Assessment of the sustainable development of the flight route

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Abstract. The article provides an assessment of the sustainable development flight route servicing in the absence of a regular schedule. It is not possible to establish a schedule of such flights due to poor forecasting of the requirements for applications for transport, so a calculation mechanism is required to adapt the situation to the usual conditions for formalization in a short time. The most convenient mathematical device in this case is the application of a multiplier form of integral penalty function, considering the operating costs that depend on the downtime of free aircraft. In the case of short-term transportation planning for service in local emergency zones, it is expected to reduce the waiting time for operational applications by 15-20% compared to the known method of routing planning using a "greedy algorithm". The paper provides a specific example of a practical performance assessment, influenced by these criteria of operational nature and urgency of execution, which are expressed by weights. This methodology can be applied to the planning of small aviation flights, including those in agriculture.

1 Introduction

Planning optimal routes for group flights of unmanned and small aircraft is an urgent multi-criteria task. The subject of the research is to evaluate the effectiveness of a genetic algorithm for multidimensional routing, subject to the availability of area navigation based on the GNSS satellite system. Traditionally, when planning the implementation of requests for services, only free channels are considered, the role of which in this task is performed by aircraft. The efficiency of routing can be significantly increased by using an algorithm for target distribution of requests in combination with a genetic algorithm. This combination allows us to consider service channels as possible for the implementation of requests not only in a free state, but also in a busy state [1,2].

Fundamentally, a service channel is a system of a number of characteristics, including the duration of servicing the current request [3]. In this work, the process of implementing the application is the execution of a flight to transport people, mail and cargo by aircraft. The purpose of this work is to develop an approach to multidimensional routing of aircraft flights based on requests, based on a combination of a genetic algorithm with the distribution of

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incoming requests between free and busy aircraft, the state of which is known at each planning step.

1. It is believed that applications for the use of airspace (AVP) arise randomly [4] and represent a Poisson distribution of a random variable. The number n of these applications exceeds the number N of aircraft.
2. Destinations in accordance with applications are located randomly according to Poisson's Law [5], or are located in separate areas with high density.
3. Each application is characterized by known parameters: application number m, coordinates X_i, Z_i of the initial i-th departure point and coordinates X_j, Z_j of the final j-th arrival point, as well as the waiting time for their service τ_m in the general queue to ensure priority.
4. The number N of aircraft and the current values of their coordinates X_i, Z_i are specified, either parked or in flight at any current time.
5. It is required to formulate an effective approach to multidimensional routing of aircraft, based on a combination of a genetic algorithm (GA) with the operation of distributing targets at each step of priority requests between free and busy aircraft, and to evaluate the effectiveness of the proposed approach in comparison with known routing algorithms.

2 Materials and methods

In problems of servicing requests for group flights for the transportation of passengers, mail and cargo in the absence of a regular schedule due to poor predictability of traffic volumes, the most effective transportation planning is achieved by using a genetic algorithm with targeted distribution of requests between both free and occupied aircraft [6]. This approach includes:

– formation of the initial “elite” of multidimensional routes by repeatedly using different options for the criterion for assigning priority requests at each routing step using the following dynamic priority (Π_j), including normalized parameter values.

$$\Pi_j = \ max_{j=1\ldots N}\left[\frac{r_{min}}{r_{ij}} + m_1\right]\left[\frac{\tau_j}{\tau_{max}} + m_2\right] \tag{1}$$

where: r_{ij} – distance from the start of the route along *j-th* application to the settlement intermediate point *i-th* route;

r_{min} – minimum distance between points;

τ_j – waiting time for an application in queue;

τ_{max} – maximum allowable waiting time;

m_1 *and* m_2 – weighting coefficients of the significance of the factors (the smaller the value m_1, the more important the first factor is, provided that $m_1 + m_2 = 1$).

– the set of generated routes M is divided into a number of blocks containing at least two or more requests, after which, as a result of their “crossing” and partial rearrangements, an expanded set of “descendants” is formed. The final operation is genetic selection of the best solution using the integral penalty function $\mathcal{J}_v$ assessing its effectiveness, taking into account the often conflicting interests of performers and customers

$$\mathcal{J}_v = min_{v=1\ldots MN}\left[\left(max_{i=1\ldots N}\frac{\eta_i}{\mathrm{T_{max}}}(v) + m_3\right)\left(\frac{\sum_{i=1}^{N} L_i(v)}{L_{max}} + m_4\right)\right] \tag{2}$$

where: $\mathcal{J}_v$ – integral penalty function;

ν – number of solution option after “crossing” and “mutation”»;
T_{max} – maximum waiting time for an order to be completed;
L_{max} – maximum total path length of all aircraft;
$L_i(\nu)$ – path length of each route in the i-th optione;
$_{max}\,\eta_i(\nu)$ – the maximum time an application remains in the queue in the ν-th variant.

The purpose of the work is to evaluate the practical effectiveness of aviation flight planning using a genetic algorithm together with an algorithm for targeting applications in comparison with known approaches to air transportation planning.

Computer modeling is used as the main tool for solving the problem. First, let us consider the well-known approach to multidimensional group flight routing, based on the use of a “greedy” algorithm, the essence of which is as follows. Any analyzed aircraft is selected as the first one and the nearest point is assigned to it for service. Then, while maintaining the right of initial choice, another aircraft is selected and “its own” nearest point is assigned to it from the same set of applications [7,8]. If the items in the first and second choices do not match, the targeting process continues. Otherwise, a conflict situation arises, and the selected point belongs to the aircraft that is closer. Thus, each aircraft will be assigned “its own” points, however, their flight routes may intersect, which, when flying at the same altitude, will reduce its safety and lead to an increase in the length of the total route.

The block diagram of the computer model of the “greedy” algorithm is shown in Fig. 1. At any planning step k, a “random” moment is simulated for other variants of the initial data [9-11].

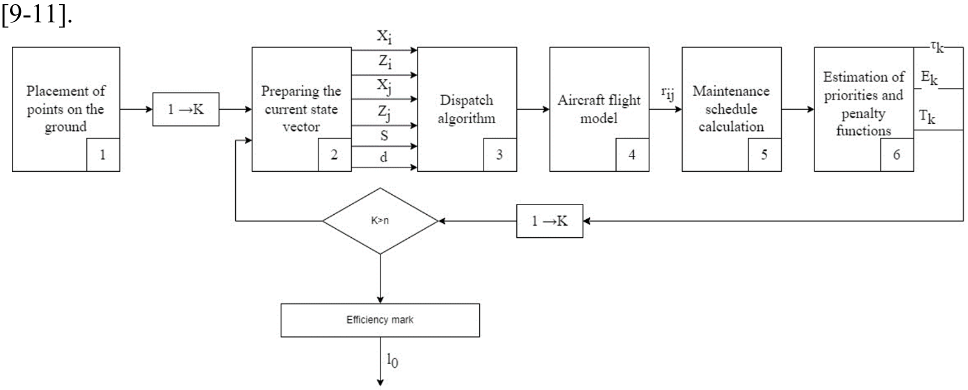

Fig. 1. Block diagram of computer modeling of the order servicing system in "air taxi" mode

The developed modeling program allows you to analyze various dispatching algorithms, as well as determine at each step the number of free requests and the number of free and busy aircraft. As a result, the output is a quantitative assessment of the penalty functions necessary to take into account the interests of both customers and performers [13-15].

Example 1. Routing when servicing requests for flights along a given trajectory. The problem of routing a group flight of three aircraft from the point of departure to the point of arrival (a total of 24 points) is solved in accordance with the requests on area 250, as shown in Fig. 2. Initially, 12 applications were received, each indicating the coordinates of the point of departure, and the corresponding point of arrival as shown in Table 1. 1 $км^2 X_i Z_i X_j, Z_j$. The placement of all 24 points on the territory corresponds to the Poisson distribution of the random variable and is uneven [12]. Initially, the aircraft are located at points with coordinates XA = 50, Z A = 50; XB=150, ZB=50; XC= 50, ZC= 150;

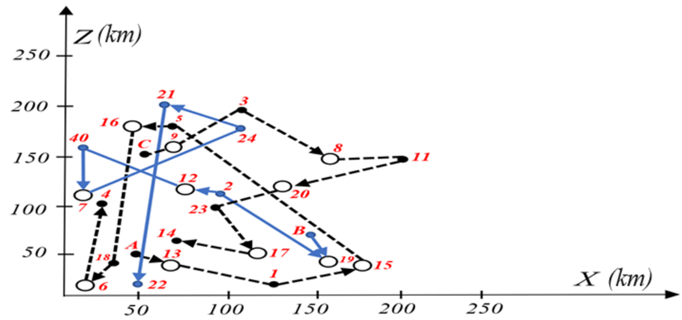

Fig. 2. A picture of the location of the serviced points in a given area. Sign O is the point of departure according to the application

We believe that the receipt of applications is subject to the Poisson distribution, and the waiting time in the general queue is not the same [13], but it is known τ_j (Table 2).

Table 1. Initial data of departure and arrival points

Application No.	1	2	3	4	5	6	7	8	9	10	11	12
Departure Point No.	6	7	8	9	12	13	15	16	17	19	20	21
X_i (km)	10	20	170	70	80	70	190	50	120	160	130	70
Z_i(km)	10	110	130	150	120	20	30	170	50	30	120	200
Arrival Point No.	4	24	11	3	10	1	5	18	14	2	23	22
X_j(km)	30	90	200	150	10	130	70	50	70	100	120	60
Z_j(km)	120	170	140	180	160	10	170	0	70	120	150	10

Table 2. Order Execution Waiting Time

J	6	7	8	9	12	13	15	16	17	19	20	21
$\tau_{j\min}$	152	150	149	148	146	130	120	90	87	84	80	68

To solve the routing problem, let's use formula (1) for two dynamic priority assignments η_1= 0.2 and η_2= 0.8. At the first step k = 1, there are three LA and 12 applications with the corresponding characteristics (Table 1). Having selected applications with the longest waiting time τ_j and the shortest distance, we obtain applications 6 and 13 for the first LA1 (6;13), respectively for LA2 (13;15;19) and LA3 (5;9;16). Calculations show that the "elite" included applications 13; 19; 9, respectively, for points 1,2,3 (Table 1). At the second and subsequent steps, one of the three aircraft is released before the others, and calculations are made taking this circumstance into account.

So, when *k=2*, LA1 is released first, for which 7 is the next request (LA12-7). Applications for (LA23-12), (LA34-8) are determined in a similar way. In table Figure 3 shows options for selected routes with η_1=0.2 (Fig. 1).

Table 3. Optimal route configuration when η_1=0.2

A/C1	A	13	1	15	5	16	18	6	4
A/C12	B	19	2	12	10	17	24	21	22
A/C13	C	9	3	8	11	20	23	17	14

In the same way, we make calculations when η_2=0.8. The data is summarized in Table. 4.

Table 4. Optimal route configuration when η_1=0.8

A/C11	A	6	4	7	24	12	10	21	22
A/C12	B	17	14	16	18	13	1	19	2
A/C13	C	9	3	8	11	20	23	15	5

Significant differences in the results of Table 3. Figures 3 and 4 indicate that it is possible in principle to use a genetic algorithm to solve such problems, since the original "elite" contains different "ancestors" that do not have the same properties. To carry out genetic selection, we will divide each route into two blocks, the beginning and the end, belonging to the two applications [16]. Then, for each aircraft, we will cross four blocks according to the principle "each block is combined with each of the remaining ones", As a result, the total number of permutations is 9 variants. Using the expression (2), we will select one of the 9 options with the minimum value of the penalty function, and we will set the values *T0 = = 30 minutes, which approximately corresponds to the minimum waiting time for the execution of the order when the interests of supply and demand are equal. Taking into account the maximum wait time and the total length of the routes* τ_0 T_{max} и L_{max} Let's make calculations for each of the 9 options. As a result, for everyone LA_1, LA_2, LA_3 New routes have been formed, which differ from the values in Table 1.3 and 4.

Table 5. Optimal Route Configuration for Genetic Selection

A/C 1	A	6	4	7	24	17	14	15	5
A/C 2	B	12	10	21	22	13	17	19	2
A/C 3	C	9	3	8	11	20	23	15	18

The use of a genetic algorithm in this problem showed:

– for option 1 – for all three routes, the maximum wait time was = 187 out of all 12 values, and the path length was respectively T_{max} $L_1 = 27$, $L_2 = 29$, $L_3 = 30$. Average Operating Costs $T_{cp} = 29$, a integral penalty function $\mathcal{J}_v$=13020;
– For the variant 2 — $T_{max} = 165$, $T_{cp} = 34$, $\mathcal{J}_v = 12500$;
– Genetic selection — $T_{max} = 155$, $T_{cp} = 36$, $\mathcal{J}_v = 11470$.

Example 2. Planning of short-term flights of small aircraft in case of evacuation due to an emergency situation.

A case is considered in which the location of service requests is not concentrated in the entire service area, but in its local locations. In particular, the case of evacuation in case of flood is considered (Fig. 3).

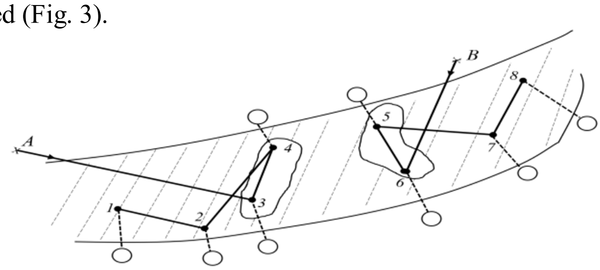

Fig. 3. Picture of the location of ground points in the flood area

The distance between the served points is an order of magnitude longer than the length of the path to the base of concentration of the evacuated population. A picture of the location of ground points in the flood area is shown in Figure 3. At points A and B, the parking places of the two aircraft before departure are indicated. The sign O stands for points of arrival at a safe place, the dotted line stands for short-term flights during evacuation, and the continuous lines indicate flights planned during the routing, taking into account the service of eight points [17,18].

The greatest danger is posed by paragraphs 3 ... 6 located on the islands. The maximum distance between these points does not exceed 50 km. The distance to the evacuation points does not exceed 10 km. All coordinates (X_j , Y_j) points and parking lots are known. Accept the flight speed of 120km/h or 2km/min.

An equally important piece of information in the initial data of the problem to be solved is the waiting time *τj for* each application in the queue for evacuation, depending on the degree of danger. The τj values for the eight applications are presented in Table 6.

Table 6. Evacuation queue waiting time data

j	1	2	3	4	5	6	7	8
τ_j (min)	10	20	100	75	70	100	40	50

3 Research and results

According to the proposed approach, the solution to the problem is as follows:

- in conditions of preference for reducing operating costs at m_1 = 0,2, according to expression 2, routing is performed for two aircraft *i=1,2*, as a result of which the integral penalty function for the first case is estimated;
- similarly, for the second case, the integral penalty function is estimated at m_1 = 0,8, with priority consideration given to the interests of quickly moving people to a safe place;

In connection with the emergence of an "elite" of routing options using genetic selection through crossing and rearrangement, a more effective solution for the third case is identified and its effectiveness is assessed [19].

In each case, for i = 1 and simultaneously for i = 2, using formula (1) for priority "P", the next flight route point of one and the other aircraft is selected, for which, according to the above, it is necessary to set the values $R_{\min} = 20$ km , $\tau_{max} = 100$ min.

Consider m_1=0,2 and i = 1. Consecutive use of the dynamic priority "P", while simultaneously assigning points to LA1 and LA2 allowed us to form the first route:

$$A–1–2–3–4 \tag{3}$$

which coincides with the results of the actions of the "greedy" algorithm, which selects the next closest point when departing from point A (Fig. 2.). Route 3 is characterized by two parameters: path length $L_1=120$ km and $\tau_1=140$ min. Flight planning for the second aircraft (i=2) determines the route:

$$B–8–7–6–5 \tag{4}$$

which also corresponds to the actions of the "greedy" algorithm when departing from point B. Route (4) corresponds to the parameters $L_2=190$ km, $\tau_2=148$ min.

Based on the obtained characteristics of routes 2 and 3, we can estimate the integral penalty function using the formula:

$$\mathcal{J}_0 = \left[max\left(\frac{\tau 1}{\tau 2}\right) + 20\right]\left[\frac{L_1+L_2}{2_v} + 20\right] = 16490 \tag{5}$$

where $\frac{L_1+L_2}{2_v}$_v is the penalty time of average operating costs, and the values of τ_1 and τ_2 are determined not only by the waiting time for requests before departure, but also by the additional flight time of the aircraft from the i-th starting point to the j-th point served. In particular, in the first case we have: τ1 = 150, τ2=148.

With similar actions in the second case, the following routes with their own penalty parameters are formed:

– for i = 1, A–4–3–2–1, L1=140 km, τ1 =140 min;

$$\text{for } i = 2, \text{B–5–6–7–8}, L2=160 \text{ km}, \tau 2 = 145 \text{ min} \quad (6)$$

The nature of the received routes (6) indicates that their appearance exactly corresponds to the point assignment mode adopted in the theory of queuing requests according to the "first come, first served" principle. To assess the effectiveness of this principle for our problem, we define the second integral penalty function

$$\mathcal{J}_0 = \left[max\left(\frac{140}{145}\right) + 20\right]\left[\frac{140+160}{4} + 20\right] = 15840 \quad (7)$$

Finally, as a third case, we find a compromise solution between the "greedy" algorithm and the rule of priority servicing of requests with maximum waiting time, using crossing and permutation operations based on a genetic algorithm. To do this, we divide each route into two blocks containing two points, as a result we get: for i = 1, 1–2, 3–4, 4–3, 2–1, and for i = 2, 8–7, 6– 5, 5–6, 7–8.

Thus, it was possible to create new routes that do not coincide with the previous ones:

– for i = 1, A–3–4–2–1, L1=130 km, τ1 =125 min,

$$\textit{– for } i = 2, \textit{V–6–5–7–8}, L2=200 \text{ km}, \tau 2 = 130 \text{ min} \quad (8)$$

Using the obtained route parameters (8), we obtain the third integral penalty function:

$$\mathcal{J}_0 = \left[max\left(\frac{125}{130}\right) + 20\right]\left[\frac{130+200}{4} + 20\right] = 15700 \quad (9)$$

When comparing the results obtained in the three routing options, it is obvious that genetic selection reduced the maximum waiting time by 11% compared to the best indicator with a slight increase in operating costs, which has a lower priority when evacuating the population [20,21].

In conclusion, it should be noted that, despite the relative simplicity of optimization due to the small dimension of the problems being solved, the genetic algorithm turned out to be more effective due to the following factors:

- low complexity of calculations due to the rational choice of the initial "elite" and a limited number of options when combining not the elements themselves, but a small number of blocks when they are "crossed";
- the results of improving the quality of planning become known already in the first steps of evolution, and not at the end, as happens with a complete search of all options.

4 Conclusion

Thus, the results of scientific research and practical developments to improve the process of Based on the conducted research, the following conclusions can be drawn:

1. The problem of multidimensional routing of aircraft flights when servicing "on-call" requests under conditions of increased navigation accuracy, ensuring full awareness of the current location of the aircraft in parking lots and in the air, is considered.
2. An approach to solving the problem is proposed, based on a combination of a genetic algorithm with group target distribution of requests between routes, which takes into account not only free, but also occupied aircraft located closer to the point of arrival.
3. It has been established that due to the successful formation of the initial "elite" of routes using a special multiplicative criterion and their subsequent crossing in a genetic algorithm, an increase in planning efficiency is ensured in a small number of "evolution steps".
4. The main difference between the integral penalty function used in genetic selection is that one of the indicators is not the average, but the maximum waiting time for any application in the queue, which is minimized when choosing the final option. This

corresponds to the principle of a guaranteed result as the most acceptable for the customer (especially in emergency situations).

5. The developed computer program for modeling the processes of appearance and servicing of requests, as well as calculations when optimizing multidimensional routes, make it possible to estimate the final value of the minimized penalty functions, to distinguish between the modes of "idle" aircraft at parking and "peak" modes with waiting for requests to be fulfilled in a queue.
6. It is shown that in the case of Poisson distribution of requests over the entire area of the serviced territory, the positive effect from route optimization is small due to the influence of the customer in half the cases on the implementation of his request, regardless of planning.
7. In the case of emergency service to points concentrated in certain significant areas of the territory, a significant improvement in the quality of routing has been established. At the same time, the maximum waiting time for requests to be completed was reduced by 15–20% compared to the well-known routing method using a "greedy" algorithm.

References

1. A. Korchagin, et.al, Transportation Research Procedia **63,** 1521-1533 (2022) https://doi.org/10.1016/j.trpro.2022.06.164
2. M. Akhmatova, et.al, Transportation Research Procedia **63,** 1512-1520 (2022) https://doi.org/10.1016/j.trpro.2022.06.163
3. D. Yurin, et.al, E3S Web of Conferences **244** (2021) https://doi.org/10.1051/e3sconf/202124411010
4. I. Pocebneva, et.al, E3S Web of Conferences **110** (2019) https://doi.org/10.1051/e3sconf/201911001074
5. A. Kolosov, et.al, Transportation Research Procedia **63**, 1621-1630 (2022) https://doi.org/10.1016/j.trpro.2022.06.176
6. G.N. Kravchenko, et.al, Lecture Notes in Mechanical Engineering, pp. 322-330 (2021) https://doi.org/10.1007/978-3-030-54814-8_39
7. V.I. Butenko, et.al, Russian Engineering Research **42(5),** 464-467 (2022) https://doi.org/10.3103/S1068798X22050082
8. B. Safoklov, et.al, Transportation Research Procedia **63,** 1534-1543 (2022) https://doi.org/10.1016/j.trpro.2022.06.165
9. S. Salimbeni, A. Redchuk, Lecture Notes in Mechanical Engineering **546,** 287-297 (2023) https://doi.org/10.1007/978-3-031-16281-7_28
10. V.I. Bekhmetyev, et.al, Lecture Notes in Electrical Engineering **857,** 287-297 (2022) https://doi.org/10.1007/978-3-030-94202-1_28
11. O. Dolgov, et.al, Transportation Research Procedia **63,** 1639-1659 (2022) https://doi.org/10.1016/j.trpro.2022.06.178
12. A.V. Bosov, et.al, Informatika i Ee Primeneniya **16(1),** 10-19 (2022) https://doi.org/10.14357/19922264220102
13. Y. Li, et.al, Robotics and Computer-Integrated Manufacturing **79** (2023) https://doi.org/10.1016/j.rcim.2022.102443
14. H. Yu, et.al, Robotics and Computer-Integrated Manufacturing **79** (2023) https://doi.org/10.1016/j.rcim.2022.102418

15. P. Calvo-Bascones, et.al, Computers in Industry **144** (2023) https://doi.org/10.1016/j.compind.2022.103767
16. F. Franchi, et.al, Lecture Notes in Civil Engineering **253**, 89-97 (2023) https://doi.org/10.1007/978-3-031-07254-3_10
17. D. Milanoski, et.al, Lecture Notes in Civil Engineering **253,** 213-222 (2023) https://doi.org/10.1007/978-3-031-07254-3_21
18. W. Kim, et.al, Mechanical Systems and Signal Processing **181** (2022) https://doi.org/10.1016/j.ymssp.2022.109471
19. J. Jiang, et.al, Scientific Reports **12(1)** (2022) https://doi.org/10.1038/s41598-021-04545-5
20. J. Liu, et.al, Advanced Engineering Informatics **54** (2022) https://doi.org/10.1016/j.aei.2022.101737
21. K. Chen, et.al, Mathematics **10(14)** (2022) https://doi.org/10.3390/math10142514