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ARTIFICIAL AND COMPUTATIONAL INTELLIGENCE

An algorithm for automatically arranging flight training plans

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Abstract. With a continued strong pace of artificial intelligence, the way of formulating the flight day plan has a significant impact on the efficiency of flight training. However, through extensive research, we find that the scheduling of flight days still relies on manual work in most military aviation academies. This method suffers from several issues, including protracted processing times, elevated error rates, and insufficient degree of optimization. This article provides a comprehensive analysis of automated flight scheduling using a goal programming algorithm and details the implementation of the corresponding algorithm on the LINGO platform. The study enhances the flexibility and robustness of the model by setting bias variables, wherein the flight courses for students and instructors can be automatically and reasonably scheduled.

Keywords: flight day plan; goal programming algorithm; military aviation.

1. INTRODUCTION

Flight day planning is a crucial task for military aviation colleges. Several factors must be coordinated throughout the planning phase, such as student preferences, weather, instructor availability, aircraft availability, and flight schedules [1]. These plans guarantee the safe and efficient provision of practical flight training and experience to students. Overall, proper planning and organization of flight day plans are essential for the effective training and development of aviation students [2].

However, our investigation in various military aviation academies shows that, in some aviation schools of less developed countries, due to economic and technological development reasons, the flight planning process still mostly relies on traditional tools, such as Excel. In some large aviation schools, such as the United States Air Force Academy, large software like AFORMS or Flight Schedule Pro is used for crew and flight scheduling when making the daily flight schedule. However, the software is difficult to operate and has a complex interface, which limits its performance and usage scope. Moreover, the model embedded in the software lacks flexibility and requires constant parameter adjustments to adapt to changing training scenarios. At this time, a large amount of manpower is still required to rectify the schedule. In such situations, the lack of human resources can lead to increased costs and an overall decline in organizational performance.

spfsciences@The topic of automatic arrangement of flight day plans has attracted attention in recent years. Naval Postgraduate School, located in California, is renowned for its advanced national defense research and education. In this school, scholar Robert F. Dell has long been committed to research on flight day planning and operations. In 2018 and 2019, he guided two theses, which optimized the tactical and weapons flight training process for naval air station trainees based on integer programming, creating a daily schedule within a one-week timeframe [3, 4].

Other researchers have also analyzed the scheduling of flight training programs from different perspectives. In 2019, Sofi Suvorova and Ana Novak described how a Markov decision process (MDP) could be used to minimize costs and control recruitment across the training continuum of helicopter pilots and optimize the aviation training schedules for the Royal Australian Navy [5]. This method possesses a certain level of robustness. Jay Foraker *et al.* discussed the problem of creating daily flight schedules for two-week training detachments of U.S. Navy Strike Fighter Squadron 106 (VFA-106) in Key West, Florida in 2021 [6]. They formulated a binary integer program to automate the scheduling of flight events to maximize daily events scheduled. In 2022, Shuangfei Xu and Wenhao Bi introduced a multi-level optimization model of flight test task allocation and sequencing to improve flight test efficiency, where the flight test period was the main optimization objective, and a penalty function evaluating tasks testing dates was the minor optimization objective [7].

Many scholars have conducted systematic research on the optimization methods of military-related flight day training plans [8, 9]. However, the establishment of flight training schedules needs to consider various complex factors, and setting too many hard constraints in the model may lead to diminished adaptability and robustness. Moreover, if the constraints are too strict, it might be difficult to find effective solutions. To address these issues, this paper presents an optimization model for daily flight planning based on goal programming [10, 11].

The model in this article involves eight flying instructors, ten students, and eight military flight training courses. The algorithm can efficiently and systematically arrange these elements in a specific order. Lingo software is used to analyze and pro-

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cess the relevant data, by which the researchers can identify patterns, trends, and relationships within the data that may not be immediately apparent.

Based on the analysis above, there is still a significant research gap in the field of automated flight plan scheduling [12]. The findings of this study can be applied to optimize flight day plans for military aviation academies and enhance the efficiency of daily flight operations. This paper focuses on the actual training situation of military aviation academies and a more flexible and adaptive goal programming method was adopted. We allocate a certain amount of reward points to students who complete specific flight training courses and add up the reward points of all students. To enhance the understanding of the model, we begin by introducing the principles and assumptions underlying the model settings.

2. OPTIMIZATION MODEL FOR FLIGHT DAY TRAINING PLAN

2.1. Principles of goal programming

Goal programming, a special type of linear programming, is a mathematical method used for decision analysis involving multiple objectives to solve practical problems in economics, the military, and other domains that linear programming cannot address. It aims to minimize the deviation of the objectives from the specified values and takes the weighted sum of the objectives as the final objective function [10].

The flight day plan can be refined as a multi-objective decision-making problem. When formulating the flight day plan, it is essential to consider not only the completion goals of the flight missions but also various factors such as aircraft, personnel, and the sequence of tasks. These objectives are often contradictory which poses challenges for balancing multiple goals to maximize training efficiency. In this case, goal programming offers a robust solution to this matter.

In contrast to linear programming, the objective function of goal programming does not seek the maximum or minimum value but seeks the gap between these goals and the expected outcomes. The smaller the gap, the higher the possibility of achieving the goal. In goal programming, there are two types of gaps: exceeding the goal and not meeting the goal. We generally use d^+ to represent the gap exceeding the goal and d^- to represent the gap not meeting the goal. One of d^+ and d^-must be zero, or both are zero. When the goal is consistent with the expected outcome, both are zero, i.e. there is no gap.

Hence, d^+ and d^- satisfy the condition below:

$$d^+ \times d^- = 0. \tag{1}$$

Thus, in goal programming, we will encounter two different types of constraints: hard constraints and soft constraints. Hard constraints are those that must be satisfied, which is constant with that of linear programming. In this situation, we do not need d^+ and d^- to set constraints or objectives.

Soft constraints are those that can be violated. However, these constraints usually lead to an increase in some costs. For instance, we may wish for the number of airplanes flying at the same time to not exceed a certain specific number, but under certain specific circumstances, this condition may not be met. Then d^+ and d^- should be used to set constraints and balance multiple goals in three scenarios:

1. The requirement to meet the target value, meaning both positive and negative deviation variables should be as small as possible:
$$\min z = d^+ + d^-. \tag{2}$$
2. The requirement not to exceed the target value, meaning the positive deviation variable should be as small as possible:
$$\min z = d^+. \tag{3}$$
3. The requirement to exceed the target value, where the excess is unlimited, but the negative deviation variable should be as small as possible:
$$\min z = d^-. \tag{4}$$

Assuming there are a total of q biases, the objective function is:

$$\min z = \sum_{k=1}^{q} d_k^- + \sum_{k=1}^{q} d_k^+. \tag{5}$$

Based on the above analysis, the objective function contains all d^+ and d^-, then greater flexibility can be demonstrated by continually adjusting d^+ and d^-. That is, we can attach or remove d^+ and d^- to achieve mutual conversion between hard constraints, soft constraints, and the objective function. Therefore, it transforms the hard-verse-soft problem into a convertible issue.

In actual flight training, there are both hard constraints and soft constraints. The following conditions must be met, namely hard constraints:

• Matching of personnel and aircraft

During the same period, a student or instructor cannot be present in two aircraft at the same time. During a teaching session, one instructor can only match with one student. In formation flight missions, one lead aircraft must be matched with two wingmen.

• Sequence of course execution

Students have strict sequence restrictions when carrying out flight subjects, which are clearly explained in the flight training syllabus. A student can only proceed to the next flight subject after completing the previous one.

• Aircraft quantity limitation

The total number of aircraft used by all pilots in the same batch must not exceed the number of available aircraft. If the number of aircraft is exceeded, the flight plan cannot be executed normally.

The following are soft constraints:

• Control of flight density

Before formulating each flight plan, it is necessary to designate the number of sorties each student needs to complete for each subject, and these indicators should be achieved as much as possible. Additionally, due to airspace restrictions, the number of aircraft flying in the same batch should ideally not exceed the specified indicators. However, due to the complex nature of the actual flight environment, the above indicators may not be met.

• Maximizing overall benefits

The learning progress and training duration can vary for each individual based on factors such as aptitude, dedication, and the specifics of the training program. However, it is important to prioritize the overall training benefits rather than try to estimate every aspect. To maximize the overall benefits, it is crucial to identify clear goals and determine which specific benefits should be maximized. This way, efforts, and resources can be concentrated accordingly [13, 14].

Moreover, this article also presents the following assumptions, based on the actual situation of military aviation academies.

- Due to the unique nature of flight training, it is generally assumed that one instructor can only teach one student at a time. This approach improves the efficiency of flight instruction.
- Unexpected circumstances can cause disruptions to military flight training, including bad weather, technical problems, and safety mishaps, political or military developments. The unexpected aspects stated above are not considered in this essay.
- Students in flight must follow the curriculum timetable, moving on to the subsequent lesson only after finishing the preceding ones in a flying day.

2.2. Sets, parameters, and decision variable description

The following notations are defined before the presentation of the mathematical model.

Sets

E	set of flight courses, $e \in E$
E_F	set of formation courses, $e_f \in E_F$
S	set of students, $s \in S$
I	set of instructors, $i \in I$
P	set of a batch of aircraft released, $p \in P$
I_{EF}	set of teachers who possess the ability to fly a leader aircraft $i_{ef} \in I_{EF}$
$R \subset E \times E(e', e)$	set of two courses that course e' is in front of course e
C_S	set of courses completed by student s

Parameters

v_e	the execution values of course e in the first batch
r_{ep}	the reward value of course e in batch p
IL	counts the instructor's daily flight course sorties limit
SL	counts the student's daily flight course sorties limit
E_s	the number of sortie allocations per student each day, $s \subset S$
M_p	the maximum number of aircraft that can be flown in batch p, $p \subset P$
T_e	flight time for course e, $e \subset E$

Decision variables

X_{sep}	if course e of student s has been arranged in batch p, the value is 1, otherwise the value is 0
Y_{iep}	if the course e of instructor i has been arranged in batch p, the value is 1, otherwise, the value is 0, $i \in I_e$
L_{iep}	if the task of flying a leader aircraft was assigned to instructor i in batch p to formation course e, the value is 1, otherwise, the value is 0, $i \in I_{EF}$, $e \in E_F$
d^+, d^-	the gap between the goals and the expected outcomes

2.3. Establishment of an objective function

2.3.1. Soft constraints setting

The helicopter training syllabus at a military aviation academy comprises eight subjects. These courses are familiarization flight (FAM), visual flight (VF), instrument flight (IF), low-level flight (LLF), boundary flight (BF), formation flight (FORM), search and rescue operation flight (SROF) and reconnaissance and patrol flights (RPF).

Familiarization flight (FAM) refers to a flight taken by a pilot or crew member to become familiar with a specific aircraft, route, or operating procedure. These flights are often conducted before a pilot starts flying a new type of aircraft or before operating in a new area. Visual flight (VF) refers to a type of flying where pilots rely primarily on their visual observations to navigate and control the aircraft. In visual flight, pilots typically fly at lower altitudes and in good weather conditions. Instrument flight (IF) refers to a type of flying where pilots rely solely on the instruments in the aircraft cockpit to navigate and control the aircraft, rather than visual references outside the aircraft. Based on FAM, pilots require extensive practice in VF skills and IF to enhance their proficiency in flying.

Low-level flight (LLF) requires special skills due to the increased risks and challenges involved. Pilots must be able to navigate obstacles while maintaining a safe and controlled flight profile. Boundary flight (BF) refers to a specific flight maneuver that involves flying at the boundary of the aircraft performance envelope. Formation flight (FORM) is the practice of flying multiple aircraft in a pre-determined arrangement and pattern. The lead aircraft plays a crucial role in this practice, with the lead pilot responsible for setting the pace, determining the flight path, and providing instructions to the other aircraft in the formation. These three courses can significantly enhance pilots' overall capabilities.

First, it is necessary to set the initial reward values. Since the fundamental courses are more important for students in the early stages, the basic courses e_1(FAM), e_2(VF), e_3(IF), and e_4(LLF) are given relatively high initial reward values; The transitional courses e_5(BF) and e_6(FORM) should be assigned moderate initial reward values. Similarly, we set lower initial values to e_7(SROF) and e_8(RPF).

Assuming the eight flight courses are: e_1, e_2, e_3, e_4, e_5, e_6, e_7, e_8, the execution values of the course items in the first batch are v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8, respectively, with n_p representing the batch number. To ensure that the course can achieve a higher reward value if completed earlier, we divide the execution value of the first batch by the square root of the batch. Square root transformation is a method often used in data processing and statistical analysis. Applying this transformation can reduce the adverse effects of extreme values on the overall analysis outcome. It can enhance the robustness of data analysis. The relationship between the reward value of the course and the change in the batch is as follows:

$$r_{ep} = \frac{v_e}{\sqrt{n_p}}. \tag{6}$$

Based on the relative importance of each course in this stage, the value of the first batch of courses in this stage is set to be 4, 3, 2.8, 2.8, 2.2, 2.2, 2, 2. The value of the course in each batch is shown in the Table 1.

Table 1
Rewards for each course that changes with batch number

	1	2	3	4	5
e_1	4.00	2.83	2.31	2.00	1.79
e_2	3.00	2.12	1.73	1.50	1.34
e_3	2.80	1.98	1.62	1.40	1.25
e_4	2.80	1.98	1.62	1.40	1.25
e_5	2.20	1.56	1.27	1.10	0.98
e_6	2.20	1.56	1.27	1.10	0.98
e_7	2.00	1.41	1.15	1.00	0.89
e_8	2.00	1.41	1.15	1.00	0.89

The primary objective of the military flight academy is to train students, and the quality of their training serves as the most crucial measure of the academy's training ability. Therefore, we primarily assess the reward value of the enrolled courses. A core goal of flight training is to enhance overall training effectiveness. Specifically, the total reward values for all training activities should be maximized. It is calculated as follows:

$$\sum_e \sum_s \sum_p r_{ep} * X_{sep}. \tag{7}$$

Maximizing the overall reward value is our primary goal in pursuit. However, within the framework of goal programming, we must convert it into the following constraints:

$$\sum_e \sum_s \sum_p r_{ep} * X_{sep} + d_1^- - d_1^+ = \mathrm{Inf}. \tag{8}$$

Inf is usually a relatively large number, and this value is not specifically defined, here we take Inf = 1000. In formation flying, there is usually a designated leader aircraft that leads the formation. The instructor in the leader aircraft sets the pace, direction, and maneuvers for the rest of the formation. In addition to formation flying, the main task of the instructor is to provide flight guidance on the training plane. A three-aircraft formation comprises a lead aircraft and two wingman aircraft. Usually, only instructors occupy the lead aircraft, while other instructors guide students in each wingman aircraft. In this scenario, the total number of flights for an instructor in a flight day is determined by the combined number of flights in a leader aircraft and the number of flights dedicated to other instructional purposes, the maximum number of flight sorties for each instructor is preferable not to exceed IL:

$$\sum_p \sum_e Y_{iep} + \sum_p \sum_e L_{iep} + d_{i2}^- - d_{i2}^+ = IL \quad \forall i. \tag{9}$$

For students, the sum of daily flight sorties is preferable not to exceed SL:

$$\sum_p \sum_{e \notin C_S} X_{sep} + d_{s3}^- - d_{s3}^+ = SL \quad \forall s. \tag{10}$$

Each student should preferably complete the assigned sorties each day:

$$\sum_{e \notin C_S} \sum_p X_{sep} + d_{s4}^- - d_{s4}^+ = E_s, \quad \forall s. \tag{11}$$

Positive and negative deviations must meet the following conditions:

$$d_n^- \times d_n^+ = 0. \tag{12}$$

2.3.2. Hard constraints setting

Setting the sequence of pilot flight training courses can vary depending on the specific training program. Using a specific aviation college as an example, we illustrate the implementation sequence of flight training courses as shown in Fig. 1.

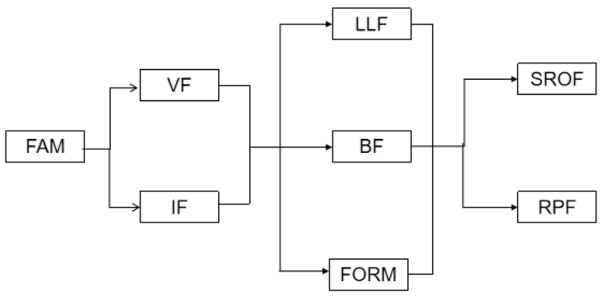

Fig. 1. The implementation sequence of flight training courses

During a flight day, the flight courses on the left will be executed before the flight courses on the right. The courses in the upper and lower positions can be executed simultaneously without any specific order. As shown in Table 2, we should read the column index in the first before reading the row index. Therefore, set (VF, FAM) belongs to set R, and set (FAM, VF) does not belong to set R. Both set (LLF, BF) and set (BF, LLF) belong to set R. To quantify the order of the courses, we set the matrix $Z_{e'e}$.

If $Z_{e'e} = 1$, the course e' can be set before the course e. If $Z_{e'e} = 0$ and $Z_{ee'} = 0$, there is no order for two courses that can be sorted arbitrarily. Thus, the following inequality is used to limit the course schedule:

$$\begin{aligned} &X_{sep} * Z_{ee'} \le X_{se'(p+n)} * Z_{e'e} \\ &\forall s, e, e', p, n \in N, \quad e' \notin C_S, \quad e \notin C_S, \quad n \in N. \end{aligned} \tag{13}$$

Table 2
Course implementation sequence quantization chart

	FAM	VF	IF	LLF	BF	FORM	SROF	RPF
FAM	0	1	1	1	1	1	1	1
VF	0	0	0	1	1	1	1	1
IF	0	0	0	1	1	1	1	1
LLF	0	0	0	0	0	0	1	1
BF	0	0	0	0	0	0	1	1
FORM	0	0	0	0	0	0	1	1
SROF	0	0	0	0	0	0	0	0
RPF	0	0	0	0	0	0	0	0

The upper limit of flight sorties in each batch can vary depending on various factors such as aircraft availability, crew availability, operational requirements, and maintenance schedules. However, for the sake of simplicity in calculations, we will set the number of flights in each batch to M_p, which represents the number of available aircraft. In each batch, the instructor and the student share the same aircraft, and the total number of flight sorties includes the flight sorties of the students and lead aircraft flight sorties of the instructors:

$$\sum_s \sum_{e \notin C_s} X_{sep} + \sum_{i \in I_{EF}} \sum_e L_{iep} \leq M_p \;\; \forall p. \tag{14}$$

In three-plane formation flight training, the number of sorties for the lead aircraft is twice that of the wingman in each batch:

$$\sum_s X_{sep} = 2 \sum_{i \in I_{EF}} L_{iep} \;\; \forall\, e \in E_F, p. \tag{15}$$

In mentoring courses, the number of flight sorties for instructors is equal to that of students in each batch:

$$\sum_s X_{sep} = \sum_{i \notin I_{EF}} Y_{iep} \;\; \forall\, e \notin C_S, p. \tag{16}$$

In a batch, each student can only take one course:

$$\sum_{e \notin C_S} X_{sep} \leq 1, \;\; \forall\, s, p. \tag{17}$$

Similarly, within a batch, an instructor can only guide one course:

$$\sum_e Y_{iep} + \sum_e L_{iep} \leq 1, \;\; \forall\, i, p. \tag{18}$$

Based on the analysis above, the objective function is as follows:

$$\min = d_1^- + \sum_i d_{i2}^+ + \sum_s d_{s3}^+ + \sum_s d_{s4}^-, \;\; \forall\, i, \;\; \forall\, s. \tag{19}$$

In the above equation, the smaller d_1^- and $\sum_s d_{s4}^-$, the larger reward values will be in equation (6). The smaller $\sum_i d_{i2}^+$ and $\sum_s d_{s3}^+$, the smaller the various sortie counts will be.

3. MODEL TESTING AND VALIDATION

In the previous section, we specified the objective function, decision variables, and constraints of the goal programming model that we aim to test. The next step involves the testing of data. The generated simulated data should accurately reflect the characteristics of the real-world problem. Subsequently, we can proceed with the execution of the goal programming model using the simulated data. The solver will then determine the solution that either maximizes or minimizes the objective function while satisfying the given constraints. Finally, we will analyze the outputs of the goal programming model.

In Section 2.3.1, we set some variables, p_1, p_2, p_3, p_4, and p_5 represent the batch value. Rewards for each batch are shown in Table 1.

Based on simulated data extracted from actual flight training data, the completion status of the students' flight training courses is as Table 3.

Table 3
Completed flight training courses for students

Students	Completed flight training courses
s_1	Not started taking flight courses
s_2	$e_1\ e_2\ e_3\ e_4$
s_3	$e_1\ e_2\ e_3\ e_4$
s_4	$e_1\ e_2\ e_3\ e_4\ e_5\ e_6$
s_5	e_1
s_6	$e_1\ e_2\ e_3\ e_4\ e_5\ e_6$
s_7	Not started taking flight courses
s_8	e_1
s_9	Not started taking flight courses
s_{10}	Not started taking flight courses

The courses that military aviation academies require students to complete are listed in Table 4. Courses required by the Military Aviation Academy.

Table 4
Courses required by the Military Aviation Academy required for students to complete

	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
s_1	2	0	0	0	0	0	0	0
s_2	0	0	0	0	2	2	0	0
s_3	0	0	0	0	2	3	0	0
s_4	0	0	0	0	0	0	2	2
s_5	0	1	2	2	0	0	0	0
s_6	0	0	0	0	0	0	2	2
s_7	2	0	0	0	0	0	0	0
s_8	0	1	2	2	0	0	0	0
s_9	1	2	0	0	0	0	0	0
s_{10}	1	2	0	0	0	0	0	0

Table 5
Test results

Test number	Verification target	The expected output result	Test results
1	Total reward value	The total reward value should be maximized.	–
2	Instructor and student daily flight sorties limit	The sorties of each instructor and student should not exceed three.	Some instructors have flown more than three sorties.
3	Student daily allocated subject sorties quantity	All students are able to complete their assigned sorties.	Some students have not completed their task.
4	Limitations on the order of flight courses	Implementation sequence of the course meets the requirements in Fig. 1.	Meeting the constraints
5	Flight density restrictions	In each batch of flights, the total number of sorties should not exceed M_p.	Meeting the constraints
6	The restrictions of formation course	The number of sorties for lead aircraft is twice that of the wingman.	Meeting the constraints
7	The restrictions of flight sorties for students and flight sorties for instructors	In each batch, the number of flight sorties for students and the number of flight sorties for instructors are equal.	Meeting the constraints
8	The restrictions for flight sorties for students in each batch	In each batch, the number of flight sorties for students cannot exceed one.	Meeting the constraints
9	The restrictions for flight sorties for instructors in each batch	In each batch, the number of flight sorties for each instructor cannot exceed one.	Meeting the constraints

Assuming instructors i_5, i_6, i_7 and i_8 can drive leader aircraft, it is best for all students and instructors not to exceed three sorties per day, and the number of aircraft available for deployment daily is eight.

Using the Lingo platform, we can establish a testing environment and evaluate the model through simulations. All restrictions need to be verified one by one to ensure the program executes correctly and error-free, as shown in Table 5.

Assuming each batch can accommodate a maximum of eight aircraft, by running the lingo program, a flight schedule was generated which can assign instructors and students to their respective batches. The resulting reward value was 83.29, and the arrangement of courses is shown in Table 6.

Table 6
The arrangement results of the model running

<table>
<tr><th colspan="3">Batch 1</th><th colspan="3">Batch 2</th><th colspan="3">Batch 3</th><th colspan="4">Batch 4</th><th colspan="4">Batch 5</th></tr>
<tr><td>i_3</td><td>s_1</td><td>e_1</td><td>i_1</td><td>s_1</td><td>e_2</td><td>i_3</td><td>s_2</td><td>e_5</td><td rowspan="2">i_5</td><td>i_3</td><td>s_2</td><td>e_6</td><td rowspan="2">i_7</td><td>i_1</td><td>s_2</td><td>e_6</td></tr>
<tr><td>i_2</td><td>s_7</td><td>e_1</td><td>i_2</td><td>s_7</td><td>e_2</td><td>i_1</td><td>s_3</td><td>e_5</td><td>i_1</td><td>s_3</td><td>e_6</td><td>i_2</td><td>s_8</td><td>e_6</td></tr>
<tr><td>i_4</td><td>s_9</td><td>e_1</td><td>i_8</td><td>s_9</td><td>e_2</td><td>i_4</td><td>s_5</td><td>e_4</td><td colspan="2">i_4</td><td>s_4</td><td>e_7</td><td colspan="2">i_3</td><td>s_4</td><td>e_7</td></tr>
<tr><td>i_5</td><td>s_{10}</td><td>e_1</td><td>i_4</td><td>s_6</td><td>e_2</td><td>i_6</td><td>s_8</td><td>e_4</td><td rowspan="2">i_6</td><td>i_2</td><td>s_5</td><td>e_6</td><td colspan="2">i_3</td><td>s_6</td><td>e_8</td></tr>
<tr><td>i_6</td><td>s_5</td><td>e_2</td><td>i_5</td><td>s_5</td><td>e_3</td><td>i_2</td><td>s_9</td><td>e_3</td><td>i_8</td><td>s_8</td><td>e_6</td><td rowspan="2">i_8</td><td>i_6</td><td>s_5</td><td>e_6</td></tr>
<tr><td>i_7</td><td>s_8</td><td>e_2</td><td>i_6</td><td>s_8</td><td>e_3</td><td>i_5</td><td>s_1</td><td>e_3</td><td colspan="2">i_7</td><td>s_6</td><td>e_8</td><td>i_4</td><td>s_3</td><td>e_6</td></tr>
<tr><td>i_8</td><td>s_2</td><td>e_5</td><td>i_7</td><td>s_3</td><td>e_5</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

In batch 4 and batch 5, i_5, i_6, i_7 and i_8 are responsible for piloting the leader aircraft of the formation. Based on the table above, it is evident that the implementation sequence of all students' courses adheres to the requirements outlined in Fig. 1. Additionally, high-value courses, specifically courses 1 and 2, are assigned to the initial two batches, while courses 6 and 7 are allocated to the final two batches. It is observed that no student or instructor appeared on both aircraft at the same time during the same batch of flights.

However, some of the soft constraints are not satisfied. For example, in Table 4, s_3 is required to conduct e_6 three times, but the result is two. Some instructors fly more than three sorties within a single day, such as the i_7 performing four sorties, and i_8 also completing four sorties.

Based on the results in Table 6, the generated training schedule was found highly executable. In the schedule, each student is paired with only an instructor, and different individuals within the same batch appear only once. Additionally, important subjects are arranged early in the schedule. Also, within the same batch, the number of aircraft sorties does not exceed the prescribed limit.

4. CONCLUDING ANALYSIS AND OUTLOOK

This article systematically introduces the application method of goal programming in the automatic scheduling of flight plans, using deviation decision variables to control constraints and set objective functions. The program running results show that all hard constraints are met, but some soft constraints are not satisfied. However, this is more in line with the actual training situation. In real training scenarios, due to the multitude of limiting factors, inevitably, some constraints cannot be satisfied. The method proposed in this paper is quite flexible, allowing adjustments to be made between hard and soft constraints at any time. Additionally, the designed model can generate a feasible plan within a few seconds. In actual work situations, military staff often spend several hours formulating plans and they easily make mistakes. This algorithm overcomes the above drawback and greatly improves the efficiency of plan formulation.

This article also provides an important basis for the development of the flight day plan for the Air Force aviation unit. The model in the article integrates algorithms and flight daily plans which can develop the plan formulation in a quantitative direction. The model proposed in this article can be further improved in the following aspects:

- The process of using this model requires a large amount of actual data involving pilot flight intensity restrictions, mission implementation requirements, and so on. The data may still contain some errors if input manually. Integrating the model into an advanced information management system or software can address this issue, thereby enhancing the model execution efficiency.
- Aircraft types and training methods are different in each unit of the military, which leads to significant differences in the methods of planning. This is not conducive to communication between superiors and subordinates. A more versatile flight day planning software can be developed based on this model to overcome the shortcomings.

The automatic generation of flight day plans in military aviation colleges is a development trend that involves the use of advanced technology and data analysis. This involves several aspects:

- AI and machine learning: By employing machine learning algorithms and artificial intelligence, flight day plans can be generated automatically which can take into account multiple parameters such as weather conditions, aircraft availability, pilot schedules, mission requirements, and maintenance schedules. Furthermore, AI can optimize these plans by continuously learning from historical data and progressively enhancing its performance [15, 16].
- Predictive analytics: This involves using data, statistical algorithms, and machine learning techniques to identify the likelihood of future outcomes based on historical data. In the context of flight day planning, predictive analytics can anticipate potential disruptions, delays, or safety concerns, enabling better planning and risk management [17–19].
- Digital twin technology: This involves creating a digital replica of a physical system. In this case, it refers to the entire flight day operation. The digital twin enables simulation and analysis, optimizing flight day plans and anticipating potential issues in advance.
- Blockchain technology: Blockchain could also contribute to the automatic generation of flight day plans by offering a secure, transparent, and tamper-proof record of all flight day planning activities. This implementation could result in a more efficient and reliable system.
- Integration of IoT: IoT devices can provide real-time data on aircraft status, weather conditions, and other critical factors. This data can be integrated into the automatic generation of flight plans, resulting in more accurate and efficient planning.

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