant, a power supply for it, a power supply system, on-board radio electronic equipment (on-board control equipment and electronic elements of the target load). The UAV scheme in NATO countries is presented in Figure 2.1.

The UAV should consist of three main elements: air vehicle element, payload element and control system (UAV air component). To analyze the possibility of external influence it is expedient to consider elements that can interact with other components using a wireless communication line (radio, optical, acoustic). In this case it may be a control system and a target load.

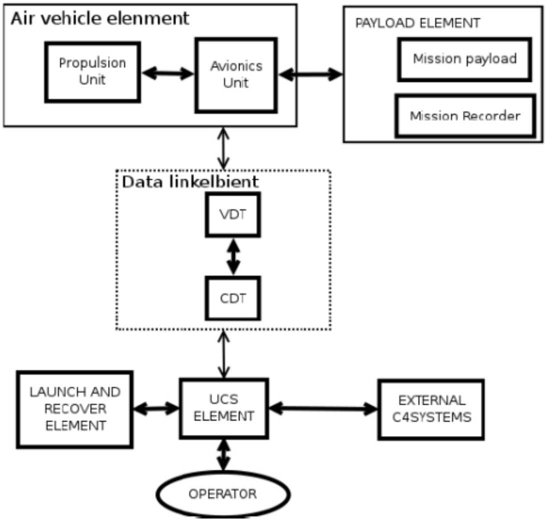

Fig 2.1 Energy supply system for unmanned aerial vehicles

UAVs are characterized by the following advantages over manned aeronautics, such as: the lack of a need for crew and systems for its life support, in aerodromes; relatively low cost and low costs for their creation, production and operation; relatively small weight and dimensions in combination with high reliability, significant length and range of flight, maneuverability and a list of target equipment that can be placed on board, etc.

The type of control system determines the type of UAV.

Remotely manned aircraft are guided directly by the operator within the visibility through the ground station. They are equipped with a digital data channel that can be transmitted to the ground in real-time through direct line of sight or through a satellite channel up to 50 Mb/s.

Remotely controled operate autonomously, but can be driven by a pilot that uses only feedback through other control subsystems. Such aircraft include analog and digital channels, the first one providing a stable transmission of information up to 40 km and the other one up to 15 km.

Automatic aircraft perform pre-programmed actions. At UAVs of this type there are integrated systems of automatic piloting with GPS receivers, gyroscopes, accelerometers, various sensors, which allows working in real time and transmitting data through a communication channel with a frequency of 1 MHz Remotely controlled aviation systems are controlled by embedded systems, such as the UAS Analyzer.

Consider a more detailed control system; the scheme is presented in Fig. 2.2.

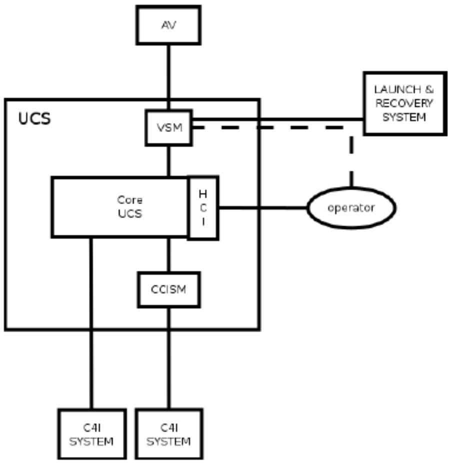

Fig. 2.2 – Power control system of unmanned aerial vehicles

The unmanned aerial vehicle control system has the following functional architecture:

- engine, maneuvering and flying support (air vehicle / AV);
- operation controller for AV (VSM);
- operator interface (HCI);
- core (core USC);
- launch and recovery system;
- agrees target load unit (CCISM);
- external connecting c4I systems can be target load (c4I system).

The height of the flight significantly affects the work of the whole complex of electrical equipment and other airborne equipment of the aircraft.

External influences on electrical installations can lead to various types of damage, for example, to breakage of wires and windings, especially in the places where they are soldered, until cracks and damage to electrical insulating materials, accelerated wear of the axes and bearings in actuators, deviations from normal operation of spring and moving elements of mechanical systems.

The tactical and technical requirements for aircraft equipment, developed taking into account the conditions of operation of the electrical equipment and its purpose, include the following indicators: reliability and faultiness, requirements for mass and dimensions, strength of electrical equipment, chemical resistance of electrical equipment, ease of operation and repair of electrical equipment, economic requirements.

From the onboard generators all the electronics are emitted on board the aircraft, so the failure of generators will lead to the discharging of all on-board equipment. In this case, in some types of aircraft, manufacturers install retractable wind power units (RWPUs) that produce current due to the fact that the wind wheel is spinning under the influence of the counterflow of air on the blade, which makes it possible at least to keep track of critical technical indicators of the state of airborne equipment and aircraft systems.

At present, solar batteries (SBs) are one of the most promising alternative sources of electric energy in aircraft. Taking into account the fact that the SBs have been used in cosmonautics, which occupy a dominant position among other sources of autonomous power supply, we can talk about the further active their implementation in the system of primary emergency power supply aircraft systems, as additional sources of electrical energy.

Therefore, in view of the urgency of the problem of increasing the reliability of the operation of the entire complex of aircraft equipment, in order to increase the safety of operation, it is expedient to consider the issues of modernization of the airborne power supply aircraft, including renewable energy sources.

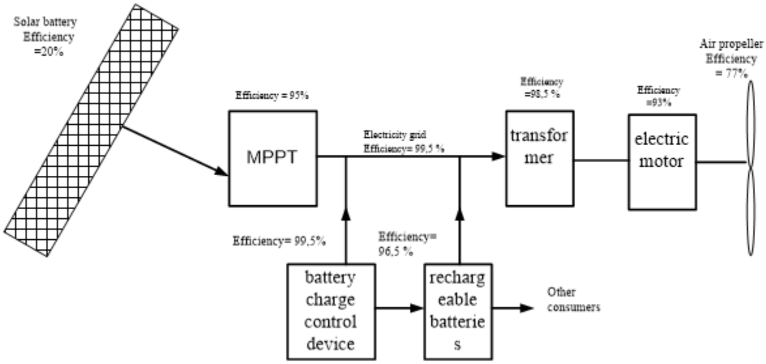

Fig. 2.3 Principle diagram of power plant for unmanned aerial vehicles using solar energy

2.2 Development of energy supply system for unmanned aerial vehicles using alternative energy sources

Taking into account the features of modern aircraft, the authors recommend the structure of the power supply system of the aircraft (Fig. 2.3), which contains: RES1 and RES2 - renewable energy sources, BP - battery pack, BMU- battery monitoring unit, CS - control system, EMC1 and EMC2 - electromechanical complexes of the power system of electric motors based on asynchronous motors with short-circuited rotor (AMSCR), G1 and G2 - generators, E1 and E2 - aviation engines of internal combustion.

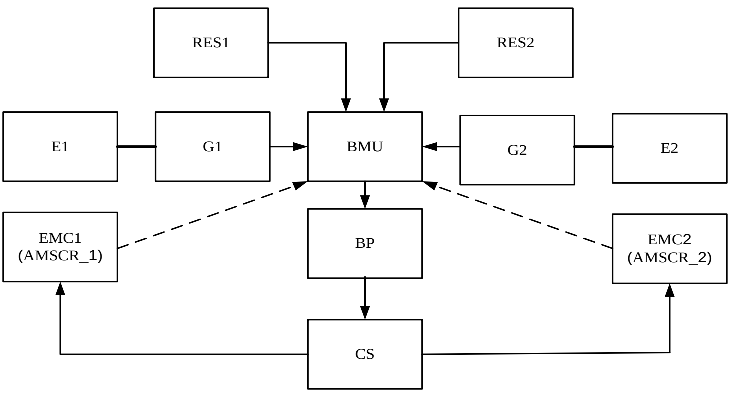

Fig. 2.4 Recommended structure of the aircraft power supply system

In modern aircraft, the structure of the power supply is built in such a way that the main sources of electric energy (EE) are generators, whose work is directly connected with the operation of the internal combustion engines (aircraft engines). In case of failure of internal combustion engines, aircraft in-flight power system is powered solely from the batteries, which is the emergency source EE onboard. Meanwhile, the emergency power supply system on the basis of batteries designed to supply electro starter and equipment ignition when starting the aircraft engines, it is vitally important to consumers during the flight. The lifetime is an important characteristic for battery and depends on many internal and external factors [8]. Complicated specific operating conditions dictate the necessity of monitoring the status of aircraft on-board batteries. The authors propose to implement condition monitoring on-board batteries in the BMU unit (see Fig.2.4). Meanwhile, the unit BMU battery will perform the functions of the charger. It is also proposed in addition to aircraft engines, is standard on the aircraft, in parallel to set the motors and as an additional source of the primary side of the power supply system, renewable energy sources. Given the basic tendencies of development of aircraft in the world today, among the major indicators of the Autonomous aircraft power systems is their energy efficiency, reliability and manageability. Thus, we will consider each indicator separately. The main factors that shape the features of the application of additional electrical power sources of low power onboard include minimizing weight and size characteristics and the need for interim energy storage with a specialized charge-discharge controller. The recommended option of the aircraft power supply system (Fig. 2.5) the battery pack has a capacity sufficient to supply in an emergency situation during the flight is not only responsible consumers (controls and navigation), but also the supply of electromechanical complexes power system motors (EM).

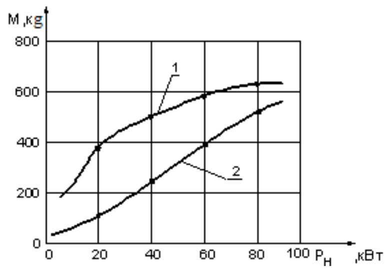

Fig. 2.5 Dependence of the mass of asynchronous and synchronous generators on power: 1 - synchronous generator, 2 - asynchronous generator with short-circuit rotor

Although in the generator mode, the short-circuit induction motor (AMSCR) is rarely used due to the presence of an external cool-down characteristic and imperfect condenser excitation, but such application has a number of undeniable advantages over synchronous generators [5] such as: simplicity and reliability of the design; small weight and dimensions; low cost; easy installation and maintenance.

Taking into account the possibility of EE, including AMSCR, to work both in power and in generator mode, and optimum weight and weight indices, AMSCR is the optimal option for the implementation of additional power sources of low power on board the aircraft.

The energy efficiency of the on-board power supply system can be expressed as the ratio of the difference between the energy produced W_{ps} and the energy losses in the converters ΔW_p and rechargeable batteries ΔW_b:

$$k_e = (W_{ps} - \Delta W_p - \Delta W_b) / W_{ps\_\max} . \tag{2.1}$$

From the analysis of formula (2.1) it can be seen that the energy efficiency of the airborne power supply complex-electric power consumption of the aircraft depends on its structure and the coefficients of the usefulness of the transforming devices. An integrated approach to building a power supply system-power consumption of the aircraft will reduce losses in the distribution board network [9-10].

Next we will consider the reliability index, which is closely related to the reservation. Since in case of general reservation, the failure of the on-board electrical equipment of the aircraft will come with the refusal of all backup and one main, then with a separate reservation and in the presence of backup chains probability of failure of aircraft on-board electrical equipment will be equal to the product of the probability of failure of the main $Q_{осн}$ and backup $Q_{резі}$ chains:

$$Q(t) = Q_{осн}(t)\prod_{i=1}^{m} Q_{резі}(t) = \prod_{i=1}^{m+1} Q_i(t) . \tag{2.2}$$

In the case of a separate reservation, if each main element has m backup elements, the probability of failure of the on-board electrical equipment of the aircraft due to the failure of elements of the i-th type is equal to the product of the probabilities of failures of the i-th element q_i and all its reserving elements, i.e.:

$$Q_i(t) = \prod_{i=1}^{m+1} q_i = \prod_{i=1}^{m+1} (1 - p_i(t)) , \tag{2.3}$$

Where $p_i(t)$ is the probability of failure-free operation of the i-th element and all its reserve ones:

$$p_i^{'}(t) = 1 - \prod_{i=1}^{m+1}(1 - p_i(t)) \qquad (2.4)$$

As can be seen from formulas (2.2-2.4), when connecting additional power sources to the on-board power supply system of the aircraft using backup chains, the probability of the failure of on-board electrical equipment will decrease, which will increase the reliability of the electrical supply system of the onboard assembly.

Moreover, the probability of failure-free operation of the power supply system of the airborne complex in the general reservation was 0.98, and in the scheme of the previous connection 0.85.

The modern concept of aircraft development sets forth the requirements related to the miniaturization of on-board power and electronics systems, as well as requirements for the use of advanced technologies for manufacturing aircraft designs. Given the application of nanotechnology in the production of SB, there is a prospect of increasing the efficiency of their functioning and at the same time, a significant reduction in their cost. The implementation, if possible, of such implementation (depending on the design of the aircraft) as additional sources of the main electrical power supply system, the retractable wind power installations and the use as power systems of electric motors to install asynchronous motors with a short-circuited rotor, with the possibility of their use in generator mode, is also relevant.

2.3 System for managing power supply of unmanned aerial vehicles using alternative energy sources

Based on the tree of the logical conclusion of constructive and technological factors, we model the structure of the hierarchical neuro-fuzzy network (Fig. 2.6).

Each element of this structure represents a certain level of the logical tree of influence on the system of power supply of an unmanned aerial vehicle during operation. Each element has a term-set of expert estimates, which is indicated on the input of parameters on the line: "L - low", "BA - below average", "A - average", "AA-above average"; "H - high".

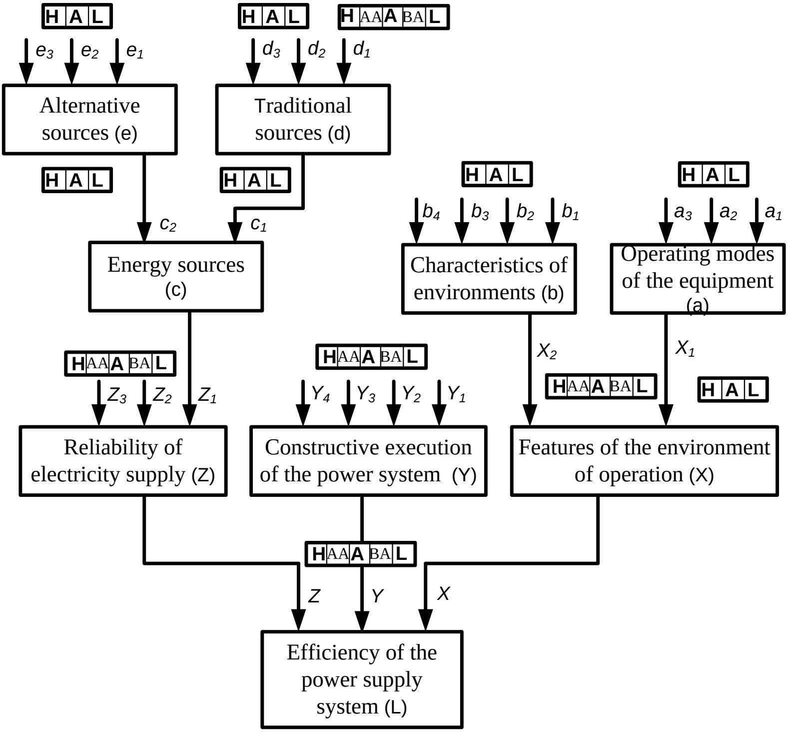

Fig. 2.6 Structure of a hierarchical neuro-fuzzy network to determine the effective system of power supply to an unmanned aerial vehicle

Influence factors influencing the efficiency of power supply of an unmanned aerial vehicle are shown

$$L = f_L\ (X, Y, Z), \qquad (2.5)$$

$$X = f_X(x_1, x_2), \qquad (2.6)$$

$$Y = f_Y(y_1, y_2, y_3, y_4), \qquad (2.7)$$

$$Z = f_z(z_1, z_2, z_3), \qquad (2.8)$$

$$x_1 = f_{x1}(a_1, a_2, a_3), \qquad (2.9)$$

$$x_2 = f_{x2}(b_1, b_2, b_3, b_4), \qquad (2.10)$$

$$z_1 = f_{z1}(c_1, c_2), \qquad (2.11)$$

$$c_1 = f_{c1}(d_1, d_2, d_3), \tag{2.12}$$

$$c_2 = f_{c2}(e_1, e_2, e_3, e_4), \tag{2.13}$$

where X is a linguistic variable describing the specifics of the environment of exploitation; Y - a linguistic variable describing the influence of the constructive execution of the power supply system; Z - a linguistic variable describing the reliability of power supply; x_1 - operating mode of the equipment; x_2 - characteristics of the environment; y_1 - weight of the equipment; y_2 - peculiarities of fastening of equipment; y_3 - volume of equipment; z_1 - energy source; z_2 - battery charge level; z_3 - electric supply system; a_1 - standard operating mode of the equipment; a_2 - failure of the traditional system of electrorazing; a_3 - power from batteries; b_1 - density; b_2 - insolation; b_3 - cloudiness b_4 - wind speed; c_1 - traditional energy sources; c_2 - non-traditional energy sources; d_1 - generator 1; d_2 - generator 2; d_3 - battery; e_1 - low-potential energy; e_2 - solar energy; e_3 - wind energy.

Based on the logical conclusion tree of the constructive and technological factors of influence on the aircraft power supply system [4] and the structure of the hierarchical neuron-fuzzy network, we will make an assessment of the levels of linguistic variables.

Table 2.1 Fuzzy matrix of knowledge about the relation on the system level

	IF		THEN
Low potential energy (e_1)	Solar energy (e_2)	Wind energy (e_3)	Effect of alternating energy sources (e)
Low	Low	Low	Low
Low	Medium	Low	
Low	Low	Medium	
Medium	Medium	Low	Medium
Low	Medium	High	
Medium	Low	High	
Medium	Medium	Medium	
Low	High	Medium	

High	Low	Medium	
Medium	Medium	High	
High	Medium	High	High
High	High	Medium	
High	High	High	

The following system of fuzzy logic equations corresponds to the linguistic statement describing the influence of different parameters of energy alternative sources on the efficiency of the aircraft power supply system (Table 2.1):

$$\mu_{\mathrm{H}}(e) = \mu_H(e_1) \wedge \mu_H(e_2) \wedge \mu_H(e_3) \vee \mu_H(e_1) \wedge \mu_H(e_2) \wedge \mu_H(e_3) \vee \mu_H(e_1) \wedge \mu_H(e_2) \wedge \mu_C(e_3), \quad (2.14)$$

$$\mu_C(e) = \mu_C(e_1) \wedge \mu_C(e_2) \wedge \mu_H(e_3) \vee \mu_H(e_1) \wedge \mu_C(e_2) \wedge \mu_E(e_3) \vee \mu_C(e_1) \wedge$$
$$\wedge \mu_H(e_2) \wedge \mu_E(e_3) \vee \mu_C(e_1) \wedge \mu_C(e_2) \wedge \mu_H(e_3) \vee \mu_H(e_1) \wedge \mu_E(e_2) \wedge \mu_C(e_3) \vee \mu_E(e_1) \wedge$$
$$\wedge \mu_{\mathrm{H}}(e_2) \wedge \mu_C(e_3) \vee \mu_C(e_1) \wedge \mu_C(e_2) \wedge \mu_E(e_3), \quad (2.15)$$

$$\mu_2(e) = \mu_E(e_1) \wedge \mu_C(e_2) \wedge \mu_E(e_3) \vee \mu_E(e_1) \wedge \mu_C(e_1) \wedge \mu_C(e_3) \vee \mu_E(e_1) \wedge \mu_E(e_2) \wedge \mu_E(e_3). \quad (2.16)$$

The technique of fuzzy logical conclusion, which was applied to the information in the previous stages, allows calculating indicators that are predicted as fuzzy sets. Fuzzy sets determine the degree of fermentation efficiency when choosing an alternative energy source for a fixed vector of influence factors. To move from fuzzy sets to quantification, you need to complete the dephasing process. Among the various methods of dephasing we will use the method "Centroid" [1]. We carry out defazification at the level of alternative energy sources for the temperature stabilization of anaerobic fermentation the value of the membership functions of pair comparisons is calculated, and we will use the Saati scale for the expert evaluation of the elements [2].

The matrix of pair comparisons of various alternative energy sources, in terms of their proximity to the term "low", is given in Table 2. The factor e - alternative energy sources is defined on the universal set U (e) = {1, 2, 3} (o.y.). The linguistic values of this factor are given by the term-set T (e) = <low, medium, high> [5].

Table 2.2 Paired comparisons of non-traditional energy sources according to their proximity to the term “low”

		e_1	e_2	e_3
$Alow(e) =$	e_1	1	6 / 9	1 / 9
	e_2	9 / 6	1	1 / 6
	e_3	9	6	1

In the formation of this matrix expertly determined only the third row and the elements of other lines were calculated, based on the properties of the resulting matrix [2].

According to the data of the table 2 the degree of membership of the elements e_1, e_2, e_3 is obtained, to the term "low":

$$e_{low}(e_1) = \frac{1}{1+\frac{6}{9}+\frac{1}{9}} = 0{,}5625, \tag{2.17}$$

$$e_{low}(e_2) = \frac{1}{\frac{9}{6}+1+\frac{1}{6}} = 0{,}375, \tag{2.18}$$

$$e_{low}(e_3) = \frac{1}{9+6+1} = 0{,}0625. \tag{2.19}$$

Similarly, the matrices of pair comparisons of various alternative energy sources are determined in terms of their proximity to the term "medium" and "high".

Table 2.3 Paired comparisons of non-traditional energy sources in accordance with their proximity to the term "medium"

		e_1	e_2	e_3
$A_{medium}(e)=$	e_1	1	9 / 1	6 / 1
	e_2	1 / 9	1	6 / 9
	e_3	1 / 6	9 / 6	1

Table 2.4 Paired comparison of alternative energy sources according to their proximity to the term "high"

		e_1	e_2	e_3
A_{high} (e)=	e_1	1	1 / 6	9 / 6
	e_2	6 / 1	1	9 / 1
	e_3	6 / 9	1 / 9	1

According to the data of the Table 3 the degrees of membership of the elements e_1, e_2, e_3 are obtained, to the term "average":

$$e_{\text{medium}}(e_1) = \frac{1}{1+9+6} = 0{,}0625, \tag{2.20}$$

$$e_{\text{medium}}(e_2) = \frac{1}{\frac{1}{9}+1+\frac{6}{9}} = 0{,}5625, \tag{2.21}$$

$$e_{\text{medium}}(e_3) = \frac{1}{\frac{1}{6}+\frac{9}{6}+1} = 0{,}375. \tag{2.22}$$

According to the data of the Table 4 the degrees of membership of the elements e_1, e_2, e_3 are obtained to the term "high":

$$e_{\text{high}}(e_1) = \frac{1}{1+\frac{1}{6}+\frac{9}{6}} = 0{,}375, \tag{2.23}$$

$$e_{\text{high}}(e_2) = \frac{1}{6+1+9} = 0{,}0625, \tag{2.24}$$

$$e_{\text{high}}(e_3) = \frac{1}{\frac{6}{9}+\frac{1}{9}+1} = 0{,}5625. \tag{2.25}$$

The obtained values of membership functions are normalized per unit by dividing by the highest degree of membership. As a result, different levels of use of alternative energy sources are presented in the form of such fuzzy sets:

- alternative energy source "low"

$$e = \left\{ \frac{0,5625}{1}; \frac{0,375}{2}; \frac{0,0625}{3} \right\};$$

- alternative energy source "average"

$$e \quad = \left\{ \frac{0,0625}{1}; \frac{0,5625}{2}; \frac{0,375}{3} \right\};$$

- alternative energy source "high"

$$e = \left\{ \frac{0,375}{1}; \frac{0,0625}{2}; \frac{0,5625}{3} \right\}.$$

Fuzzy sets characterizing membership functions for the linguistic variable "alternative energy sources" are shown in Fig. 2.7.

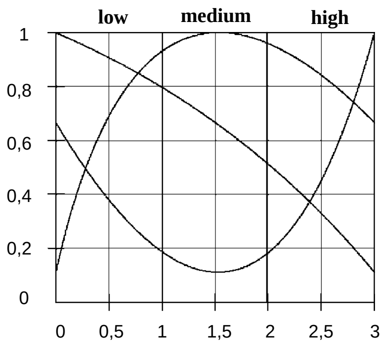

Fig. 2.7 Functional features for the linguistic variable "alternative energy sources"

As a result of constructing charts of the functions of belonging to Fig., graphical models of the dependence of the efficiency of the power supply system of an unmanned aircraft on the use of various non-traditional energy sources were obtained. The received knowledge base on the connections of fuzzy terms of input and output linguistic variables allows optimizing the choice of effective configuration of the power system of an unmanned aerial vehicle.

The structure of the airborne complex of electric power supply of the UAV with the use of additional sources of electric energy and additional power plants based on short-circuited asynchronous motors is proposed.

It is determined that the main among the indicators of aircraft autonomous power systems are their energy efficiency, reliability and mass-size. The structure of the hierarchical neuro-fuzzy network of energy efficiency of the power supply system of an unmanned aerial vehicle with the use of alternative sources of electric power is proposed.

Fuzzy matrix of knowledge about the relation at the systemic level of influence of non-traditional energy sources is given.

A system of fuzzy logical equations is made up to linguistic statements that characterize the dependence of variables on the corresponding terms.

Defazification at the level of alternative sources of electricity has been carried out; the degree of membership of the elements has been defined to the terms "low, medium, high".

The use of alternative sources of electricity is presented in the form of fuzzy sets, which are described by the membership functions for the linguistic variable "alternative sources of electricity".

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CHAPTER 3 DECISION MAKING OF UNMANNED AERIAL VEHICLE'S OPERATOR IN EMERGENCY

In this chapter, the authors present an algorithm of Unmanned Aerial Vehicle's (UAV) operator in emergency situations (ES) decomposition of the process of decision making (DM) by UAV's Operator in ES; development of the structure of decision support system (DSS) for Remotely Piloted Aircraft (RPA); development of a database of local DSS operators Remotely Piloted Aircraft Systems (RPAS); working-out of models DM by UAV's Operator (DM in Certainty, DM in Risk and DM in Uncertainty). In this research of the process of flight of RPA, requirements to exploitation of RPA, integration of RPAS to modern civil aviation, criteria of DM in uncertainty are considered. Also the method of determination of optimal place of RPA landing in uncertainty and programming method of calculation of optimal place of landing of RPA in Certainty, Risk and Uncertainty according to criteria are considered.

3.1 Background

Remotely piloted aircraft systems (RPAS) are a new component of the aviation system, one which the International Civil Aviation Organization (ICAO), States and the industry are working to understand, define and ultimately integrate. These systems are based on cutting-edge developments in aerospace technologies, offering advancements which may open new and improved civil/commercial applications as well as improvements to the safety and efficiency of all civil aviation. Remotely piloted aircraft (RPA) is an aircraft piloted by a licensed "remote pilot" situated at a "remote pilot station" located external to the aircraft (i.e. ground, ship, another aircraft, space) who monitors the aircraft at all times and can respond to instructions issued by ATC, communicates via voice or data link as appropriate to the airspace or operation, and has direct responsibility for the safe conduct of the aircraft throughout its flight. An RPA may possess various types of auto-pilot technology but at any time the remote pilot can intervene in the management of the flight. This equates to the ability of the pilot of a manned aircraft being flown by its auto flight system to take prompt control of the aircraft. The safe integration of RPAS into non-segregated airspace is a long-term activity with many stakeholders adding their expertise on such diverse topics as licensing and medical qualification of remote pilots, technologies for detect and avoid systems, frequency spectrum (including its protection from unintentional or unlawful interference), separation standards from other aircraft and development of a robust regulatory framework. Civil aviation has, to this point, been based on the notion of a pilot operating the aircraft from within the aircraft itself and more often than not with passengers on board. Removing the pilot from the aircraft raises important technical and operational issues, the extent of which is being actively studied by the aviation community [1].

As knowledge increases in the coming years, guidance for resolving the issues will become ever more refined. It is anticipated that information and data pertaining to RPAS will evolve rapidly as States and the aerospace industry advance their work and bring their input to ICAO. The goal of ICAO in addressing RPAS is to provide an international regulatory framework through Standards and Recommended Practices (SARPs), with supporting Procedures for Air Navigation Services (PANS) and guidance material, to underpin routine operation of RPAS throughout the world in a safe, harmonized and seamless manner comparable to that of manned operations. Most importantly, introduction of remotely piloted aircraft into non-segregated airspace and at aerodromes should in no way increase safety risks to manned aircraft. The roles of RPA will continue to expand as technologies and performance characteristics become better understood. Long flight durations, covert operational capabilities, and reduced operational costs serve as natural benefits to many communities, such as law-enforcement, agriculture and environmental analysis. As technologies develop, mature and become able to meet defined standards and regulations, RPA roles could expand to include operations involving carriage of cargo and eventually — possibly — passengers. In addition, domestic operations will likely expand to trans-border flights subject to pre-approval by the States involved. RPA may have the same phases of flight — taxi, departure, en-route and arrival — as manned aircraft or they may be launched/recovered and/or conduct aerial work. The aircraft performance characteristics may be significantly different from traditional manned aircraft. Regardless, the remote pilot will operate the aircraft in accordance with the rules of the air for the State and airspace in which the RPA is operating [2]. This will include complying with directions and instructions provided by the air traffic services (ATS) unit.

Aside from civil use unmanned aerial vehicles have transformed the idea of the air power in modern war times. They are smaller than jet aircraft. They are less expensive, and they don’t put the pilots at risk when they crash. RPAS offers a less stressful environment, it is used for better decision making. It presents safer environment. They can fly longer hours as long as the vehicle allows for it (no human fatigue in the plane). RPA can go faster. Even if the plane crashes, the pilot will be safe. They can be used for border patrol security using the software to fly the planes.

In the long run, they will be cheaper than paying for the personnel to do the task. They are able to fly into the zones where it would be dangerous for the pilot, capable of flying for long periods of time, can enter the environments which are dangerous to the human life and they can reduce the exposure risk of the aircraft operator. The drone pilots or operators can easily hand off controls of the drone without any operational downtime. It can save lives. They greatly reduce putting the military personnel in harm's way or in combat. They have low cost. They are cheaper to purchase, fuel, and maintain than the regular airplanes. Drones offer low risk. Since the drones are smaller and they can fly lower than the traditional airplanes, there is less risk to the military hardware. Without the human pilot and they can stay in operation for longer hours of operation without fatigue. The drones can have more pinpoint accuracy from greater distances thus reducing the collateral damage to the civilians and the infrastructure. The drones are as lethal to the enemy combats as regular airplanes.

Unmanned aircraft has several advantages, namely low operating cost, good concealment and flexibility, simplicity and availability of technology compared to manned aircraft and Unmanned Aerial Vehicles (UAV) can be used in cases where the usage of manned aircraft is impractical, expensive or risk [1; 2].

Advantages of UAV’s are to perform the tasks associated with the risk for man and effectiveness in solving economic problems. In this sense, the use of UAVs is more appropriate: to relay communications in those places - where the antenna coverage cannot be set because of difficult terrain, agriculture (group of spraying fields), with photo/video monitoring (group survey of large areas, monitoring of forest fires, patrol areas, etc.), moving cargo [2]. Obviously is the usage of UAVs for military purposes. Noted additional useful properties: faster coverage of area fragment and consequently more effective at photo/video monitoring, relay communications, agricultural operations - owned group compared UAV using one UAV [4 - 8]. But despite a number of advantages there are some drawbacks, namely the main problem associated with the use of airspace allocation of the frequency range for UAVs management and transmission of information from the board to the ground; lack of recommendation action algorithm of UAV operator in case of emergency situations [5; 6]. In [2; 7; 8] investigated an emergency engine stop, electrical problems, in excess of the maximum and minimum the display height of the flight of the parachute release is done automatically, with transferring the coordinates of the forced landing site to the operator's monitor. The use of a parachute landing system will not only provide reliable survival craft in an emergency situation, but also to simplify its operation.

Emergency situations (ES) may occur when flying both in manual, and in the autonomous management. For operations carried out "manually", plays an important role the human factor and a significant part of emergency arises due to wrong actions of the operator. Using a constant two-way radio comes to continuous Manual control device parameters, which leads to certain restrictions and inconveniences - the operator can’t be distracted from the management and takes full responsibility for the state-controlled UAVs, for his safety and for the safety of the environment and people.

Let we have some UAV that performed different tasks purposes. Air traffic controller (ATC) using technological procedures “ASSIST” (Acknowledge, Separate, Silence, Inform, Support, Time) decides in ESs of flight. At a certain stage of flight is probable extraordinary or ESs (for example: loss of control, engine failure, etc.), where it is some risk to lost UAVs. Taking into account the high cost of UAVs it is proposed to build an algorithm of UAV’s operator actions using module «ASSSIST» (Acknowledge, Separate, Synergetic ((Coordinated, Cooperation, Consolidation)) Silence, Inform, Support, Time) for each type of UAV. Module «ASSSIST» includes in Distributed Decision support system (DDSS) and has models of the Decision Making (DM) by H-O under Certainty, Risk and Uncertainty [5].

Emergency situations [1]:

a) loss of line C2,
b) complex meteorological conditions;
c) emergency landing / emergency landing
d) electromagnetic interference,
e) disasters, etc...

Emergency situations according «ASSSIST» [18]:

f) Birdstrike
g) Bomb Warning
h) Brake Problems
i) Communication Failure VMC
j) Loss of line C2,
k) Electrical Problems
l) Emergency Landing
m) Engine failure

n) Engine on fire or APU on fire
o) Fuel problems - Critical fuel status
p) Gear problems - Unsafe indication
q) Unlawful Interference
r) Hydraulic Problems
s) Icing
t) Lightning Strike
u) Low oil pressure
v) Take-off Abort
w) Pilot incapacitation / remote pilot
x) Turbulence

When a loss of communication with the UAV made an immediate report to the ATM unit. The report states the time and place of loss of communication, the height of the UAV flight, the estimated remaining time of flight and follow the course of landing area (falling) UAV [1]. When hovering UAV in the crown of the trees must be up to the crown, fix the UAV tether and if necessary, to cut the branches and holding, drop to the ground [2]. Remotely piloted aircraft controlled with remote piloting station (RPS) with the management and control line (C2). Together with other components such as the starter equipment and equipment for the return, if it is used, remotely piloted aircraft (RPA), remote piloting station RPS and the line C2 constitute RPAS [9].

The purposes of the article are: lack of recommendation action algorithm of UAV operator in f emergency situations; decomposition of the process of DM by UAV’s Operator in Emergency Situations; development of the structure of DDSS for remotely piloted aircraft; development of a database of local DSS operators Remotely Piloted Aircraft Systems (RPAS); working-out of models DM by UAV’s Operator (DM under Certainty, DM under Risk and DM under Uncertainty).

3.2 Decision making of unmanned aerial vehicle's operator

The UAVs (drones) can be used in spying. Years before the drones were used in combat. The drones have proven to increase the surveillance, reconnaissance, and general military intelligence. The drones are easier and faster to deploy than most alternatives [14]. There are, of course, some signification disadvantages that are worth mentioning. One disadvantage of drones is that they can be considered an invasion of privacy in the sense that they are constantly surveilling. Drones can carry high-power zoom lenses, night vision, and see-through imaging. Figuring out this privacy issue will certainly be a hot topic in the near future.

Another disadvantage of drones is that they may cause people to become desensitized to war and killing in general. The problem is that drones are a nice way of turning war into a contest between robots, they are too easy a placeholder for all of our technological anxieties. Actually being in the war zone and having to kill people is much different than sitting in front of a screen and pushing a button that will kill people. Drones disconnect people from the killing and this is definitely not a good thing. One last disadvantage of drones is that they leave behind collateral damage. As stated earlier drones have the capability to be used very precisely but that is not always the case. Many civilian casualties have been taken by drones including children.

When it comes to drones the losers are pilots who used to fly military aircraft. The creation of drones completely changed their careers and a lot of them lost their jobs while a new type of "pilot" was created. The new type of "pilot" the ones who sit in a cubicle and fly the drones are also losers. They become desensitized to war and often suffer from the post-traumatic stress disorder. This job can also be confusing because they sit in an office all day and shoot things, and then at the end of the night, they walk out into the real world, not a war zone. The people we are using these drones against are also the losers. People who are being fired on by drones have no way to defend themselves and innocent people are often killed [15].

Integration of remotely piloted aircraft systems operations into ATM and ATM procedures

The integration of RPA in non-segregated airspace will be a gradual process that builds upon technological advances and development of associated procedures. The process begins with limited access to airspace, and while some RPA may eventually be able to seamlessly integrate with manned flights, many may not. When adding any new type of airspace user into the existing air navigation system, consideration must be given to minimizing risk to all airspace users. States and service providers under oversight should therefore apply safety management principles and analyses to the introduction of RPAS operations. These principles and analyses should reflect on-going developments in RPAS capabilities. RPAS operations should conform to the existing airspace requirements. These airspace requirements include, but are not limited to, communication, navigation and surveillance requirements, separation from traffic and distances from clouds. Controlled airspace. In order for RPA to be integrated into non-segregated controlled airspace, the RPA must be able to comply with existing ATM procedures. In the event that full compliance is not possible, new ATM procedures should be considered by the aviation authorities and/or ANSPs in consultation with the RPAS operator and representatives of other airspace user groups. Any new ATM procedures should be kept as consistent as possible with those for manned flights to minimize disruption of the ATM system. Uncontrolled airspace. In order for RPA to be integrated into non-segregated uncontrolled airspace, the RPA will need to be able to interact with other airspace users, without impacting the safety or efficiency of existing flight operations [1].

Take-off and landing phases. RPAS may be operated in either VMC or IMC, and the associated VFR and IFR restrictions applicable to manned aircraft will apply. These operations may also be conducted within VLOS or BVLOS depending on the capability of the RPAS involved. Of particular note is the requirement for the RPAS operator to be able to determine the meteorological conditions in which the RPA is operating during these phases, in order to ensure the RPA is indeed operating in accordance with applicable flight rules [1; 13].

Take-off and landing phases. RPAS may be operated in either VMC or IMC, and the associated VFR and IFR restrictions applicable to manned aircraft will apply. These operations may also be conducted within VLOS or BVLOS depending on the capability of the RPAS involved. Of particular note is the requirement for the RPAS operator to be able to determine the meteorological conditions in which the RPA is operating during these phases, in order to ensure the RPA is indeed operating in accordance with applicable flight rules.

En-route phase. The operational, equipage and performance requirements imposed on the RPAS will again depend upon the class of airspace through which the RPA will be transiting and any additional requirements prescribed for the airspace or operation.

Communication, navigation and surveillance (CNS). Functionality and performance requirements for RPA should ideally be equivalent to those established for manned aircraft and appropriate to the airspace within which the RPA is operated and where ATS is being provided. The performance and equipage requirements will be determined by factors associated with the operating environment which may include classes of airspace, proximity to heavily populated areas, terrain, etc. [1]. ATCO must have a general knowledge of RPA performance characteristics and be familiar with specific characteristics of RPA operating in the airspace. The following performance characteristics should be considered:

a) speed;

b) climb, descent or turn rates;

c) wake turbulence;

e) latency; and

f) effect of bank angle on C2 and ATC communications link capability and reliability.

The absence of an onboard pilot will necessitate some unique procedures in the integration of RPA into non-segregated airspace. To the greatest extent practicable, procedures should be identical to those developed for manned aircraft. Some of the issues that will need to be addressed to integrate RPA flights include the following:

a) flight planning:

1) RPA type designators;

2) phraseology (to be used with/by ATC);

b) VFR flight:

1) separation standards;

2) right-of-way rules;

c) IFR flight:

1) separation standards;

2) right-of-way rules;

d) contingency and emergency procedures:

1) C2 link failure;

2) ATC communications failure with remote pilot; and

3) intercept procedures/compliance with air defence.

Control instruction response times (e.g. the length of time between ATC issuing an instruction, the remote pilot complying with the instruction and the RPA responding to the inputs) may affect the controller's ability to support RPA operations if an inordinate amount of resources are allocated to a single aircraft. This can also be a result of other performance characteristics such as climb, descent or turn rate that may differ substantially from those of conventional aircraft. Thus, it will be essential that the ATCO be aware of and anticipate these potential underperformances and plan accordingly. Conventional instructions such as "expedite" and "immediate" may not be practical in many cases.

Classification of UAV's

There are following classification of UAV's that is shown on Table 3.1. The type of UAV designs are divided into sets, which are made of airplane (fixed - wing) and helicopter (rotary - wing) schemes and devices with flapping wings. The type of take-off UAVs are divided into sets of take-off from the runway and a vertical take-off (usually used depending of the purpose). Unmanned aerial vehicles are classified by way of take-off and landing, airfield and non-airfield, also taking off from the runway or with a catapult; landing to the runway or by parachute or by using snares [2; 3; 14; 15].

Table 3.1 UAV types

№	Class	Classification	Subclass	Code name
1	A	UAV classification by purposes	Surveillance UAVs	A1
			Agricultural UAVs	A2
			Relays communications UAVs	A3
			…	An
2	B	UAV classification by duration of the flight	UAV of a short flight (1 hour)	B1
			Medium-flight UAV’s(from 1 to 6 hours),	B2
			Early flight UAV’s (6 hours).	B3
			…	Bn
3	C	UAV classification by weight.	Micro UAVs (to 1kg).	C1
			Small 1 - 100 kg.	C2
			Lightweight 100 - 500 kg.	C3
			Medium 500 - 5000kg.	C4
			Heavy 5000 - 15000 kg.	C5
			Superheavy 15,000 kg or more	C6
			…	Cn
4	D	UAV classification by the type of aircraft	UAVs airplane (fixed-wing)	D1
			UAVs helicopters (rotary-wing)	D2
			UAVs with flapping wings.	D3
			…	Dn
5	E	UAV classification by way of take-off	Airfield take off UAV	E1
			Non-airfield UAV taking off from a catapult;	E2
			Non-airfield UAV taking off from hands	E3
			…	En
7	F	UAV classification by landing way	Airfield landing UAV	F1
			Non-airfield UAV landing with the help of parachute;	F2
			Non-airfield UAV landing with the help of snares;	F3
			…	Fn
8	G	UAVs by the number of applications	UAV of single usage	G 1
			UAV of repeated usage	G 2
			…	G n

By the purpose, the UAV classified as agricultural, surveillance, search and rescue, cargo and relays communications. As the number of applications classified as single and multiple applications. Typically, these UAVs are used in monitoring forest fires and search and rescue operations where there is a high probability of loss of the aircraft. For the duration of the flight of the UAV are classified on the aircraft a short flight (1 hour), medium-flight (from 1 to 6 hours), and early flight (6 hours). Given the rather large variety of UAVs also classified by weight. Micro to 1kg., Small 1 - 100 kg., Lightweight 100 - 500 kg., Medium 500 - 5000kg., Heavy 5000 - 15000 kg., Extra heavy 15,000 kg or more. All the above types of UAVs by weight are classified depending on flight distance and maximum take-off weight.

So, according to ASSIST there are such types of ES which can be on a board of UAV: bird strike, brake problems, communication failure, electrical problems, emergency descent, engine failure, fire on a board, fuel problems, gear problems, problems with the hydraulic system, icing, fuel dumping, emergency landing, take off abort, low oil pressure were obtained models of DM of UAVs operator and actions of UAV's operator almost the same like actions of a pilot of a civil aircraft [3; 6; 9]. For example, let us consider the pre-flight preparing of UAV Birdeye 500 (Fig. 3.1). There are 7 main steps of preparing (Table 3.2, 3.3):

1. Make sure that the system is deployed, all cables are connected and the power is turned on remote controll and UAVs.
2. As data channel, set the channel maintenance.
3. Ensure you have a strong signal reception of UAV.
4. Put terrestrial channel to mode «Чисто».
5. Check for a strong signal transmission.
6. Set the working channel.
7. Set the operating mode Secure (if necessary), and set the number sequence.The middle index of t_n is shown in Table 3.3, for example time of 1st step

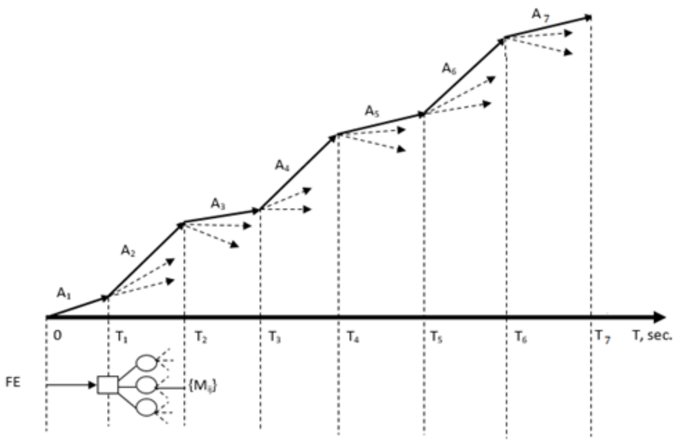

Fig 3.1 Determination grapf of preparing process

Table 3.2 Generalized structural-hourly table of the technology of the air traffic controller work in FE

№	Contents of the work	Designation of the work	Set of the operations	Support on the work	Time of the performing the work
	Setting of primary connection				
1.	Make sure that the system is deployed, all cables are connected and the power is turned on remote controll and UAVs.	A1	{a11, a12, …, a1n}	–	{t11, t12, …, t1n}
2.	As data channel, set the channel maintenance.	A2	{a21, a22, …, a1n}	A1	{t21, t22, …, t2n}
3.	Ensure you have a strong signal reception of UAV	A3	{a31, a32, …, a3n}	A1 ∩ A2	{t31, t32, …, t3n}
4.	Put terrestrial channel mode Чисто.	A4	{a41, a42, …, a4n}	A1 U A2 U A3	{t41, t42, …, t4n}
5.	Check for a strong signal transmission.	A5	{a51, a52, …, a5n}	A1 ∩ A2 ∩ A3 ∩ A4	{t51, t52, …, t5n}
6.	Set the working channel.	A6	{a61, a62, …, a6n}	A1 ∩ A2 ∩	{t61, t62, …, t6n}

				A3 ∩ A4 ∩ A5	
7.	Set the operating mode Secure (if necessary), and set the number sequence.	A7	{a61, a62, …, a7n}	A1 ∩ A2 ∩ A3 ∩ A4 ∩ A5∩ A6	{t11, t12, …, t1n}

So, according to ASSIST there are such types of emergency situations which can be on a board of UAV: birdstrike, bomb warning, brake problems, communication failure, electrical problems, emergency descent, engine failure, fire on a board, fuel problems, gear problems, problems with the hydraulic system, icing, fuel dumping, emergency landing, takeoff abort, low oil pressure. And actions of UAV’s operator almost the same like actions of a pilot of a civil aircraft (Fig.3.2). For planning and flight control UAV developed a distributed Adoption Support System Solutions (ASSS), which represents a complex system with complex interactions geographically distributed local ASSS operators of UAS. During the flight UAVs may be controled by remote piloting station (RPS). At any given time t_i k-UAV must piloted by only one j-th RPS, if necessary, at time t_{i+1} to be transmitted to the control (j + 1) th RPS (Fig. 3.3). This transfer flight control of the j-th RPS to (j + 1) -th RPS to be safe and effective, which is provided through the local DSS operators UAV.

Table 3.3 Main steps of preparing

Setting of primary connection	min
Make sure that the system is deployed, all cables are connected and the power is turned on remote controll and UAVs.	5 minutes
As data channel, set the channel maintenance.	15 seconds
Ensure you have a strong signal reception of UAV	5 seconds
Put terrestrial channel modeЧисто.	5 seconds
Check for a strong signal transmission.	5 seconds
Set the working channel.	30 seconds
Set the operating mode Secure (if necessary), and set the number sequence.	30 seconds

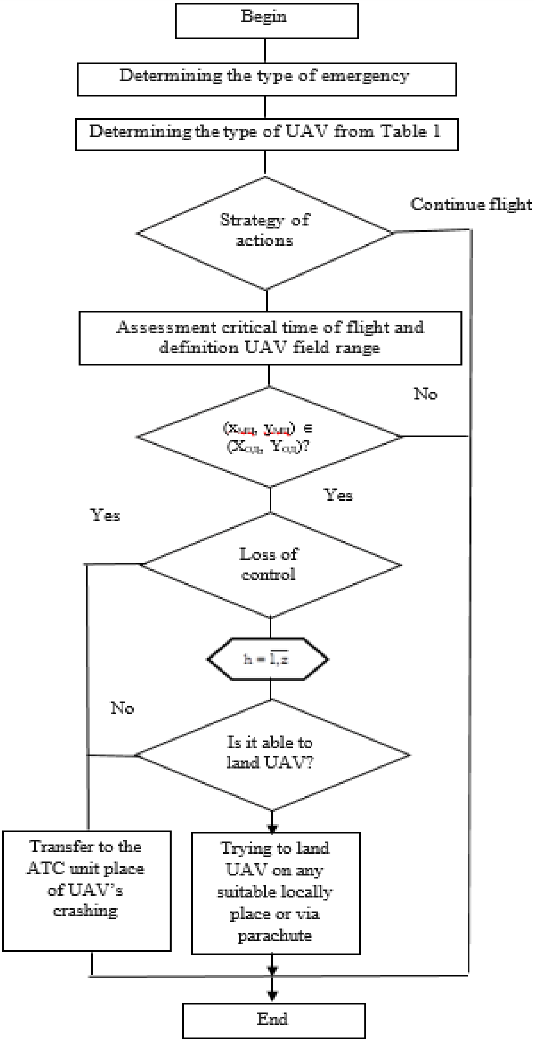

Fig. 3.2 Algoritm ofactions of UAV operator

At any given time t_i k-RPA can be controlled from only one j-th RPS, if necessary, at time t_{i+1} to be transmitted to the control (j + 1)th RPS for using DDSS (Figure 3.3). This transfer flight control of the j-th RPS to (j + 1) -th RPS to be safe and effective, which is provided through the local

DSS operators RPAS (Figure 3.2). According to the recommendations of the ICAO guidelines [9] task system can perform one or more nodes (local DSS operators RPAS). With the formation of the database addresses issues related to the inclusion of RPA the existing regulatory framework of civil air navigation system; description and classification of UAVs and related components; rules of flight, such as instrument flight rules (IFR) and Visual Flight Rules (VFR) flights in the visual line of sight (VLOS) and beyond line of sight (BVLOS) [9]. To coordinate interaction and exchange of information between remoted pilots developed database of local RPS NoSQL [10]. During developing a database of local RPS, UAV users, it was made UAS components analysis, UAV, RPS, C2, and so on. For optimization the solution of problems are developed models of determination the optimal landing site in case of an extraordinary situation, search for optimal flight routes UAS with the module «ASSSIST». The investigation into the processes of modelling the DM by UAV’s operator in the normal and unusual situations enabled to build the following models: DM under Certainty, DM under Risk and DM under Uncertainty [3-6]. For example, for determine of the optimal landing aerodrome in flight emergencies (FE) we using model of DM under Uncertainty [3;11;12].

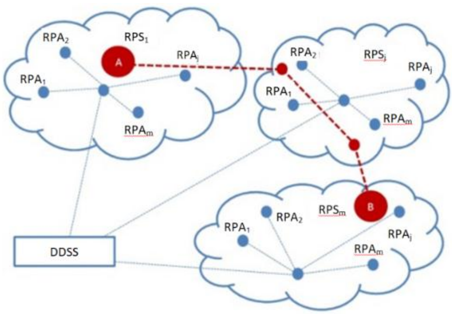

Fig 3.3 The structure of distributed RPS Mission Control UAVs

Pre-flight planning should include consideration to alternate aerodromes / recovery sites, as appropriate, in the event of the emergency or meteorological-related contingency. Before selecting an alternate recovery / landing, location the remote pilot should consider the adequacy fuel / energy, reserves, reliability of C2 links with the RPA, ATC communication capability as necessary and meteorological conditions at the alternate. For using known criteria of decision making under uncertainty are finding optimal landing aerodrome in FE [1].

To coordinate interaction and exchange of information between remoted pilots developed database of local RPS NoSQL [11]. During developing a database of local RPS, UAV users, it was made UAS components analysis, UAV, RPS, C2, and so on. Taking into account the UAVs operating procedure that includes the purpose of the flight, flight rules, flight areas, functional level C2 lines and other standards (Fig. 3.4).

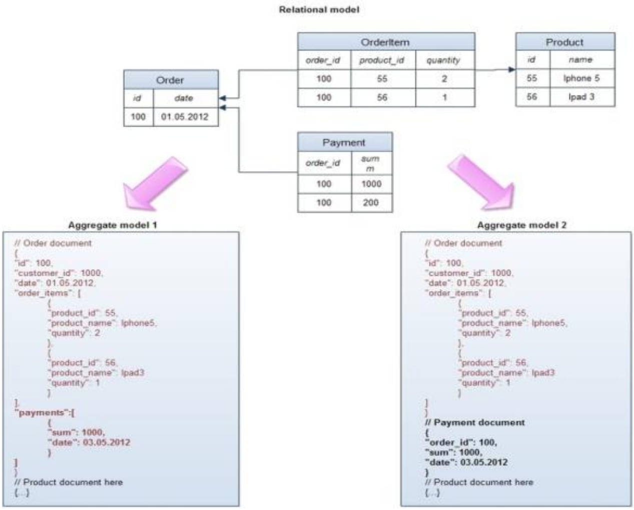

Fig. 3.4 Fragment of NoSQL database of local RPS UAVs users

Algorithm of determination of the optimal landing aerodrome in flight emergencies:

1. Formation of the set of alternative decisions {A}:

$$\{A\} = \{A_{dest}\ U\ A_{dep}\ U\ \{A_{alt}\}\} = \{A_1, A_2, \ldots A_i, \ldots, A_n\},$$

where

A_{dest} – is an alternative decision to land at the destination aerodrome; A_{dep} – is an alternative decision to return to the aerodrome of departure; A_{alt} – is a set of the alternative decision to alternate aerodromes / recovery sites.

2. Formation of the set of factors $\{\lambda\}$, influencing the choice of alternate aerodromes / recovery sites:

$$\{\lambda\} = \lambda_1, \lambda_2, \ldots, \lambda_j, \ldots, \lambda_m,$$

where

$\lambda_1, \lambda_2, \ldots, \lambda_j$ – is set of factors (fuel level, remoteness of the aerodromes, technical characteristics of runways of destination aerodromes, meteorological conditions, reliability of C2 links with the RPA, etc.).

3. Formation of the set of possible results of decision making under the influence of specified factors in FE, that were determined by the method of expert estimates by rating scales according to the regulations:

$$\{U\} = U_{11}, U_{12}, \ldots, U_{ij}, \ldots, U_{nm}.$$

4. Formation of the decision matrix $M = \|M_i\|$ (Table 1). It was created computer program [12] for optimal solutions using criteria decision making under uncertainty (Fig. 3.5).

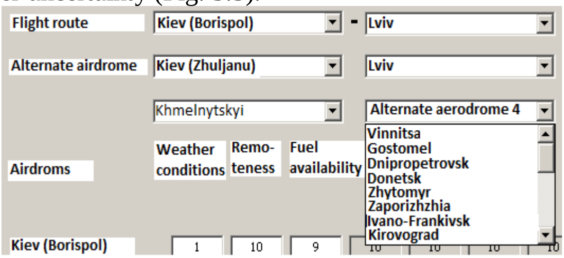

Fig. 3.5 The program „UAV_AS": choosing of alternate airdrome

The program "UAV_AS" gives to UAV operator recommendations on how to act in case of emergency. To start you must select the file UAV_AS.exe and run it. After starting the main file software opens the main window (Fig. 3.6).

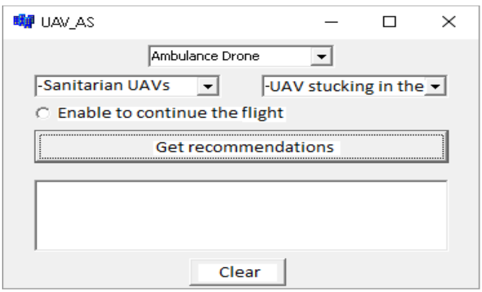

Fig. 3.6. The program „UAV_AS": the main window

Choosing of the optimal aerodrome, in case of forced landing is carried out by the methods of decision making under uncertainty [10].

Selection of criterion of DM in uncertainty (Wald, Laplace, Hurwitz, Savage) is conducted according to the type of flight.

Wald criterion (min/max) is based on the principle of "conservative attitude", and is applied if it is necessary to find a guaranteed solution in case of primary flight:

$$A^* = \max_{A_i} \left\{ \min_{\lambda_j} u_{ij}(A_i, \lambda_j) \right\}.$$

Laplace criterion is based on the principle of "insufficient reason" and applied is in case of regular flight:

$$A^* = \max_{A_i} \left\{ \frac{1}{m} \sum_{j=1}^{n} u_{ij}(A_i, \lambda_j) \right\}.$$

Hurwitz criterion uses coefficient of a pessimism-optimism α ($0 \leq \alpha \leq 1$) and is applied in case of flight once in 2 weeks:

$$A^* = \max_{A_i} \left\{ \begin{array}{l} \alpha \max\limits_{\lambda_j} u_{ij}(A_i, \lambda_j) + \\ + (1-\alpha) \min\limits_{\lambda_j} u_{ij}(A_i, \lambda_j) \end{array} \right\}$$

Table 3.4 Matrix of possible results of decisions in the task of choosing of the optimal landing aerodrome / recovery site

Alternative decisions		Factors influencing the decision making					
		adequacy fuel /energy on RPA	remoteness of the aerodromes / recovery sites	technical characteristics of runways of aerodromes / recovery sites	meteorological conditions at aerodromes / recovery sites	reliability of C2 links with the RPA	ATC communication capability
A1	Adest	u11	u12	…	u1j	…	u1n
A2	Adep	u21	u22	…	u2j	…	u2n
A1	Aalt	u11	u12	…	u1j	…	u1n
An	Aalt	um1	um2	…	umj	…	umn

The optimal solution for the Savage criterion can be found using matrix of "regret". In case of win the elements of the "regret" matrix $r_{ij}(A_i, \lambda_j)$ are defined as the difference between the maximum value u_{ij} in the row and other values in the row. Then, with the help of the "regret" matrix according to the min/max principle the minimum deviations are determined:

$$r_{ij}(A_i, \lambda_j) = \underset{A_i}{\Delta} = \max_{\lambda_k} u_{ij}(A_i, \lambda_j) - u_{ij}(A_i, \lambda_j).$$

$$A^* = \min_{\lambda_j} \max_{A_i} r_{ij}(A_i, \lambda_j) \cdot$$

Thus the person, who makes a decision, expresses with the help of matrix $\|r_{ij}\|$ his "regret" if he can't make a best decision in the condition λ_j. Making this decision the person, who makes a decision, has a guarantee that in the worst conditions the obtained income would be not lower than the found income. If flight of UAV is a scheduled one, Laplace and Hurwitz ($0 \leq \alpha \leq 0.5$) criteria are used for decision making. If the flight of UAV is performed for the first time, Wald, Savage and Hurwitz ($0,5 \leq \alpha \leq 1$) criterions are used for decision making.

3.3 Illustrative Example

This example from diploma of Masters of Nation Aviation University Olecsandr Fomin, **t**heme: «Method of determining the UAV's optimal landing place»**.** In this chapter we are going to review different methods of alternate aerodrome selection under conditions of uncertainty using decision-making theory. We will build up an algorithm and find out which of the criteria gives us the best solution. Support of the safe functioning of Air Navigation System (ANS) is one of the most important scientific and technical problems. Statistical data show that human errors account for up to 80 % of all aviation accidents. Latest demands of international aviation organizations directed towards the implementation of integrated approach for the improvement of aviation safety. One of the ways to increase safety is to support the remote pilot in emergency situations. This approach is based on characteristics principles of informed decision making to achieve the desired/required results and to use facts and data for decision-making. It is a systematic approach to the mental process used by pilots to consistently determine the best course of action in response to a given set of circumstances. It is what a pilot intends to do, on the basis of latest information he has. According to the regulations, alternate aerodromes are chosen based on the following factors:

- meteorological conditions at alternate aerodromes
- amount of fuel on board
- distance to the alternate aerodrome

In-flight emergencies for ensuring the flight safety and the cost-effectiveness of the flight, finding an optimal alternative for passengers, cargo and crew, multifactorial model of choice of landing aerodrome is used, which takes into account more additional parameters: danger of the situation, type of the flight (regular, primary), technical characteristics of the AC, reliability of C2 links for connection with RPA, technical specifications of aerodromes (for example, condition of runways, navigational aids, lighting system), air navigation and airport charges. In the practical part of the current chapter we are going to be using the following decision-making criteria Wald, Laplace, Savage, Hurwicz.

Pre-flight planning and requirements. Remotely pilot aircraft are quickly becoming an indispensable part of modern aviation. As the technologies develop remotely piloted aircraft make their transition from strictly military usage to civil aviation and currently serve to fulfill many civil purposes. Preparation and pre-flight planning are obligatory procedures for both classic and remotely piloted aviation. It plays a major role in effectiveness and ensures required level of safety. This procedure includes technical diagnostics and maintenance of RPAS and associated RPS, checking of communication links, general configuration of RPS, flight planning routines. The same way as piloted aircraft unmanned aerial vehicles require clearance from an authorized ATC. Pre-flight planning demands responsible person or organization to define alternate aerodromes/airfields which will be used in case of emergency situation or any other unforeseen condition that may prevent the aircraft from being able to land at a destination aerodrome.

Algorithm of finding of optimal landing aerodrome for RPA

Formation of the set of alternative decisions

$\{A\}$: $\{A\} = \{A_{adest} \cup A_{adep} \cup \{A_{aalt}\}\} = \{A_1\ A_2,...A_b..., A_n\}$,

where A_{adest} — is an alternative decision to land at the destination aerodrome;

A_{adep} — is an alternative decision to return to the aerodrome of departure;

A_{aalt} — is a set of the alternate aerodromes.

Formation of the set of factors $\{\lambda\}$, influencing the choice of landing aerodrome in case of forced landings of the AC:

$\{\lambda\} = \lambda_1, \lambda_2,..., \lambda_j,..., \lambda_m$,

where

λ_1 — is a remoteness of the aerodromes

λ_2 — is an availability of fuel on board of RPA;

λ_3 — are the technical characteristics of runways of destination aerodrome, aerodrome of departure, alternate aerodromes;

λ_4 — reliability of C2 links;

λ_5 — are the lighting systems at destination aerodrome, aerodrome of departure, alternate aerodromes;

λ_6 — are the meteorological conditions at destination aerodrome, aerodrome of departure, alternate aerodromes;

λ_7 — are the navigational aids at destination aerodrome, aerodrome of departure, alternate aerodromes

λ_8 — are the approach systems at destination aerodrome, aerodrome of departure, alternate aerodromes

Formation of the set of possible results of DM under the influence of specified factors in flight emergencies, that were determined by the method of expert estimates by rating scales according to the regulations:

$\{U\}=U_{11}, U_{12},...,U_{ij},..., U_{nm}$.

Choosing of the optimal aerodrome, in case of forced landing is carried out by the methods of decision making under uncertainty (Table 2). Selection of criterion of DM under uncertainty (Wald, Laplace, Savage, Hurwicz) is conducted according to the type of flight.

Table 3.5 – Decision matrix with input data

Alternate decisions	Factors that influence on decision making							
	Remoteness of the aerodromes	Availability of fuel on board	Tech. characteristics of RWYs	Reliability of C2 links	Lighting systems	Meteorological conditions	Navigational Aids	Approach systems
A_1	A_{Adep}	U11	U12	U13	U14	U15	U16	U17
A_2	A_{Adest}	U21	U22	U23	U24	U25	U26	U27
A_3	A_{Aalt1}	U31	U32	U33	U34	U35	U36	U37
A_4	A_{Aalt2}	U41	U42	U43	U44	U45	U46	U47
A_5	A_{Aalt3}	U51	U52	U53	U54	U55	U56	U57
A_6	A_{Aalt4}	U61	U62	U63	U64	U65	U66	U67

Wald criterion (min-max) is based on the principle of "conservative attitude", and is applied if it is necessary to find a guaranteed solution in case of primary flight:

It is based on a careful behavior of the person who makes the decision, and reduced to selecting the best alternatives from the worst. The best solution for the Wald criterion determines by the rule:

$$A^* = \max_{A_i}\left\{\min_{B_j} u_{ij}(A_i, B_j)\right\} \quad (1)$$

Laplace criterion is based on the principle of "insufficient reason" and applied is in case of regular flight:

$$A^* = \max_{A_i}\left\{\frac{1}{m}\sum_{j=1}^{n} u_{ij}(A_i, B_j)\right\} \quad (2)$$

Hurwicz criterion uses coefficient of a pessimism-optimism a (0 < a < 1) and is applied in case of flight once in 2 weeks:

$$A^* = \max_{A_i} \left\{ \alpha \max_{B_j} u_{ij}(A_i, B_j) + (1-\alpha) \min_{B_j} u_{ij}(A_i, B_j) \right\} \tag{3}$$

The optimal solution for the Savage criterion can be found using matrix of “regret”. In case of win the elements of the “regret” matrix $r_{ij}(A_i, \lambda)$ are defined as the difference between the maximum value U_{ij} in the row and other values in the row:

$$r_{ij}(A_i, B_j) = \underset{A_i}{\Delta} = \max_{B_k} u_{ij}(A_i, B_j) - u_{ij}(A_i, B_j) \tag{4.4}$$

Then, with the help of the “regret” matrix according to the min-max principle, the minimum deviations are determined:

$$A^* = \min_{B_j} \max_{A_i} r_{ij}(A_i, B_j) \tag{4.5}$$

Thus the person, who makes a decision, expresses with the help of matrix r_{ij} his “regret” if he can’t make the best decision in the condition λ_j. Making this decision the person, who makes a decision, has a guarantee that in the worst conditions the obtained income would be not lower than the found income.

As an example for our task we are going to consider a flight from Bila Tserkva aerodrome to Konotop with possible alternate destinations at Vasylkiv, Berezan’ Nizhyn, and Pryluky (Fig 3.7). For each aerodrome we introduced risk parameters and corresponding coefficient which are going to serve as a basis for our investigation.

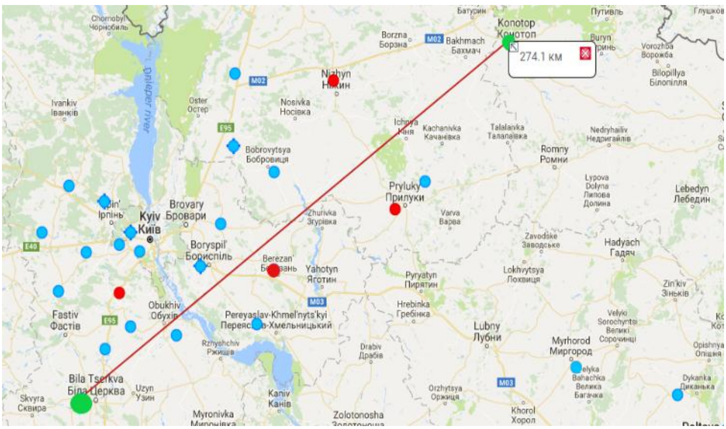

Fig 3.7 Aerodrome map

Take-off and landing points are painted in green, alternate aerodromes – red, other aerodromes – blue.

The following parameters have been introduced: remoteness of an aerodrome, availability of fuel onboard, technical characteristics of a runway, reliability of C2 links, lightning systems and approach systems at an aerodrome, navigational aids and meteorological conditions (Table 3.6).

Table 3.6 – Decision matrix with task parameters

Alternate decisions		Factors that influence on decision making						
		Remoteness of the aerodromes	Availability of fuel on board	Tech. characteristics of RWYs	Reliability of C2 links	Lighting systems	Meteorological conditions	Navigational Aids
A_1	Bila Tserkva	9	2	5	8	0	3	9
A_2	Konotop	3	5	7	9	2	4	9
A_3	Vasylkiv	2	8	8	9	2	4	10
A_4	Berezan’	7	1	8	7	1	7	7
A_5	Nizhyn	6	4	8	6	6	5	8
A_6	Pryluky	4	8	9	8	4	6	6

Selection of criteria of decision making under uncertainty in the case of selection of AAP for return operation and in the case of emergency situation:

Wald criterion**.** Using Wald criterion each action is estimated from the best to the worst states. This criterion uses estimated function that corresponds to a position of extreme caution. According to Wald criterion an optimal decision is defined for the maxmin rule, provide guarantee result and completely excludes a risk.

The resulting solution gives a guaranteed result – the best solution of the worst alternatives. This criterion is used in cases when decisions are made rarely, for instance in case of the first flight or flights performed sporadically

$A^*_i = \max_i \min_j \{U_{ij}\} = \max \{A_1, A_2, A_3, A_4, A_5\} = \max \{0, 2, 2, 1, 4, 4\} = A^*_5 = A^*_6 = 4$

Laplace criterion**.** If the probabilities of states of nature are plausible, the Laplace criterion is used to evaluate them, according to which all states of nature are assumed to be equally probable.

This criterion is used in those cases, if you frequently make a decision or if all factors are taken equal. This criterion is used in cases where a decision is often, a regular flight.

$$A^* = \max_{A_i}\left\{\frac{1}{m}\sum_{j=1}^{n} u_{ij}(A_i, B_j)\right\} =$$ max(5.142, 5.571, 6.142, 5.428, 6.142, 6.428) = 6.428= A^*_6 Pryluky

Savage Criterion. Savage minimum risk criterion recommends using strategy in which the maximum risk is minimized under the worst conditions as an optimal one.

Using the Savage criterion we minimize the loss of decision-makers

$$A_j^* = \min \max r_{ij} (a_к \{ \max u_{ij} (a_i; \lambda_j)\} – u_{ij} (a_i; \lambda_j)) \quad (4.6)$$

Let's build the matrix of regret (Table 3.6).

1st column of the regret matrix.

r_{11} = 9 - 9 = 0; r_{21} = 9 - 3 = 6; r_{31} = 9 - 2 = 7; r_{41} = 9 - 7 = 2; r_{51} = 9 - 6 = 3; r_{61} = 9 - 4 = 5;

2nd row of the regret matrix.

r_{12} = 8 - 2 = 6; r_{22} = 8 - 5 = 3; r_{32} = 8 - 8 = 0; r_{42} = 8 - 1 = 7; r_{52} = 8 - 4 = 4; r_{62} = 8 - 8 = 0;

3rd row of the regret matrix.

r_{13} = 9 - 5 = 4; r_{23} = 9 - 7 = 2; r_{33} = 9 - 8 = 1; r_{43} = 9 - 8 = 1; r_{53} = 9 - 8 = 1; r_{63} = 9 - 9 = 0;

4th row of the regret matrix.

r_{14} = 9 - 8 = 1; r_{24} = 9 - 9 = 0; r_{34} = 9 - 9 = 0; r_{44} = 9 - 7 = 2; r_{54} = 9 - 6 = 3; r_{64} = 9 - 8 = 1;

5th row of the regret matrix.

r_{15} = 6 - 0 = 6; r_{25} = 6 - 2 = 4; r_{35} = 6 - 2 = 4; r_{45} = 6 - 1 = 5; r_{55} = 6 - 6 = 0; r_{65} = 6 - 4 = 2;

6th row of the regret matrix.

r_{16} = 7 - 3 = 4; r_{26} = 7 - 4 = 3; r_{36} = 7 - 4 = 3; r_{46} = 7 - 7 = 0; r_{56} = 7 - 5 = 2; r_{66} = 7 - 6 = 1;

7th row of the regret matrix.

r_{17} = 10 - 9 = 1; r_{27} = 10 - 9 = 1; r_{37} = 10 - 10 = 0; r_{47} = 10 - 7 = 3; r_{57} = 10 - 8 = 2;

r_{67} = 10 - 6 = 4;

Table 3.7 – Regret matrix

	Regret Matrix								min (U_{ij})
A_1	Bila Tserkva	0	6	4	1	6	4	1	6
A_2	Konotol	6	3	2	0	4	3	1	6
A_3	Vasylkiv	7	0	1	0	4	3	0	7
A_4	Berezan'	2	7	1	2	5	0	3	7
A_5	Nizhyn	3	4	1	3	0	2	2	4
A_6	Pryluky	5	0	0	1	2	1	4	5

According to Savage criterion the optimal solution for destination aerodrome would be A_5 Nizhyn

Hurwicz Criterion. The optimal solution is determined by the following rule:

A_j * = max a_i {α max λ_j {u_{ij} (a_i; λ_j)} + (1 – α) min λ_j {u_{ij} (a_i; λ_j)} (4.7)

A_j * = max a_i {0.8 max λ_j {u_{ij} (a_i; λ_j)} + (1 - 0.8) min λ_j {u_{ij} (a_i; λ_j)} (4.8)

We choose the coefficient of optimism-pessimism α equal to 0.8. Optimal strategies for α = 0.8:

A_1 = {0.8 max {9,2,5,8,0,3,9} + (1 - 0,8) min {2,5,8,0,3,9}} = {0.8 * 9 + 0.2 * 0} = 7,2;

A_2 = {0.8 max {3,5,7,9,2,4,9} + (1 - 0,8) min {5,7,9,2,4,10}} = {0.8 * 9 + 0.2 * 2} = 7,6;

A_3 = {0.8 max {2,8,8,9,2,4,10} + (1-0.8) min {8,8,9,2,4,10}} = {0,8 * 10 + 0,2 * 2} = 8,4;

A_4 = {0,8 max {7,1,8,7,1,7,7} + (1 - 0,8) min {7,1,8,7,1,7,7}} = {0.8 * 8 + 0.2 * 1} = 6,6; ;

A_5 = {0,8 max {6,4,8,6,6,5,8} + (1 - 0,8) min {6,4,8,6,6,5,8}} = {0,8 * 8 + 0,2 * 4} = 7,2;

A_6 = {0,8 max {4,8,9,8,4,6,6} + (1 - 0,8) min {4,8,9,8,4,6,6}} = {0,8 * 9 + 0,2 * 4} = 8

Hurwicz criterion allows us to introduce and adjust optimism-pessimism α. Given that the consequences of choosing wrong alternate aerodrome might fatal we have decided to increase the coefficient up to 0.8 to minimize risks.

Calculations show us that the optimal solution for our task is: A_3 Vasylkiv = max {7.2; 7.6; 8.4; 6.6; 7.2; 8} = 8.4

Choosing alternate aerodrome is an indispensable part of pre-flight planning for any type of aircraft, PRAs are no exception. In order to ensure safety and efficiency in case of emergency situation we have to develop a method which will give us the best outcome in any particular situation.

In this chapter we have described different factors that may have significant effect on safety and economic efficiency and calculated an appropriate destination point using the following decision-making models:

- Wald maximin criterion
- Hurwicz criterion
- Laplace insufficient reason criterion
- Savage minimax regret criterion

Wald criterion guarantees the best solution of the worst alternatives, which in our case best suitable for rare sporadic flights.

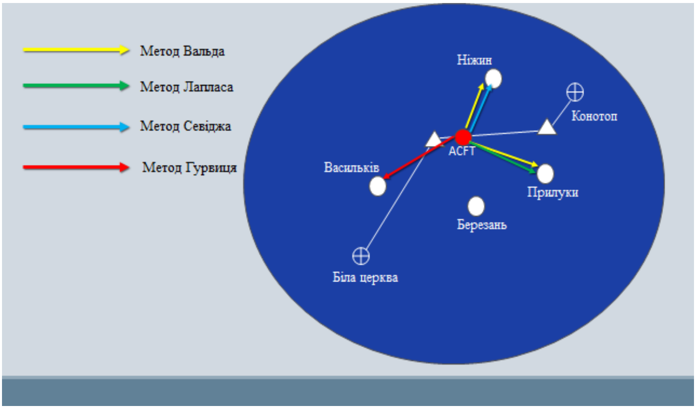

Fig 3.8 Map, different factors

Hurwicz criterion allows us to introduce "optimism-pessimism" coefficient which makes it more versatile in comparison to other methods and apply it for different situation under different circumstances.

Laplace criterion is best suited for regular decisions, for example when flights are performed. Savage criterion allows us to minimize losses and provide the best economic efficiency.

Savage criterion is applied to understand what would be the optimal decision under the most unfavorable circumstances, this criterion expresses a pessimistic assessment of the situation.

3.4 Conclusions

RPAs are a new component of the aviation system, one which the International Civil Aviation Organization (ICAO), States and the industry are working to understand, define and ultimately integrate. These systems are based on cutting-edge developments in aerospace technologies, offering advancements which may open new and improved civil/commercial applications as well as improvements to the safety and efficiency of all civil aviation. The safe integration of RPAS into non-segregated airspace is a long-term activity with many stakeholders adding their expertise on such diverse topics as licensing and medical qualification of remote pilots, technologies for detect and avoid systems, frequency spectrum (including its protection from unintentional or unlawful interference), separation standards from other aircraft and development of a robust regulatory framework.

Pre-flight planning is an extremely important stage of preparation for both conventional aircraft and remotely piloted one. It is essential for the pilot to have alternatives in case landing at the destination aerodrome becomes impossible due to different circumstance as worsening of weather conditions. Having a number of airfields within reach comes with uncertainty and necessity to make a decision under given circumstances.

Uncertainty is a state of having limited knowledge of current conditions or future outcomes. It is a major component of risk, which involves the likelihood and scale of negative consequences. Managing uncertainty and risk also involves mitigating or even removing things that inhibit effective decision-making or adversely affect performance.

Before choosing an alternate aerodrome the pilot must consider the factors that may influence cost-effectiveness and safety of flight:

- adequacy of fuel reserve;
- distance to the alternate aerodrome;
- technical characteristics and conditions of runways;
- lighting systems availability;
- meteorological conditions;
- navigation aids;
- approach system.

The model for decision making has been created based on the decision making criteria: Wald's Maximin criterion, Hurwicz criterion, Laplace insufficient reason criterion, Savage minimax regret criterion. This model can serve as a tool for effective and safe decision making during the sudden change from destination aerodrome to an alternate one.

Further research should be directed to the solution of practical problems of actions UAV's operator in case of emergencies, software creation. Models of FE development and of DM by UAV's in FE will allow to predict the H-O's actions with the aid of the informational-analytic and diagnostics complex for research H-O behavior in extreme situation.

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