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A Method for Planning the Routes of Harvesting Equipment using Unmanned Aerial Vehicles

Vitaliy Mezhuyev[1], Yurii Gunchenko[2], Sergey Shvorov[3], Dmitry Chyrchenko[3]

[1]Faculty of Computer Systems and Software Engineering, Universiti Malaysia Pahang, Lebuhraya Tun Razak, Gambang, 26300, Malaysia
[2]Institute of Mathematics, Economics and Mechanics, Odesa I.I.Mechnikov National University, Dvoryans'ka St, 2, Odesa, 65000, Ukraine
[3]Education and Research Institute of Energetics, Automation and Energy Efficiency, National University of Life and Environmental Sciences of Ukraine, 12 Heroyiv Oborony str., Kyiv, 03041 Ukraine

ABSTRACT

The widespread distribution of precision farming systems necessitates improvements in the methods for the control of unmanned harvesting equipment (UHE). While unmanned aerial vehicles (UAVs) provide an effective solution to this problem, there are many challenges in the implementation of technology. This paper considers the problem of identifying optimal routes of UHE movement as a multicriteria evaluation problem, which can be solved by a nonlinear scheme of compromises. The proposed method uses machine learning algorithms and statistical processing of the spectral characteristics obtained from UAV digital images. Developed method minimizes the resources needed for a harvesting campaign and reduces the costs of fuel consumption.

KEYWORDS: Artificial Neural Networks, Nonlinear Scheme of Compromises, Precision Farming Systems, Unmanned Aerial Vehicles, Unmanned Harvesting Equipment.

1 INTRODUCTION

A precision farming system (PFS) is a system of agricultural management aimed at minimizing anthropogenic pressure on the environment and maximizing profits by optimizing harvesting processes. To date, PFSs have been intensively used worldwide for more than 20 years. PFS allows for the reduction of costs of a harvesting campaign without decreasing the productivity of processes or the quality of agricultural products. Modern PFSs involve a range of technologies, including geographic information system (GIS) and global positioning system (GPS), allowing for automatic navigation of unmanned harvesting equipment (UHE).

Satellite and aircraft-based methods of remote sensing in PFSs are widely considered in the literature. Their use allows for the minimization of overlap and gaps between neighbouring areas in fields during harvesting. However, in most cases, the planning of UHE routes requires an operator and the manual mode. Using a GPS-based image of a landscape as input, the operator marks the actual fields in a specially designed software program. Figure 1 represents the interface of such a type of software (Inspector). Here, identification of the field boundaries requires an initial detour along the perimeter with a GPS receiver. Accordingly, an operator may determine the actual boundaries of the fields.

Such methods are costly, time-consuming and error-prone, especially for challenging terrain, resulting in complex UHE trajectories. Another problem is that existing methods provide limited support for decision-making, which is crucial in situations with high complexity and uncertainty. Additionally, satellite and aircraft-based methods for planning UHE routes have certain limitations in real-time analyses of the geometry of terrain, leading to the overlap of harvesting equipment routes and ineffective UHE use.

This paper proposes a method that uses a UAV for the continuous monitoring of the status of vegetated areas, obstacles in the way of UHEs, and their positions. This method combines the UAV-obtained aerial photography and data received from the GPS of a UHE. Optical range data, received from UAV cameras, are statistically analysed and used as an input for machine learning algorithms. The method synthesizes the optimal trajectories of UHE taking

CONTACT Vitaliy Mezhuyev vitaliy.mezhuyev@fh-joanneum.at, FH Joanneum University of Applied Sciences, Austria

into account the real-time distribution of crops and coordinates of the obstacles. The calculated optimal routes are then transmitted to the navigation system of a UHE. Correspondingly, the method allows for automated control of UHE and supports the delivery of UHE in the reception points.

2 LITERATURE REVIEW

LAN et al. (2010) focused on the use of aircrafts for pest control, as well as for controlling the growth of different crops in the United States. They demonstrated that a PFS based on the use of agricultural aircrafts and helicopters saves time and money.

Senthilnath et al. (2017) considered the use of UAV for the classification of crop areas with RGB images. The spectral-spatial method with Bayesian criterion was used to determine the optimal number of clusters. The authors concluded that the proposed spectral-spatial classification works better and is more stable in comparison with other algorithms.

Ishida et al. (2018) demonstrated that the use of UAV-based spectral imaging offers considerable advantages in high-resolution remote-sensing applications. Selecting the optimal combination of spectral bands is crucial for conventional UAV-based multispectral imaging systems. UAV-based imaging was performed in several vegetated areas, and a support vector machine (SVM) was applied to the obtained dataset, which allowed for the production of a high-resolution classification map from aerial hyperspectral images. Classification accuracy of 94.5% in green areas has been achieved through the SVM learning model.

Hamuda et al. (2016) provided a comprehensive and critical review of methods of plant segmentation published from 2008 to 2015 to determine the colour index of images for assessing the volume of harvest.

Fan et al. (2017) considered a multiple linear regression model that predicts the leaf area index (LAI) of image data for three indices of vegetation. The results show that the LAI time-series can be applied to monitor seasonal changes regardless of the environmental conditions. The V-NIR (near-infrared) camera system was employed as a cost-effective approach for monitoring seasonal changes in crop growth.

Link et al. (2013) considered aerial sensor platforms (ASPs), such as UAV or unmanned aircraft systems. In their study, ASPs were evaluated for their ability to run the specified route within the field and to collect multispectral data that can be used for the management decisions in PFS. Pantazi et al. (2017) described a similar approach using multispectral images for mapping weeds.

Chang et al. (2017) proposed a novel method of UAV use to monitor crop height. The aerial acquisition included over 200 images with significant image overlap. Orthomosaic images and a 3D point cloud were generated by applying the Structure from Motion algorithm to the images. Ground control points were installed around the experimental area, and they were surveyed using a real-time kinematic GPS unit for accurate referencing. A digital terrain model and digital surface model were generated from the 3D point cloud data and then used for harvest planning.

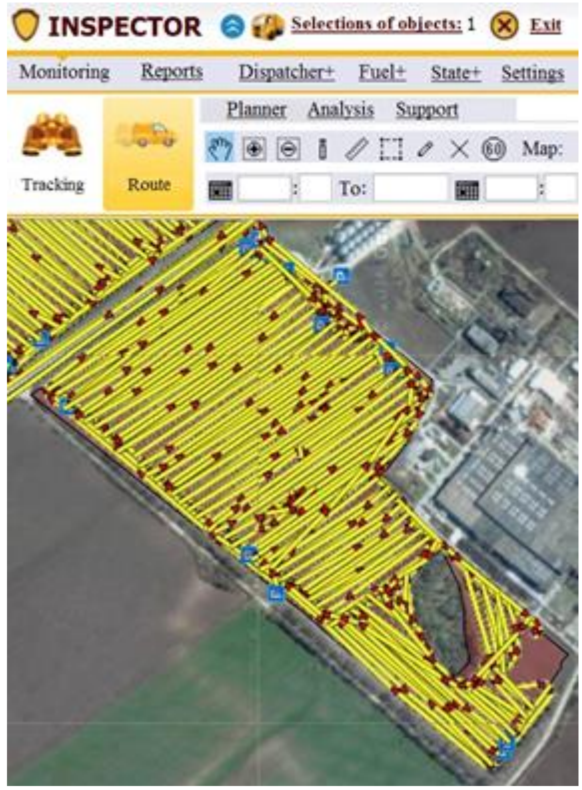

Figure 1. Use of the Inspector software tool for monitoring UHE routes during the harvesting campaign

Saleem et al. (2016) proved the necessity of comparing images from satellite and aerial images when planning a harvesting campaign. Their paper focused on the evaluation of the effectiveness of the scale invariant feature transform (SIFT) and speeded up robust features to determine the real point for images of agricultural land, using a modified normalized gradient SIFT, which resulted in better performance than other methods.

Zhou et al. (2016) considered automation of the planning of a harvesting campaign. In their work, aerial multispectral imaging was used for the assessment of hail damage. Zhou et al. showed that an assessment of crop loss after a hailstorm could be inaccurate and time consuming with the conventional method. Low-altitude, high-resolution images from UAV were utilized for a rapid assessment of target crops on a large scale, which improved the evaluation procedure. Researchers planned the routes of harvesting equipment, taking into account detours around sites with a damaged crop.

Pantazi et al. (2017) used a high-resolution multispectral camera (Green-Red-NIR) for weed mapping. Vegetation identification was carried out through the Kohonen artificial neural network, the anti-proliferation network and the XY-Fusion network. As the input features for the classifiers, they used three spectral bands of red, green, near-infrared and a texture layer.

Xiang and Tian (2011) developed an automatic UAV image geo-referencing method that does not require the use of ground control points. The method has sufficient accuracy for the most precision agriculture applications and thus can be used in the planning of routes of harvesting equipment.

Torres-Sanchez, Lopez-Granados, and Pena (2015) developed a method for optimal thresholding of UAV images for detecting vegetation in herbaceous crops. They used ultra-high-resolution UAV images and object-based image analysis (OBIA). The researchers proposed an algorithm based on Otsu's method, which was applied for vegetation detection in remotely sensed images captured by a conventional optical range camera and a multispectral camera. The tests analysed the performance of the OBIA algorithm for classifying vegetation coverage by excess green (ExG) and the normalized difference vegetation index (NDVI). The index was calculated as the difference between the values of reflection in the near infrared and red areas of the spectrum, divided by their sum. Thus, the approach requires a NIR-modified camera, which increases the cost of the equipment compared to the optical range equipment.

Bendig et al. (2015) proposed to derive plant heights from UAV-based RGB imaging. Vegetation indices were calculated from hyperspectral data and UAV-based RGB imaging.

Vega et al. (2015) also considered the use of the multispectral camera for estimation of the NDVI. Their results showed that the linear regressions between NDVI and grain yield, aerial biomass and nitrogen content were significant.

Torres-Sánchez et al. (2014) proposed to use UAVs equipped with a commercial camera (visible spectrum) to obtain high-resolution images for the wheat field at the beginning of the season. Basing on these images, six visible spectral indices (CIVE, ExG, ExGR, Woebbecke Index, NGRDI, and VEG) and their two combinations were calculated and evaluated for vegetation fraction mapping. These indices were spatially and temporally consistent, allowing accurate vegetation mapping over the entire wheat field at any date.

Thus, most of the recommended approaches require an expensive multispectral camera installed on the UAV. However, inexpensive optical-range cameras can be effectively used for the identification of crops and for the recognition of obstacles in the way of UHE (Lysenko et al., 2016).

Analysed studies show that the application of UAV for PFSs is a hot topic nowadays. Especially, the use of UAV is found more effective compared with satellite and aircraft-based methods of remote sensing. Many studies considered the methods of estimating crop volumes, monitoring seasonal changes, controlling the growth of different crops etc. At the same time, identification of compromisable optimal routes of UHE with UAV use was mostly overlooked by literature.

Considering works in this domain, Poncel et al. (2005) presented an exploration algorithm for partially or totally unknown environments, allowing to calculate a route through unexplored areas.

Liu et al. (2012) introduces a method for travel time predication combined with pattern matching, allowing to create traffic pattern rules with multi-source data fusion.

Mi and Liu (2016) devised a fuzzy neural network strategy to optimize the route decision on urban roads.

Samsuddin et al. (2018) presented a review of single and population-based metaheuristic algorithms for solving multi depot vehicle routing problems.

This study considers the problem of identifying optimal routes of UHE movement as a multicriteria evaluation problem, solved using a nonlinear scheme of compromises (Voronin, 2009). Voronin, Yasinsky and Shvorov (2002) proposed the synthesis of compromisable optimal trajectories of mobile objects in the conflict environment. Further elaboration this approach received in works of Voronin et al. (2015). Especially, it was applied to model the trajectories of aerial objects in the air traffic simulators to train flight dispatchers. Gunchenko et al. (2017) applied the approach for route planning of UHE and harvest volume measuring.

3 PROPOSED METHOD

THE proposed method for the planning of UHE routes has two steps:

Monitoring task: Obtaining real-time data from the UAV in the form of digital images, used for the identification of the distribution of crops, obstacles in the way of UHE and the actual position of UHE on the field.

Planning task: Computation of the compromise-optimal routes for UHE. The following constraints are taken into account: the length of the UHE route has to be minimal; it must bypass areas with no crop, active and passive obstacles.

To obtain a compromise-optimal UHE path, at the monitoring stage the UAV did a fly over the fields to determine and bind the coordinates of the field borders and also passive obstacles (trees, high-voltage power lines, hillocks, holes, etc.). Using both data from UAV and terrestrial GPS trackers, the exact coordinates are determined and transmitted into the GIS of the control centre.

The volumes of crops and their density distribution are identified in each elementary part of the field before the harvesting starts. At the planning stage, it allows to determine the compromise-optimal paths, optimal speed of UHEs, as well as to predict the harvesting time. During the harvest, data from the UAV and UHE are continuously transmitted and processed in the real-time to detect active obstacles (people, animals, or other moving UHEs) to prevent accidents.

NDVI is used for an assessment of the crop distributions by images, taken from the optical range cameras of UAVs. Based on the UAV images, the proposed method separates the field areas by contrasting their optical characteristics. Received data are used for training an artificial neural network (ANN).

To reduce the data size, the method analyses the spectral characteristics of digital images. Several groups of indicators are used:

- descriptors of experimental data (i.e., colour, brightness, mean, median, and mode);
- measures of distribution, which describe the dispersion of the data in relation to the central trend, including the sample variance, the difference between a minimum and maximum elements, scale, sampling interval, etc.;
- indicators of asymmetry (e.g., the position of the median relative to the mean, etc.).

The parameters of descriptive statistics are applied to estimate the maximum and minimum values of the data sample, mean, median, mode, and the mutual influence of these factors. Statistical processing of the images allows us to allocate contrasting by RGB characteristics regions of the field. The approach allows reducing an error in determining the coordinates of obstacles and volumes of the crop. For each of detected regions, statistical parameters were calculated and used to train the ANN.

Generally, ANN transforms the input vector X into the output vector Y, where the transformation is defined by network weights. Since a multi-layered network can reproduce different relationships with a continuous nonlinear function, a statistical analysis of the data can be conducted.

The statistical automated neural networks (SANN) package was used for the ANN synthesis. Different ANN architectures were studied to minimize the recognition error.

Five input parameters were used to describe the data sample of crop areas. The three variables correspond to the values of the colour in RGB format, while variables number 4 and 5 were used to fix the brightness and the ratio of values R/G, respectively.

In the experiment, a 1 ha field was divided into 10 m^2 areas. Each area was characterized by five input variables, used as the input for ANN (mean values of the colours, the brightness and R/G index, received after statistical processing). The volume of the crop was the ANN output.

The input data were divided into three blocks: training, control, and test. The analysis of the input distribution showed that the three values of the central trend coincide; the mean is approximately equal to the median and the mode (R-106,8;106;102; G-129,1;129;121; B-75,6;74;73). Thus, all five input parameters describing the state of the crops were distributed according to the normal law. The normal distribution allowed us instead of using a large volume of the input data, use the only a subset of statistical parameters (RGB colours, the brightness value, and the R/G ratio).

To find the best approach, several neural networks were synthesised: linear ANN, multilayer perceptron, regression ANN and ANN with radial basis function. Figure 2 shows the architecture of the ANN and its parameters.

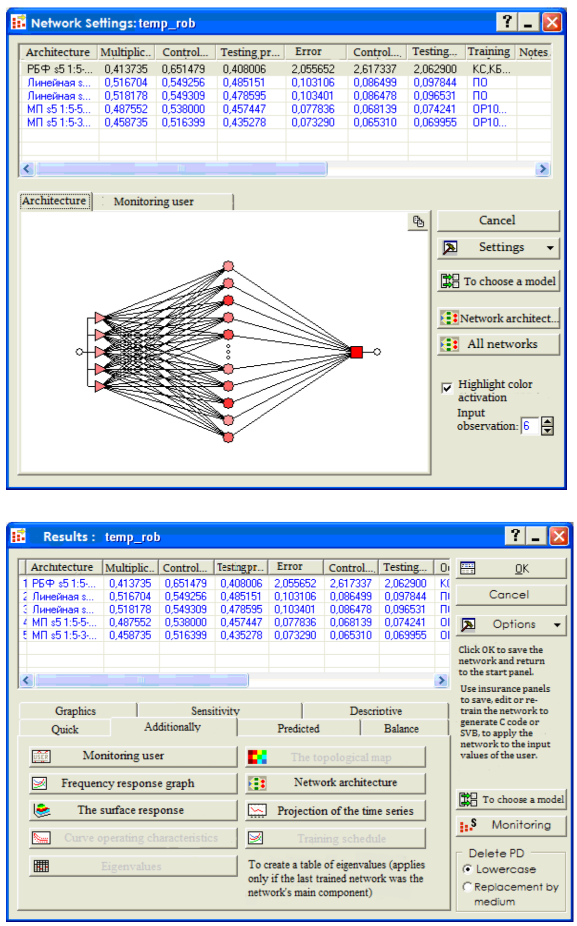

Figure 2. **Synthesis and analyses of the ANN using statistical neural networks tool**

The linear model can be described by the equation:

$$Y = XW + B, \tag{1}$$

where W is a matrix of weights and B is the bias vector.

First, the ANN without intermediate layers, which uses a linear activation function, was designed (1). The weights correspond to the elements of the matrix, W, and the thresholds are the components of the bias vector. The network actually multiplies the input vector X on the matrix of weights, W, and then adds a bias vector to the resulting vector. Figure 3 show the architecture of the linear ANN and Figure 4 the results of its application for the identification of the distribution of energy crops.

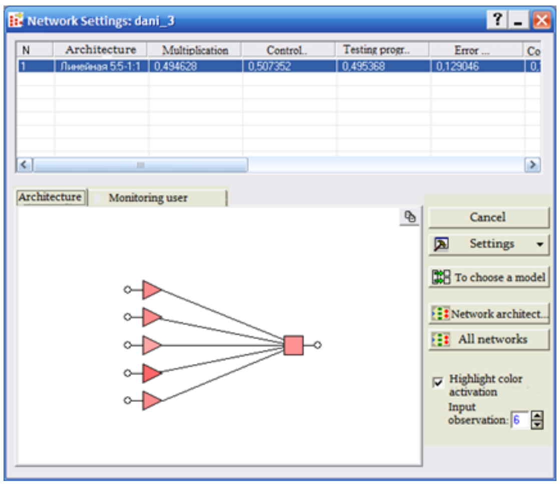

Figure 3. The architecture of the linear neural network

Next, an ANN was designed based on a multilayer perceptron, where the input signals pass through the synapses fed to the five neurons, creating a single layer, and issuing five output signals:

$$y_i = f\left(\sum_{i=1}^{n} X_i W_{ij}\right),\ j = 1,\dots,5. \qquad (2)$$

Matrix W defines the weights of the synapses of one neuron layer, where an element W_{ij} contains the weight of the i^{th} synaptic connected to the j^{th} neuron. The transformation in the neural network can be written in a matrix form:

$$Y = f(XW), \qquad (3)$$

wherein X and Y are the input and the output vectors of a signal, respectively (here and below the row vector is understood), and f is an activation function.

Using equation (3), a multi-layered perceptron was synthesized for the identification of the crop (Figure 5). Fig 6 shows the training results of this ANN.

A generalized regression neural network (GRNN) was designed to solve the regression problems. The GRNN principle is that every training sample represents a mean of a radial basis neuron. GRNN is a variation of a radial basis ANN. Each observation indicates the confidence that the response at this point has a certain weight, and the confidence decreases when moving away from the point. The GRNN uses the training sample to evaluate the response at an arbitrary point with a Gaussian function. The final evaluation was obtained as a weighted mean of the output for all data samples:

$$y = \frac{\sum_{k=1}^{N} Y^k \phi(\|X - X^k\| / \sigma)}{\sum_{k=1}^{N} \phi(\|X - X^k\| / \sigma)}, \qquad (4)$$

where X^k and Y^k are the points in the training samples.

The first intermediate layer of the GRNN network consists of radial elements. The second intermediate layer contains elements that estimate a mean of weights. Each output element generates a sum of weights at this layer. To calculate an average of the sum, this amount is divided by the sum of weights. A synthesized GRNN outputs the values of the estimated crop volumes. Figure 7 shows the architecture and Figure 8 shows a comparison of the predicted and real data.

The radial base function network (RBFN) is a two-layer network, which contains a hidden layer with a non-linear RBF activation function (template layer). For the template layer to be radially symmetric, it should fulfil the following conditions:

- it has a centre, represented as a vector, X, in the input space (space of weights from the input layer to the template layer);
- there is a method for measuring a Euclidian distance from the centre to the input X;
- there is a scalar function of one argument, which defines the output signal by use of the function of distance. In the proposed approach, the following Gaussian function was used:

$$\varphi(s) = e^{-s^2}. \qquad (5)$$

The output signal of the template is a function of the distance between the input vector X and the centre C:

$$f(X) = \varphi\left(\frac{\|X - C\|}{\sigma}\right). \qquad (6)$$

The linear output layer of the network is defined by the expression:

$$y_j = \sum_{i=1}^{K} w_{ij} \varphi\left(\frac{\|X - C_i\|}{\sigma_i}\right),\ j = 1,2,\dots,m, \qquad (7)$$

wherein C_i is the centre and σ_i is the deviation of the radial elements.

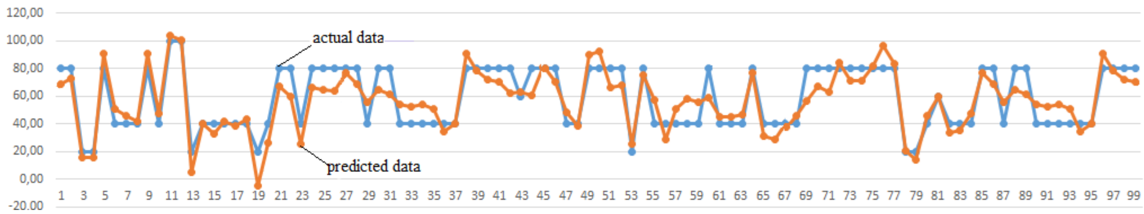

Figure 4. Results of the application of linear ANN for the identification of crop distributions

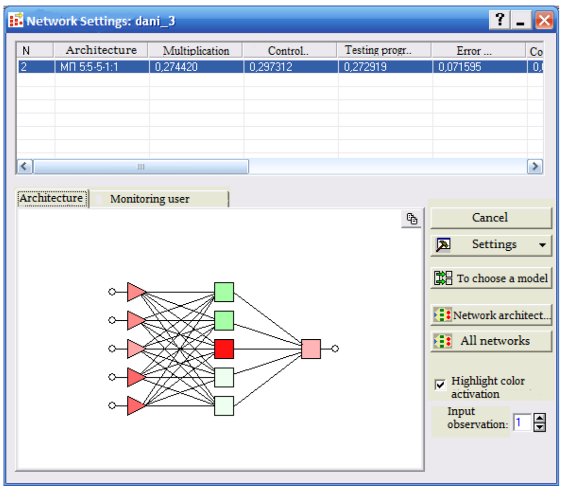

Figure 5. The architecture and characteristics of ANN based on the multilayer perceptron

The training of the RBF network had several stages. First, the centres and the deviations for the radial elements were determined. Next, the matrix *W* of the linear output layer was optimized. The criterion is that the location of the centres should correspond to the clusters found in the data sample.

4 EXPERIMENTAL STUDY

DURING the experimental study, all synthesised ANNs were applied to solve the problem of identifying volumes of energy crops based on optical range data received from the UAV. The best result shows the RBF network. Figure 9 represents its architecture.

Figures 10 and 11 show the results of RBF ANNs training and their output for 2 samples. ANN structures differ by the number of neurons in the hidden layer.

The multilayer perceptron with five neurons in the hidden layer shows the loss: training - 0.06, control - 0.071, test - 0.067. Linear with five neurons in the input layer shows the loss: training – 0,11, control – 0,12, test – 0,112. GRNN with 1358 neurons in the hidden layer shows the loss: training – 0,03, control – 0,03, test – 0,03. RBF with 107 neurons in the hidden layer shows the loss: training – 0,013, control – 0,015, test – 0,012. RBF with 154 neurons in the hidden layer shows the loss: training – 0,0103, control – 0,0132, test – 0,012.

Thus, for solving the problem on the base of given spectral characteristics in the optical range, the best result in terms of the speed and accuracy of training showed the RBF ANN. In plan of future development, the method would further select the RBF network with a fewer number of neurons in the hidden layer, because the errors of the two synthesized RBF ANN were almost identical.

5 IDENTIFICATION OF THE OPTIMAL ROUTES OF UHE

TO find the optimal routes for UHE, the following constraints were formulated: a) the minimum length trajectories of UHE, b) bypassing obstacles, and c) bypassing areas without biomass. These tasks can be complicated by possible changes in the harvesting plan, the number and the type of available UHEs and other various parameters.

First, the problem was reduced to a discrete form. It was assumed that the area of interest is covered by the network $Z^{(1)} \times Z^{(2)} \times \ldots Z^{(Q)}$ and a UHE can discretely move from one node of the network to another.

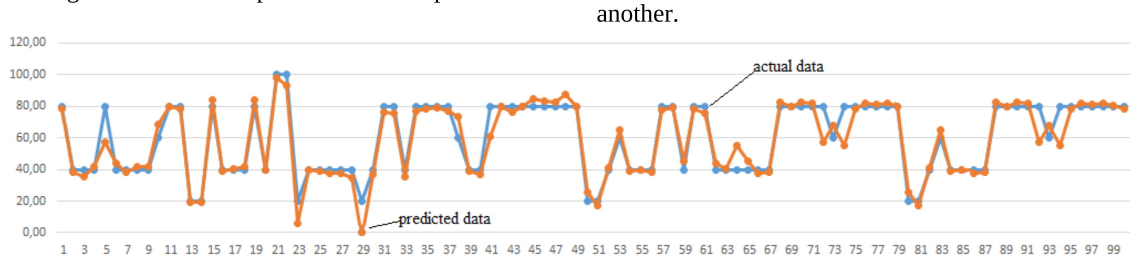

Figure 6. Results of training a multilayer perceptron

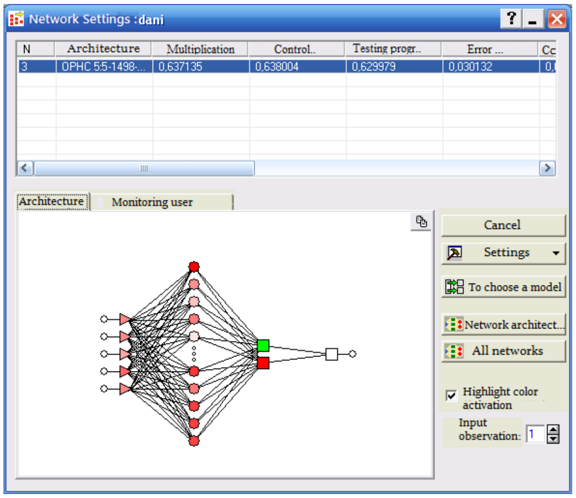

Figure 7. The GRNN architecture

The functional Bellman equation was formulated in the following form:

$$\tilde{N}(j,\tau)=\min_{i\in I_{j-1}}\left[\Delta\tilde{N}_{j-1,i}^{j,\tau}+\tilde{N}(j-1,i)\right],\ j\in[1,J], \quad (8)$$

where j is a step to the point τ, having the coordinate (x, y); S is the starting point (at the 0 step); $\tilde{N}(j,\tau)$ is the cumulative loss of optimality at the transition from the starting point $(0,S)$ to the point (j,τ); $\tilde{N}(0,S)=0$; and $\Delta\tilde{N}_{j-1,i}^{j,\tau}$ is the change of an optimality criterion when moving from point $(j-1,i)$ into the point (j,τ).

The evaluation criterion was built on the base of the methodology of the nonlinear scheme of compromises

$$\Delta\tilde{N}_{j-1,i}^{j,m}=\frac{B_{\max}}{B_{\max}-B_{j,m}}+\frac{D_{\max}}{D_{\max}-D_{j-1,i}^{j,m}}+\frac{\lambda_{\max}}{\lambda_{\max}-\lambda_{j-1,i}^{j,m}}, \quad (9)$$

wherein B is an assessment of the risk of an approaching UHE to a passive obstacle (e.g., high voltage line), D is the length of the UHE route and λ is the probability of reaching a non-harvesting area.

To assess the risk of facing an obstacle, the following function was used:

$$\hat{A}(\rho)=K\cdot e^{-\alpha\rho}, \quad (10)$$

where $\rho=\sqrt{(x-x^*)^2+(y-y^*)^2}$ (x^*, y^*) is the coordinate of a potential obstacle; (x, y) is a current UHE coordinate; and α and K are the positive coefficients that determine the probability of the risk (in the experimental study, it was assumed that α =0,1 and K =1).

For each point in the network, the potential risk was determined. At each new step, the method identifies a point of trajectory, which corresponds to the minimum loss of the criterion of optimality. Finally, iteratively calculated optimal trajectories were transmitted to the navigational equipment of the UHE (Figure 12 shows an example).

To assess the effectiveness of the developed method, research was conducted on 18 experimental fields. For the analysis of the vegetation using spectral characteristics in the optical range, a field was decomposed into areas of equal size of 10 m^2 (the size was adjusted depends on the UHE type). In the experimental setup, the altitude of the UAV was 100-120 m. A 128x128 pixel matrix was used to fix a field to 10x10 m.

Selection of the next point of UHE movement relates to the chosen level of optimality and corresponds to the minimum total loss at the generalized criterion of optimality (8). Finally, calculated optimal trajectories and other parameters of movement were transmitted into the UHE navigation equipment. To process real-time data, UHEs use FM-Tco4 HCV GPS trackers. To monitor the operation of all UHE units, an additional equipment was connected to the FM-Tco4 HCV through the RS232 and RS485 ports. In parallel, UHE navigators transmitted the real-time control information to the control centre.

Figure 13 compares the total cost of the harvest campaign with and without the use of the proposed method. Figure 14 compares the fuel consumption (liters per hectare) in a harvesting campaign for 18 experimental fields with and without application of the proposed decision support system (DSS).

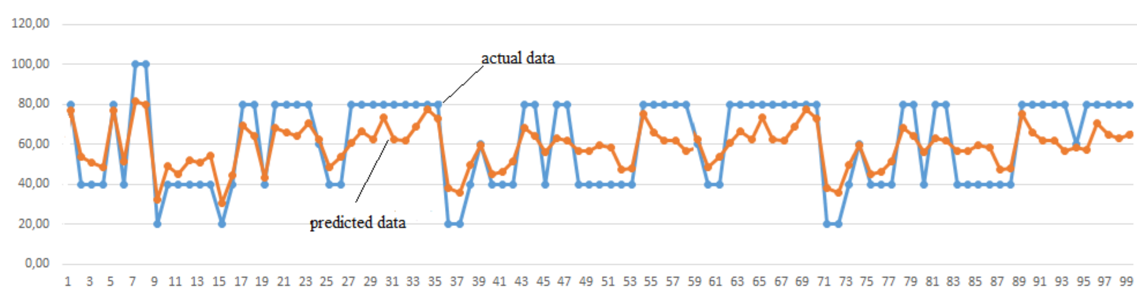

Figure 8. Comparison of the GRNN output and actual data

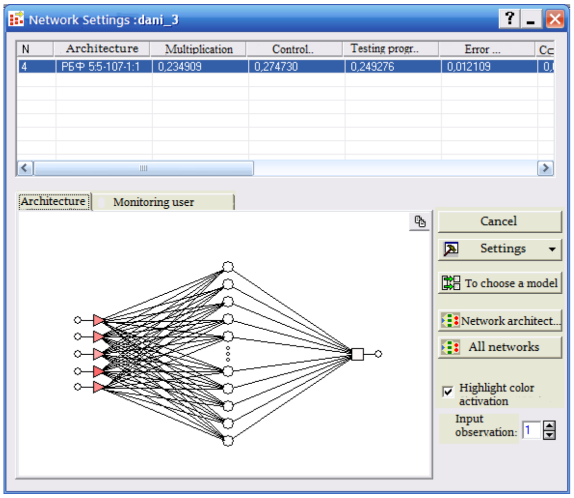

Figure 9. The architecture of the RBF network

6 CONCLUSIONS

THIS paper proposes a new solution to the problem of planning UHE routes with the use of a UAV. A new step-by-step iterative method for automating decision-making using a non-linear trade-off scheme has been developed. The problem is reduced to the search for compromisable optimal trajectories of UHE, taking into account the minimum lengths of the routes and bypassing obstacles and areas without biomass. To identify the distribution of crops and obstacles in the way of the UHE, the proposed method uses optical digital images from a UAV. Several ANN were synthesized for statistical processing of the spectral characteristics of the digital images.

The application of the nonlinear scheme of compromises allows users for the effective identification of the optimal routes of UHE and provides the necessary accuracy for UHE control.

The study shows that the proposed method reduces the total cost of a harvesting campaign by 12-15% due to the effective identification of UHE routes leading to decreased fuel consumption. In addition, an experimental study shows that the time needed for making informed decisions is significantly reduced.

7 ACKNOWLEDGMENT

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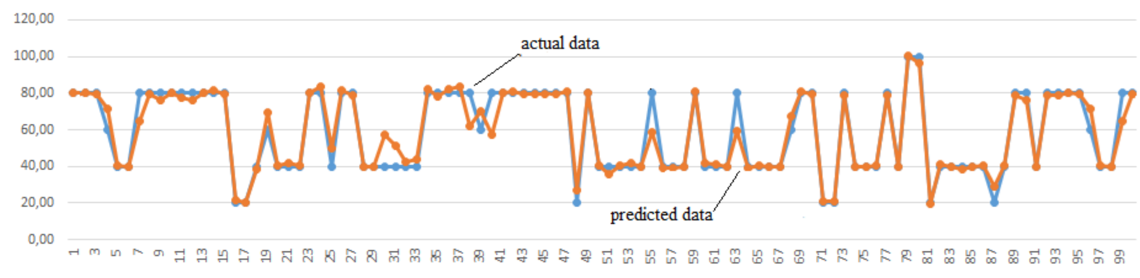

Figure 10. Results of RBF ANN training and its output (sample №1)

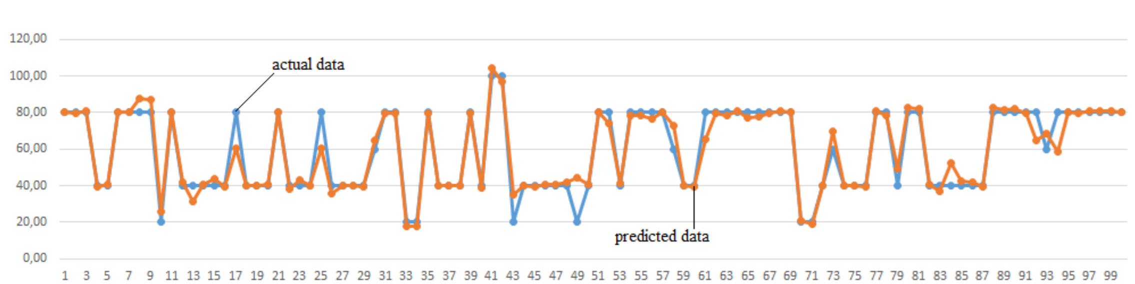

Figure 11. Results of RBF ANN training and its output (sample №2)

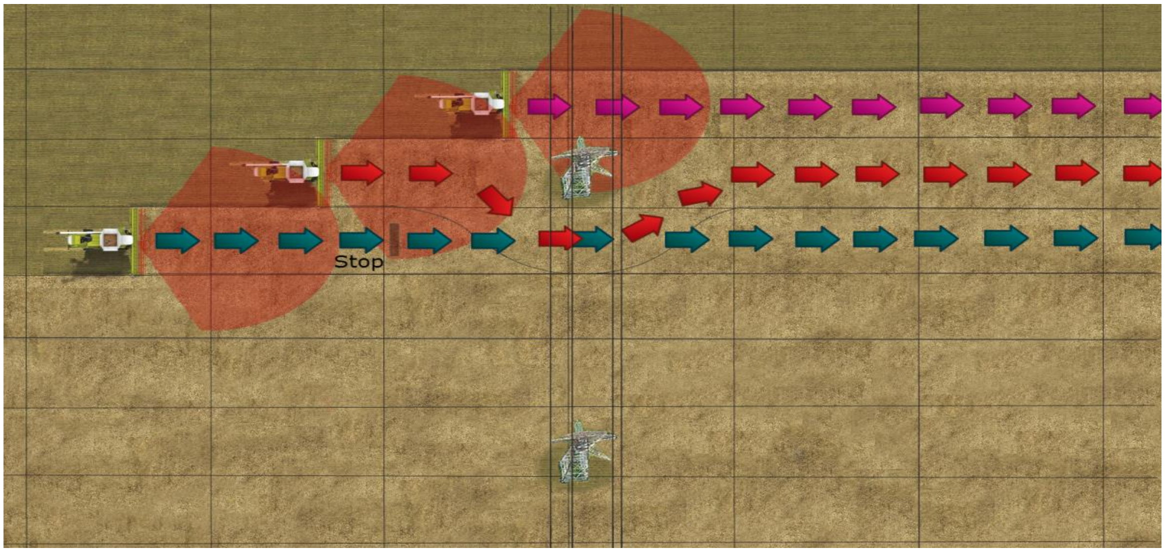

Figure 12. Routes of the movement of harvesting equipment in the case of an obstacle

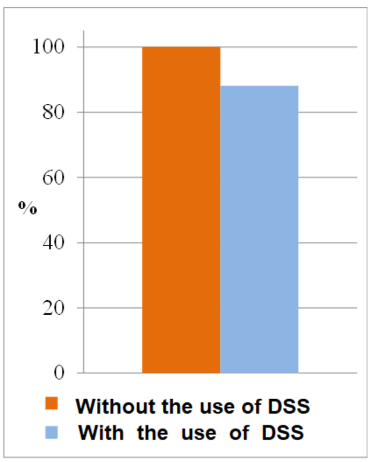

Figure 13. Cost of the harvest campaign with and without the use of the developed method

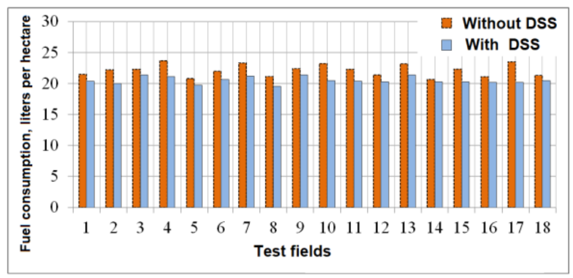

Figure 14. Fuel consumption in a harvest campaign for test fields with and without application of the proposed method

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9 DISCLOSURE STATEMENT

NO potential conflict of interest was reported by the authors.

10 NOTES ON CONTRIBUTORS

Vitaliy Mezhuyev (senior member IEEE) received a specialist degree in informatics from Berdyansk State Pedagogical University (BSPU), Ukraine, in 1997. In 2002, he received a PhD in Educational Technology from Kiev National Pedagogical University and, in 2012, a ScD in Information Technology from Odessa National Technical University, Ukraine. From 2004 until 2014, he was a Head of the Department of Informatics and Software Engineering at BSPU, Ukraine. From 2014 until 2019 he was a Professor at Faculty of Computer Systems and Software Engineering in University Malaysia Pahang, Head of the Software Engineering Research Group. Now he is a Professor at the Institute of Industrial Management in FH JOANNEUM University of Applied Sciences, Austria. During his career, Vitaliy Mezhuyev participated in the multiple international scientific and industrial projects, devoted to the formal modelling, design, and development of advanced software systems as a network-centric real-time operating system; IDEs for the automation of development of parallel real-time applications; tools for specification, verification and validation of software products; visual environment for metamaterials modelling and others. His current research interests include formal methods, metamodeling, safety modelling and verification of software systems, IoT and the design of cyber-physical systems.

Yuri Gunchenko received the specialist' degree in electronics in 1997, MS degree in informatics in 2013 from Odessa National Polytechnic University (ONPU), Ukraine. In 2009, he received a PhD in the field of Armament and military equipment and, in 2014, a ScD in information technologies from Taras Shevchenko National University of Kyiv, Ukraine. From 2000 until 2018 he worked as a professor in the Odessa National O.S.Popov Academy of Telecommunications and in the Odessa I.I.Mechnikov National University (ONU). From 2014 until now he works as a professor of the department of Mathematical Support of Computer Systems of ONU. Since 1996, Yuri Gunchenko worked as a consultant in private and state companies (including the Space Agency of Ukraine in 2007-2010) on the issues of power transformation, various purposes automation systems, real-time systems, and programming of microcontrollers. Since 2014 he is the head of the research project "Mathematical, software and modeling techniques of specialized intelligent computer systems" in ONU. His current research interests include specialized computing systems, power supply systems for direct and alternating current, automated and remote training systems, and programming of microcontrollers.

Sergiy Shvorov graduated from the Military Institute of Telecommunications and Information Technologies in 1977 and received a Specialist degree in the "Automated control systems". From 1977 to 2009 he worked in the engineering and teaching positions. In 1991 he defended his thesis for PhD degree in Kyiv High Engineering Radio Engineering College of Air Defense, by specialty 20.02.12 - military cybernetics, control and communication systems. In 1993 he was awarded the title of Senior Researcher. In 2007 he defended his thesis for the degree of Doctor of Science (ScD) in Taras Shevchenko National University of Kyiv. In 2004-2009 he held the position of Head of department in Taras Shevchenko National University. Since 2009 he worked at the Department of Automation and Robotic Systems at the National University of Life and Environmental Sciences of Ukraine. The professor degree was awarded in 2013. During his career, Sergei Shvorov participated in various research and development projects on the modeling, evaluating the effectiveness and building complex systems. Currently he is a head of the research project "Development of innovative technologies for highly efficient collection and processing of energy crops for biogas plants."

Dmitry Chyrchenko in 2011 graduated from the National University of Life and Environmental Sciences of Ukraine and obtained a master degree in the "Automated control of technological processes". In 2012 he was enrolled in the postgraduate studies at National University of Life and Environmental Sciences of Ukraine at the Department of Automation and Robotic Systems. Since 2017 he is a junior researcher at the Research Institute of Techniques, Energetics and Informatics of AIC National University of Life and Environmental Sciences. In 2017 he defended his thesis for the PhD degree at the National University of Food Technologies on the topic "System of intellectual decision support for managing the collection of energy crops for biogas plants" in specialty 05.13.06 - information technology. He currently works on a scientific project "Development of innovative technologies for highly efficient collection and processing of energy crops for biogas plants". His research interests include programming, information and computer integrated technologies, design of automation systems, and smart houses.