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Using UAV During Planned Harvesting by Unmanned Combines

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***Abstract*—The present article based on the modern tendencies of precision farming development suggests an approach and method of optimal works planning with the employment of UAV for unmanned combine harvesters in terms of harvest collection. The main difference between the developed method from the existing ones is that work planning implies each separate part of the field as a separate unit for the record instead of observing the whole field as a unit. Each separate part is observed with the determination of the scale and density of harvest and building models for the usage of unmanned agricultural machinery based on precise information from the UAV. The process of procedure and time planning for work performance is divided into two main stages: specification of density scale of expected harvest based on the usage of UAV and deciding on the plan of usage of unmanned harvesting equipment. Based on the gathered and processed data from the UAV this information is constantly being updated for a consequent harvesting plan correction. The task of harvest planning is solved by the method of dynamic programming and the criterion of maximization of the scale of gathered harvest with consideration of time and value limits of a harvesting campaign.**

***Keywords*—*unmanned aerial vehicle*, harvesting, precision farming, work planning, time limits and expenses, unmanned harvesting equipment**

I. Introduction

Precision farming is one of the modern branches in the development of sustainable farming. The strategy of precision farming usage is aimed at totally comprehensive employment and usage of different information for taking agrotechnological decisions, their optimization concerning economic conditions of agricultural enterprise and differentiated performance of basic technological operations (within the borders of the field) for the achievement of top quantitative and qualitative results. Taking into consideration everything mentioned above one more task of a high priority is to research a comprehensive usage of unmanned aerial vehicle (UAV) and unmanned harvesting equipment to increase the harvesting campaign level of efficiency.

II. Problem Statement

The analysis of the latest publications [1] – [3] shows that both abroad and in Ukraine there are "unmanned" automobiles and combines for agriculture are being actively created. It is happening since the process of harvesting is influenced by time and value limits. Sometimes agricultural enterprises experience huge losses due to impossibility of the combine operators to work for 24 hours in a row, which is physically impossible to be tolerated by a human. Thus, there is a necessity to use unmanned agricultural machinery and optimally plan harvesting works by the unmanned combines, which in turn will enable enterprises to use them in the night time to eliminate exploitation expenses. The estimate of vegetation condition is usually performed employing space-based observation and is usually determined based on NDVI (Normalized Difference Vegetation Index) [4]. The estimate is both expensive and not precise enough. With the usage of a special NIR-modified camera on UAV, the cost of observation rises significantly in comparison with regular photo equipment. Due to this fact, the issue of harvest scale estimation employing almost cost-free observation by UAV in the optical diapason is of a higher level of importance. The works of [4], [5] are dedicated to this.

In the work [6] Esmael Hamuda, et al. (2016) provides an overview of the image procession method for extraction of vegetation and their segmentation into a field. This work also provides a comprehensive and critical overview of plants extraction based on the images, preliminary image procession is being discussed, before concentrating on segmentation. Segmentation stage includes segmentation of plants on the soil background (identification of a plant on a soil background). Thus, there is a detailed discussion of approaches concerning segmentation index, based on the color index based on research conducted in the nearest pas, namely within the period from 2008 to 2015.

In the article of [7] Yubin Lan, et al. (2010) it is stated that many areas of the USA rely on easily accessible planes or helicopters for farm pest control and air applications provide decisions for the usage of field resources.

In the work of [8] Anjin Chang et al. (2017) it is claimed the planting height is a very important constituent for a general estimate of planting condition, irrigation, and estimation of the final harvest. This research suggests a new method of growth monitoring method of Sorghum bicolor with the usage of UAV.

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The main attention in the article [9] Sajid Saleem, et al. 16) is dedicated to the comparison of images between llite photos and astrophotographs of agricultural area. An mate of SIFT, SURF algorithms usage efficiency for ning images in the agricultural area is provided in this k.

In the work of [10] J. Torres-Sánchez, et al. (2014) it is wn that UAV equipped with a commercial camera ible spectrum), can be effectively used for getting the l of wheat images with high resolution at the beginning he season. However, visible spectral indexes received n the images with the usage of the inexpensive camera on board of UAV flying on the level of low heights are able instrument enabling to distinguish vegetation in the ls of wheat at the beginning of the season.

However, the existing works do not cover issues of rest amount estimation completely for harvesting ning. Taking this into consideration, to increase planning ciency and harvesting there is an issue of comprehensive e of UAV and navigation equipment of unmanned cultural machinery.

To solve this issue, there is a necessity of developing a hodological background of works planning for unmanned resting equipment depending on the scale of the harvest d on the static processing of spectral characteristics of cal photos of each area.

. METHODS OF EXPERIMENTAL STUDY AND RESULTS OBTAINED

The process of tasks and time of field works performance vided into following stages: creation of area e-map and rmination of harvest scale and density by means of ession of digital photos spectral characteristics for every on the basis of usage of static analysis methods and AI, vell as determination of harvesting equipment usage nal plan by means of dynamic programming.

As it can be seen from the results of experimental arch, regular digital cameras can be effectively used e programming harvest and determination different acles on the way of unmanned harvesting equipment on part of a field [5]. After photographing on an e-map of ield based on the static procession of RGB-signals a few rast areas by optical characteristics are being determined. scales and harvest density which are used for neural ork teaching are calculated by experimental method for e areas. Thus, on the basis of static procession of digital os spectral characteristics of each part of the area and by ns of neural network apparatus harvest scales on the way nmanned combines movement are being determined, h grants instant decision making process for ibution, route planning and management of harvesting pment movement at minimum cost (in comparison with e-based observation).

The present task is being solved by means of a special od of fuel crop scale determination in accordance with data from UAV on the way of unmanned combines ement, which includes determination of area part, its photo in optical diapason, image analysis, static ession of spectral characteristics of digital images of y part of area and forecasting of the fuel crop scale on way of unmanned combines movement.nPhotographing e defined surface is conducted employing unmanned aero equipment with the possibility to get high-resolution images. In the Fig. 1 in block 1, there is the introduction of initial data in the form of mounting points of UAV route as it is shown in the Fig. 2 (points 1-8).

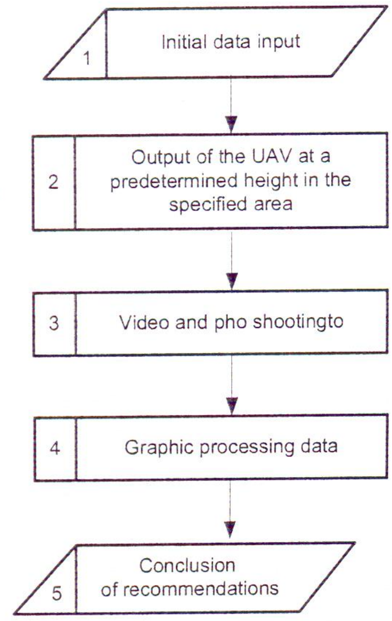

Fig. 1. Algorithm of harvest level identification following UAV data.

In the block 2 UAV is being positioned on the height of photo observation (50–100 m) over the set area of the field. Quadcopters DJI Phantom 2 and CD600 were used as UAV.

The precision of plants amount identification at the early stage of vegetation on the map depends mostly on the height of UAV and ratio between plant size and pixel size (Fig. 3). As can be seen from the Fig. 3 three central highlighted pixels are filled with the higher percentage of a whole plant, thus, for getting a satisfactory result it is necessary to have approximately 5 pixels per plant.

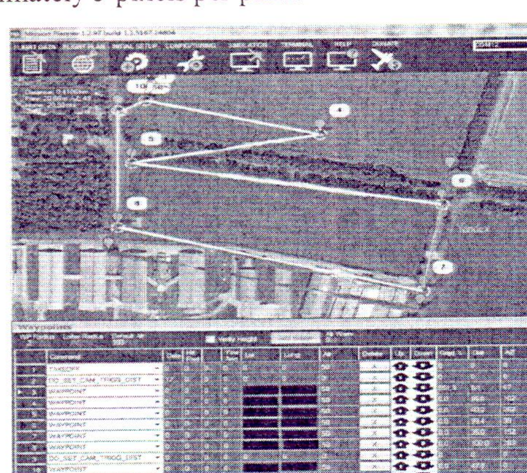

Fig. 2. Setting mounting points of UAV route.

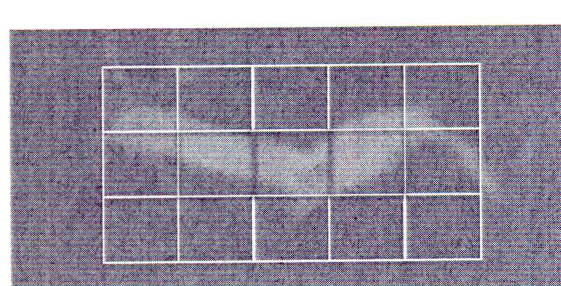

Fig. 3. A plant at an early stage of vegetation with showcasing pixels from a big height.

In Table I, there is a pixel size on the ground surface, as a function of height over the ground surface, which provides an opportunity to identify the right flight height for data collection.

TABLE I. PIXEL SIZE IN THE GROUND SURFACE (GSD), AS A FUNCTION OF HEIGHT OVER THE GROUND SURFACE

Height (m)	25	30	35	45	60	90
1p – GSD (m)	0.019	0.023	0.026	0.034	0.045	0.068
2i, 2p – GSD (m)	0.010	0.012	0.014	0.018	0.024	0.036

The methods of photographing which already exist have limited usage in conditions of partial cloudiness, which is a typical characteristic of Kyiv region. Because the time for decision making is very limited, the issue radio frequency calibration in the conditions of cloud amount is pivotal.

A perspective way of solving this issue is automated identification of photos with unequal lightning by the system of pattern recognition system and additional observation of these very areas employing UAV. taking into consideration well calibration of programming means and the ability to adaptive integration in the conditions of technological information fuzziness as the mathematical provision of pattern recognition system being developed, neural networks were chosen.

Experimental research was conducted in Kyiv region on experimental and production fields with positioning data 50° 16' 31.00" N, 31° 0' 44.00" E, та 50° 4' 28.00" N, 30° 13' 20.00" E. the monitoring was conducted with the usage of PHANTOM VISION FC200 and GoPro HERO4 cameras. Height of the flight was 100 meters. To identify the condition of agrotechnical cultures for a remote research RGB camera PHANTOM VISION FC200 with the resolution rate of 4384x2466 pix. Was used. For the preliminary procession of the initial patterns and identification of the necessary characteristics in the work, the self-written program on the Delphi language with the usage of OpenGL components was used. The file of the received picture was converted into BMP format with the subsequent change of resolution rate to 18x10. With the present size of the picture, one pixel corresponds to the area of 10x10 meters. The following stage of the program work is to create an array of subsequent data of pixel brightness per the HLS model with the addition of True or False expert conclusion at the end.

The solution of the pattern classification issue is the main element of such intellectual complex.

In blocks 3 and 4 (see Fig. 1) video and photo shooting and procession of graphical data are being conducted with the aim of identification of harvest scale following UAV data. As a result of the algorithm described above the recommendations concerning the identification of harvest gathering time limits and average speed of unmanned harvesting equipment can be conducted.

For identification of an average speed of unmanned harvesting equipment based on the software Land damage expert the harvest level map is formed, divided into squares (200x400 m), which is showcased in the Fig. 4.

Each part of the field has its field crop capacity distribution (Fig. 5).

Employing Land damage expert software with consideration of the surface of crop capacity distribution crop capacity interpretative map is formed (Fig. 6).

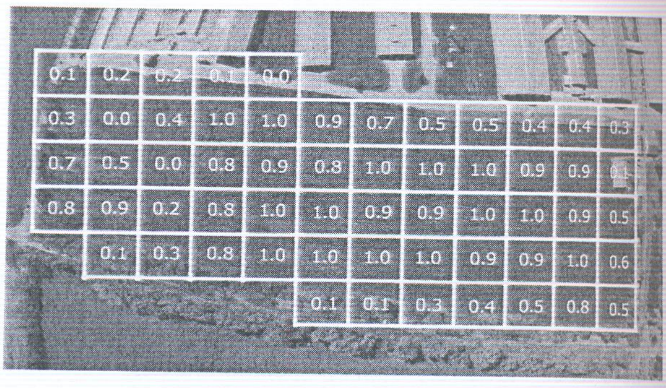

Fig. 4. Forecasting crop capacity of every part of the field based on forecasting by a neural network.

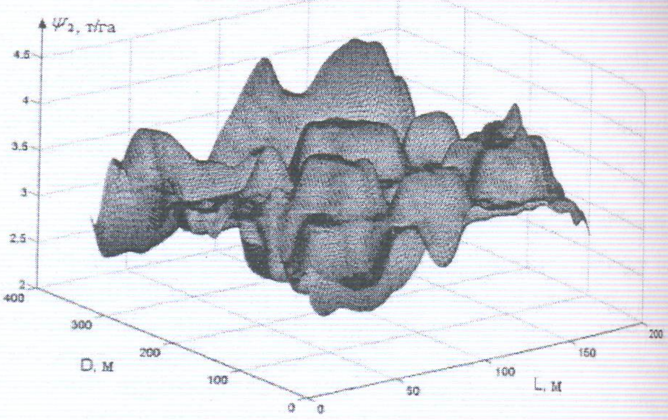

Fig. 5. The surface of field part crop capacity distribution

As it can be seen from the Fig. 6 crop capacity in one of the ways crop harvesting combine (highlighted line AB) of agriculture crop on the surface of field varies in a wide range from 9 to 33 t/ha of winter wheat. This is a particular example when it is hard to provide a smooth load of combine operating systems (in the diapason of rational operation). Significant changes in thrashed crop flow density (especially with peak load) have a negative effect on fuel expenses, qualitative indexes, spare parts wear and machine components and reliability of the harvesting combine in general as well as drive systems as a result of significant power fluctuations on the operating parts.

It means that significant harvesting fluctuations of crops in the direction harvesting equipment movement are negatively reflected on the combine operation if kinematic and technological modes of operation are not changed. Similar effects can be eliminated employing the system of automated unmanned equipment speed regulation, which is determined in the following way.

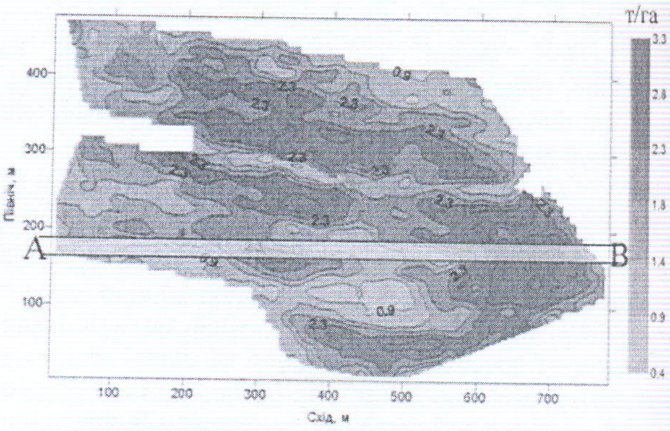

Fig. 6. Interpretative map of field crop capacity.

If the known parameters of this field are: shape - right-angled, length D is 325 m, width L–162 m. Due to interpolated data acquired from the map of field crop capacity, division surface is built (see Fig. 5), which provided initial data for identification of spectral density changes of crop capacity. [11] – [15].

Following the stated methodology, the direction of y-axis is set for a right-angled system of axes and the number of k times required for the chosen combine prototype to perform works on the whole field.

$$k = \mathrm{int}\left(\frac{L}{B}\right) = \mathrm{int}\left(\frac{162}{6}\right) = 27, \qquad (1)$$

where B is the width of the harvesting-machine header.

For the following operation with data array on field crop capacity, it is necessary to rebuild it into a vector of the combine movement path. As a result, we get a series of crop capacity indexes in a function of the distance passed by the combine along the equivalent line $\varphi_2(y)$ (see Fig. 5).

Following the present series, we will determine the average crop capacity M_h of the field as an expected function value $\varphi_2(y)$

$$M_h = 0.35\ \mathrm{kg/m^2}. \qquad (2)$$

A change of the field crop capacity on the way of unmanned combine movement as an expected function value $\varphi_2(y)$ is represented in Fig. 7.

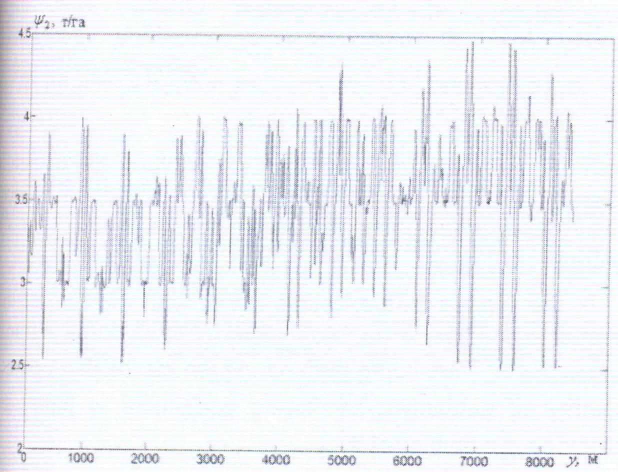

Fig. 7. Change in the field crop capacity on the way of unmanned combine movement as an expected function value is $\varphi_2(y)$.

As the following stage we will determine average combine movement speed employing the formula:

$$V_0 = \frac{Q_h}{BM_h(1+\varepsilon)} = \frac{9}{6 \cdot 0.35 \cdot 2.5} = 1.71\ \mathrm{m/s}, \qquad (3)$$

where Q_h is combine productivity.

Taking this into consideration the interpretation map of unmanned harvesting equipment movement on the field is being formed (Fig. 8).

This data basis provides adaptive speed management of harvesting equipment concerning spectral density change of crop capacity and identification of finite time resources of harvesting works (T) and cost expenses (C), which are being planned for crop harvesting from N fields.

In the process of development of optimal planning of harvesting, works imply a manageable N-stage dynamic process, which is characterized by two types of parameters on each stage: management parameters m_n (quantity of unmanned harvesting equipment or harvesting works employing unmanned combines) and condition parameters $G_n(m_n)$ (scales of the harvested crops at the n-stage). Finite-time resource of harvesting works (T) and cost expenses (C) are stated as a limitation, being allocated for a harvesting campaign.

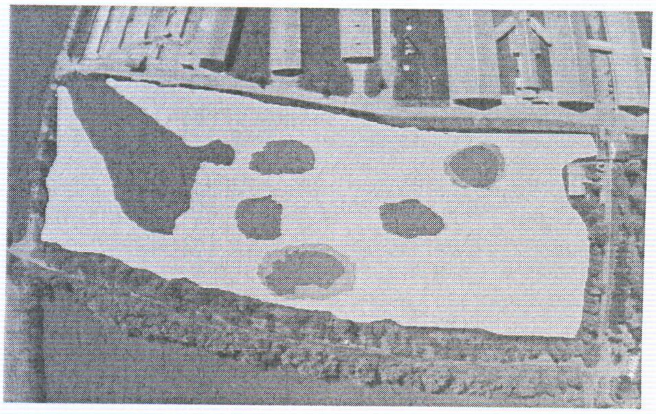

Fig. 8. Interpretational maps of unmanned harvesting equipment movement speed on the field: red – nominal speed; light green – recommended speed; dark green – 0.4–0.1 from the nominal speed; green – 0.9–0.5 from the nominal speed.

The finite aim of harvesting works planning is (W_N) a maximal amount of harvested crops.

Generally, the task of optimal planning of harvesting works and their implementation employing unmanned harvesting equipment can be provided in the following way.

Find

$$\max W_N = \sum_{n=1}^{N} G_n(m_n) \qquad (4)$$

with

$$T_N \le T, \ C_N \le C, \qquad (5)$$

where T_N is the time spent during N stages of harvesting campaign; C_N are expenses during N stages of harvesting works.

Thus, it is necessary to find such indexes (m_n) at each stage, so that it is possible to maximize the objective function (4) with the following limitations:

$$\left.\begin{aligned} &a)\quad m_n = 0,1,2,\ldots, \\ &a')\quad \sum_{n=1}^{N} t_n m_n \le T, \\ &\tilde{a})\quad \sum_{n=1}^{N} c_n m_n \le C, \end{aligned}\right\} \qquad (6)$$

where t_n is the time for works completion at the n-area of the field; C_n is the cost expenses for the usage of unmanned harvesting equipment at the n-stage implementation.

For finding optimal of the (m_n) index we will use a method of dynamic programming [16].

Since the task has two types of resources (T and C), there is a necessity to introduce two parameters of the state of ξ_T and ξ_C.

Let's mark $\max\limits_{m_1,\dots,m_k} \sum\limits_{n=1}^{k} G_n(m_n)$

with the condition that

$$\sum_{n=1}^{k} t_n m_n \le \xi_T, \quad \sum_{n=1}^{k} c_n m_n \le \xi_C, \quad m_n \ge 0, n = 1,\dots,k.$$

via $\Lambda_k(\xi_T;\xi_C)$.

After simple transformations we switch to the next main recursive relation of dynamic programming:

$$\Lambda_k(\xi_T,\xi_C) = \max_{0\le m_k \le \delta_k}\left[G_k(m_k) + \Lambda_{k-1}(\xi_T - t_k m_k; \xi_C - c_k m_k)\right],$$

where

$$\delta_k = \min\left\{\left[\frac{\xi_T}{t_k}\right], \left[\frac{\xi_C}{c_k}\right]\right\}.$$

Simultaneously $\Lambda_k(\xi_T;\xi_C)$ we find an optimal solution $m_k^0(\xi_T,\xi_C)$. At the N-stage, we identify $\Lambda_N(T;C)$ and $m_N^0(T,C)$ simultaneously.

The most significant obstacle in solving this task is its scale. That is why to reduce the scale of the task (4) – (6) we move to the task with one limitation.

$$\max W_1 = \max_{\{m_n\}} \sum_{n=1}^{N} G_n(m_n) - \lambda \sum_{n=1}^{N} c_n m_n, \tag{7}$$

under condition

$$\sum_{n=1}^{N} t_n m_n = T, \quad m_n \ge 0,$$

where λ is Lagrange multiplier.

The usage of the Lagrange method allows to decrease the scale and due to this reason task (7) is incomparably smaller than the initial one.

In any case, λ is an unknown variable, due to this fact task (7) should be solved with several arbitrary values of λ. The optimal solution of the task (7) will depend on λ:

$$m_{nopt} = m_n^o(\lambda) \qquad (n = 1,\dots,N).$$

If the found solution $m_n^o(\lambda)$ corresponds to the limitation (6), then it is a solution to the task (4-6) itself. In another case, the value of λ should be corrected. In particular, if it occurs that $\sum\limits_{n=1}^{N} c_n m_n^0(\lambda) \rangle C$, then it is necessary to increase λ.

For a fast determination of λ a method of successive approximation can be used. If for the values λ_1, λ_2 optimal solutions are found $m_1^i(\lambda_1)$, $m_2^i(\lambda_2)$, then on the following stage we get λ_3 from the formula

$$\lambda_3 = \frac{\lambda_2 - \lambda_1}{h_2 - h_1}(C - h_1) + \lambda_1,$$

where

$$h_2 = \sum_{n=1}^{N} c_n m_n^i(\lambda_2), \quad h_1 = \sum_{n=1}^{N} c_n m_n^i(\lambda_1).$$

Since one resource type is considered in the task (4) it is necessary to introduce one state parameter ξ_C.

We shall call

$$\max_{m_1,\dots,m_k} \sum_{n=1}^{k} G_n(m_n)$$

under condition

$$\sum_{n=1}^{k} t_n m_n \le \xi_T; \quad m_n \ge 0, \ n = 1,\dots,k.$$

via $\Lambda_k(\xi_C)$.

Then main recursion relationship of the dynamic programming has the following view

$$\Lambda_k(\xi_C) = \max_{m_k}\left[G_k(m_k) - \lambda c_k m_k + \Lambda_{k-1}(\xi_C - c_k m_k)\right].$$

It is necessary to note that the method of dynamic programming is a direct linear search of option, which always leads to the global maximum and an optimal task (4) solution.

In the process of harvesting works with the help of the method stated above for each stage of functioning optimal values of (m_n^i) are being defined, which means that optimal quantity of unmanned harvesting equipment is found for achieving the final aim (W_N).

The solution of this task is performed employing special automated workplace planning under the supervision of the operator. Owing to the developed mathematical apparatus and software of automated workplace planning optimal quantity of unmanned harvesting equipment is defined, which in turn means the creation of an optimal plan for the functioning of every combination with the aim of harvesting works performance employing the proposed method in a defined time sequence.

In the process of such decision making support system functioning the following sequence of actions is taken, by the time the aim is achieved: following the optimal plan, there is planning for a sequential exercise of such set of harvesting works, when a maximum value of $(\Lambda_n(\xi_n))$ is achieved; based on the comparison of the current quality value of typical tasks with the necessary $(\Lambda_n(\xi_n))$, the decision on the following procedure of harvesting campaign is taken.

If the current quality value is lower the required one, the performance of harvesting works is being conducted following the optimal plan. In other cases, depending on the acquired quality value at the n-stage, there is a necessity to implement adaptive changes (rebalancing) of the harvesting works plan. With this purpose employing the method stated above for each stage (starting with n stage) of harvesting works correction and forming of the optimal plan is performed with consideration of the current quality value (volume of the harvested crops), as well as corrections of limitations of cost expenses and the time remaining.

As the practice shows, usage of UAV while planning works with unmanned combines provide prompt identification for each stage of harvesting works and the necessary (optimal) quantity of unmanned harvesting equipment, which reduces crop losses and fuel consumption up to 12–15%.

IV. Conclusion

Thus, with the help of the proposed methodological basis of UAV usage while planning crop harvesting employing unmanned combines is provided depending on the volume of harvest, defined with the help of UAV, higher operational efficiency and management precision of unmanned harvesting equipment as well as reduction of fuel expenses. The management system of unmanned harvesting equipment development based on information on changes of field crop capacity depending on the movement of unmanned combines received from the UAV is a prospective direction.

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