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Application of graph theory to improve the efficiency of external pilot training program

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Abstract. *Process of external pilot training has a massive psychological and physiological load on trainer and trainee, so it is very important to remake the program in the most representable and effective way possible. The graph theory and its usage for external pilot simulation model simplifies visualization and evaluation of external pilot training path dramatically and the development describes what aspects can be simplified by such theory.*
Keywords: *external pilots, graph, training program, unmanned aerial vehicle.*

Introduction. During the training program for drone operators development, the task of work automating with both educational elements and professional qualities and characteristics of pilots takes place. At the same time, taking into account dynamic changes in the psychological and physiological conditions and the success of training accomplishment. It is proposed to apply graph theory to increase the efficiency of the training program for drone operators.

Purpose: To improve the effectiveness of external pilot training programs by applying graph theory.

Materials and methods:

For effective educational processes modeling of educational groups with different levels of initial training, adaptive approaches to training should be developed. According to the study [1], the use of graph theory has increased interest among researchers for the visualization and structuring of educational programs, where each element of the course is represented as a node, and connections between them are represented as oriented edges. It allows optimizing educational trajectories, identifying dependencies, and ensuring a logical sequence of learning.

However, a typical UAV operator training program is much more complex, as it covers not only theoretical disciplines, but also a wide range of practical skills, training scenarios, specializations by type of application (infrastructure monitoring or agromonitoring), as well as physiological and psychophysical factors. In this regard, as shown in [2], it is advisable to use knowledge graphs to create adaptive training systems. Such graphs allow taking into account the individual path of each trainee's training program, their initial experience and the speed of learning accomplishment.

Such approaches are particularly relevant in case of end-to-end adaptive training, where the learning process is continuous and it constantly adjusts to dynamic changes in the operator's level of training. For example, under the conditions of our concept, students start from level zero, and then - depending on their success, psychophysiological suitability and speed of learning - the program could be adapted in a semi-automatic mode. This is confirmed by research [4], where the authors describe a system that uses knowledge graphs and artificial intelligence for personalization based on previous activity of the student.

Besides, the article [3] emphasizes the importance of student interaction as a dynamic system, which can be applied to situations where UAV operators perform missions as part of a crew or under the guidance of an instructor. These interactions can be formalized in the form of subgraphs that reflect the communication and role relationships between participants of a flight task. Cited sources indicate that representing the training program as a graph model is valuable for further analysis, for optimization and partial automation purposes.

One of the effective ways to optimize the learning path is to use Dijkstra's algorithm that allows you to find the shortest or least expensive way in a weighted graph of learning modules. This approach is especially effective under conditions of presence of a fixed course structure and clear dependencies between learning elements. As shown in [6], proposed algorithm can be quite accurate for routing problems.

However, with the aim of implementing an individual approach to the student in real time, it makes sense to pay attention to greedy search algorithms. Simple and straightforward heuristic algorithms that make the best decision based on data availability at each stage, regardless of possible consequences, hoping eventually get the optimal solution [7]. Particularly, during the work in a more dynamic environment, when it is necessary to ensure flexible adaptation to changes in the progress of learning and operational adjustment, the result from the article [8] should be used. It shows how greedy algorithms can be used for systems primarily directed to the adaptability of the perspective to create an effective system for external pilots training.

Results. Representation of the external pilot training program was created in the form of external pilot model using graph theory that allowed to represent training, skills, transitions between levels and dependencies as a flexible, adaptive system.The external pilot was modeled as nodes in a graph that accomplishes various stages of training, competency acquisition, testing, and specialization. Each training element, condition, or obstacle is a node or edge in the graph. Table 1 represets an example of the components of such a graph.

Table. 1. Graph components

Component	Description
P0	Initial pilot status (level 0, no experience)
T1, T2, ...	Theoretical modules
S1, S2, ...	Simulation training
F1, F2, ...	Practical flights
Eval1, Eval2	Evaluation stages (test, case, flight task)
Spec_Agri, Spec_Energy	Specializations: agro, energy infrastructure, etc.
PsyCheck	Psychophysiological testing
w(t, c)	Time and cost of the training element

Fig. 1 shows the simplest example of graph representation.

P0 --> T1 --> S1 --> Eval1 --> F1 --> Eval2 --> Spec_Agri, (1)

where starting from the initial node P0, after completing the training modules of the first stage T1 and S1, the Eval1 assessment takes place and the transition to the stage of practical flights F1 occurs, which ends with an assessment at the Eval2 node with a subsequent transition to specialized cases.

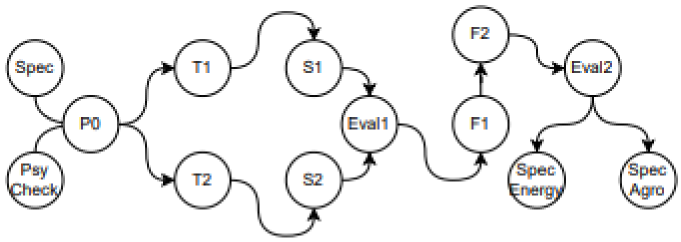

Fig. 1. Individual training program visualization

Constraints are set through the weight of the edge. Thus, the student starts from node P0, after that the system builds an individual route depending on: initial assessment (PsyCheck), goal (desired node Spec) and constraints (time, resources, physical/psychological limits). Results and progress are recorded as a path in the graph. The system can recalculate the route in case of unsuccessful, successful, or accelerated passage as represented on fig. 2.

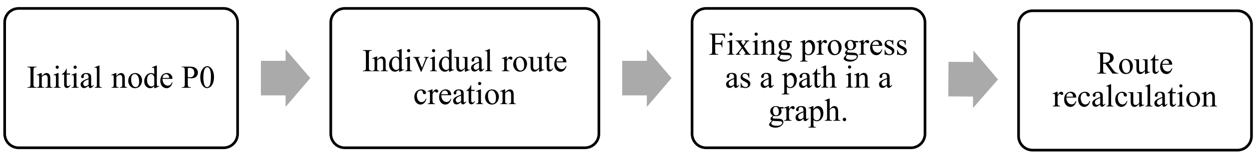

Fig.2. Work principle with the model of external pilot

Using graph methods, it is possible to identify “bottlenecks” in training, conduct semi-automatic program adaptation, taking into account dynamic data on changes in health status, time characteristics of success, and optimize the training route in terms of costs or time.

A solution to the problem of edge weights assigning at the graph model of the external pilot training program was proposed to formalize the costs of passing each stage. The edge weights formation is proposed in the following form:

$$w = \alpha \cdot t + \beta \cdot c + \gamma \cdot r + \delta \cdot d, \quad (2)$$

where: t – duration (hours);

c – price (conditional currency units);

r – risk (degree of potential failure to complete a task);

d – resource shortage (e.g., simulators, instructors).

and for more presice personalization, it is proposed to introduce priority coefficients that are configured in the system.

where α, β, γ, δ – priority coefficients configurable in the system.

It is proposed to use the A* algorithm to construct the shortest training route and, in case of an excessive number of nodes, replace it with the Dijkstra`s algorithm. It will allow using the capabilities of machine learning to predict the success of passing nodes and integrate with psychophysiological monitoring systems in real time.

Conclusion. An external pilot representation in the form of a model using graphs is already reflected in information technologies of education, and is proposed for usage, particularly, during the development of operator training programs. Usage of well-known A* and Dijkstra algorithms allows you to automate the management of dynamic changes in training programs and opens up ways to expand usage of training complexes and new methods for forming components of individualized training programs in various industries and to involve widely the capabilities of modern artificial intelligence in the development of specialized education in Ukraine and in the world.

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