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A Data-drive Approach for Robust Cockpit Crew Training Scheduling

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Abstract

This work addresses the cockpit crew training scheduling problem. The objective is to produce a robust cockpit crew training schedule, including the assignment of trainees, instructors and simulators. To attain this objective, we propose a scheduling framework composed of four modules: a Training Scheduling & Assignment Model (TS&AM), a Disruption Generator (DG), a Rule-Based Recovery (RBR) algorithm, and a Neural Network (NN). The TS&AM is an integer programming model that integrates the scheduling of courses and the assignment of resources. The output roster serves as input for a data-driven DG based on Monte-Carlo Simulation. The disruptions are then solved using the RBR algorithm. Finally, The NN feedback algorithm learns the recovery costs experienced in the disruption impact simulator and updates these costs in the TS&AM to generate more robust rosters. The proposed modelling framework was calibrated, tested, and demonstrated in a simulation environment developed using four years of historical crew training data from a major European airline. The experiment showed that our approach outperformed the roster produced by the airline. The approach proposed produces rosters that reduce recovery costs by 21 percent, while still decreasing total training costs by 3 percent.

Keywords: crew training schedule; integer linear programming; neural network; robust scheduling

1. Introduction

Airline schedules are constantly updated to deal with disruptions originating from crew absence, upstream delays, mechanical failures and other sources. Such disruptions can become very costly. Numerous researchers such as Barnhart et al. (2003) and Kohl et al. (2007) showed that significant savings are possible when efficiently dealing with disruptions. This field of study is known as disruption management and deals with (1) robustness and (2) recovery. Recovery focuses on disruptions re-actively by efficiently restoring schedule feasibility (see Hassan et al., 2021 for a recent review paper on airline disruption management). Robustness is defined as the capability to deal with or absorb

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the negative effects of unexpected events and is accounted for proactively. Clausen et al. (2010) listed slack, reserve crew, simplified schedules and swap opportunities as examples of robustness. These robustness indicators are studied extensively, especially for the crew, as this is one of the most expensive resources employed by the airline. However, all researchers examined the robustness of the crew assigned to flight pairings.

Although the primary task of a cockpit crew is to operate these flights, large airlines invest up to thousands of working days in simulator-based crew training for legal licensing purposes (recurrent training) and crew conversion between fleets and ranks (conversion training). Furthermore, the crew is trained by a specially qualified subset of cockpit crew members known as instructors, which are typically removed from flight operations to give training. Each training event thus takes away resources from production. Any disrupted training activity, due to illness or leave (such as parental leave or care-related leave), potentially impact crew availability by means of missed due dates in case of recurrent training (e.g., training to maintain the level of proficiency) or postponed employment in case of conversion training (i.e., training to the quality crew to operate a specific aircraft type). This is even more critical because most of these training events necessarily involve a fixed combination of instructors and multiple crew members. If one of the instructors or crew members becomes unavailable, all the other training session participants will have their schedules affected. Constructing a robust cockpit crew training schedule can thus improve the airlines' operational performance by minimizing the impact of disruptions. The current scientific body of knowledge has limited research into the cockpit crew training schedule. Many researchers only consider segregated training scheduling problems for conversion training, recurrent training or instructor assignment. Resource dependencies are all neglected. In the absence of a well-performing integrated training scheduling model, robustness is not considered yet.

This paper addresses this cockpit crew training scheduling problem. More specifically, the research objective was to develop a modelling approach that could contribute to the computation of a robust crew training schedule capable of dealing with schedule disruptions. Throughout this research, robustness is defined as the capability to deal with or absorb the negative effects of disruptions. This capability is expressed as a combination of scheduling cost and expected recovery cost. This definition follows, e.g., the research from Ingels and Maenhout (2015) and Shebalov and Klabjan (2006).

A modelling framework integrating several models and solution methods was developed and applied to attain our research objective. More precisely, the modelling framework consists of a Training Scheduling & Assignment Model (TS&AM), a Disruption Generator (DG) algorithm, a Rule-Based Recovery (RBR) model, and a Neural Network (NN) algorithm. The discussion of this framework is provided in Section 3. Before that, in Section 2, we present a description of the problem and report related literature. In Section 4 we present the results from a case study using data from a European airline. Conclusions are presented in Section 5.

2. Problem Description and Literature

To legally allow pilots to fly, each flight crew member must complete numerous training programs throughout their career. These crew training activities have various objectives and different frequencies. According to Yu et al. (2004) defined three overarching categories of airline crew training described below.

- **Conversion training:** Each crew member undergoes initial qualification training each time that person transitions to operate a new aircraft type or operate in another rank (Yu et al., 2004). Typical conversion training programs take four weeks. At least four to six weeks of route instruction follows, in which the trainee flies the aircraft together with a certified instructor (Kohl, 2004). At Continental Airlines, as much as 15 to 20 percent of all pilots were awarded a new position every half year and undergo conversion training accordingly (Yu et al., 2004).
- **Recurrent training**: Each pilot must complete annual recurrent training Sohoni et al. (2003), typically consisting of one or two full days of ground and simulator training (Yu et al., 2004; Kozanidis, 2017). According to Xu et al. (2006), sixty percent of all training resources are devoted to providing recurrent training.
- **Re-qualification training**: Pilots that are unable to fly for a prolonged period of time must complete re-qualification training (Yu et al., 2004). Such a program can take several days or a couple of weeks consisting of a mix of ground, simulator and route instruction.

Simulator training is restricted in both training device capacity and instructor capacity. According to Xiangtong Qi (2004), both the trainees and instructors are drawn from the pool of regular pilots for the entire duration of training. As this makes airline crew simulator training an expensive operation, the focus is directed towards the airline crew simulator training schedule. This is, however, not a straightforward problem, considering the complex governing rules described by Kohl (2004); Kozanidis (2017). Examples of such rules are the various crew compositions allowed for the different types of training, the required qualifications and number of instructors, the geographical location of training resources, and airline-specific requirements.

Airline crew training scheduling has received little attention in research. Still, early research focused on optimizing workforce planning (Yu et al., 1998) because conversion training programs decrease the number of available pilots considerably (up to 3.5 percent of the airlines' pilots can be involved in conversion training at any given time). In a following paper, Yu et al. (2004) describe the commercialization of this earlier workforce planning research. They applied a deterministic approach to consider the inter-dependency between training capacity restrictions and planning pilot transitions. Sohoni et al. (2003) focused on deterministic scheduling of recurrent training activities instead of conversion training. The authors consider the assignment of help-out pilots in the case the crew for training was incomplete. The help-out can either be instructors, regular or reserve crew members. More integrated approaches have been researched by, among others, Xu et al. (2006) and Holm (2008). Xu et al. (2006) are one of few to address the flight instructor scheduling problem and target to cover a set of training activities by a qualified instructor. More recently, Kozanidis (2017) proposed an integer programming formulation and an exact solution methodology to address the crew training problem while considering crew seniority, preference, capacity, and language compatibility restrictions. A military version of the problem, for helicopter crew training, was discussed in a recent paper from Mak-Hau et al. (2021). The authors presented several formulations and suggested a column-generation algorithm to produce the training schedules of a training syllabus.

Despite the mentioned research efforts, all models presented only proved to perform well under deterministic operating conditions. The impact of disruptions is omitted, and so is the inter-dependency with the flight schedule. Crew training requirements bound the availability of crew members for operating regular flights, and operating flights limit the number of available instructors for training purposes.

3. Modelling Framework

To attain the research objective of making recommendations on increasing the robustness of the cockpit crew training schedule, a research model framework is proposed in Figure 1. Each layer is explained below in order of input, process, output and evaluation. The process layer is treated in more detail. It consists of multiple models and algorithms. First, a robust training schedule is generated using an integer programming model that we called Crew Training Schedule & Assignment Model (TS&AM). The schedule is then disrupted and recovered to test the schedule's performance in a stochastic environment. This allows quantifying the robustness, which is defined as the trade-off between stochastic recovery cost and deterministic schedule cost. The objective is to bring down the expected recovery cost while keeping the schedule cost low. The simulation results on the reference roster are then used in a learning/feedback loop to update the expected recovery cost coefficients in the TS&AM to generate rosters that are more robust. The disruption and recovery process is then repeated for the robust schedule to make a comparison afterwards. All models are briefly described below in order of occurring in the framework.

3.1. Input

Training demand and supply data were used as input to our model framework. This data was used to estimate training needs and ensure the flight schedule feasibility for both trainees and instructors. That is, that the obtained training schedule does not lead to crew availability issues later on when scheduling flights. It was, however, assumed that that training scheduling is prioritized over the scheduling of other activities than flights, as mentioned by Kohl (2004). Furthermore, we considered the Collective Labor Agreement (CLA) rules from the partner airline to ensure the schedule feasibility. The disruptions in the Disruption Generator (DG) model were generated based on historical data on disruptions experienced by the airline. The disruptions were scoped to short(er) term disruptions only. Any decision on disruptions known long in advance is postponed until the last 72 hours before the start of that duty.

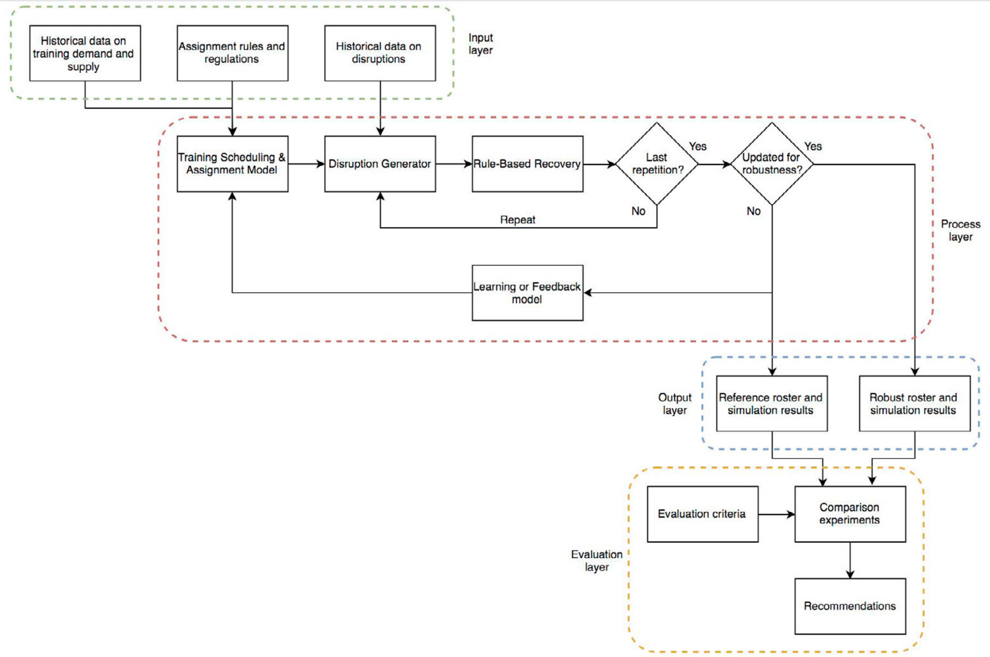

Fig. 1. Crew training scheduling model framework.

Moreover, the scope was limited to primary disruptions. This means that illness and leave are modelled and solved for, but any subsequent disruption or impact was neglected.

3.2. Airline Crew Training Schedule & Assignment

A cost-minimization integer programming model was formulated to schedule the training courses and assign trainees, instructors, and helpouts when needed. The latter is required whenever the trainees are not of complementary rank or whenever a single trainee is assigned. Working rules are in place in order to ensure that instructors meet aircraft exposure requirements. The model is inspired by research (e.g., Xu et al. 2006; Holm 2008) but has novel adjustments. First of all, scheduling and assignment are integrated as these decisions are interdependent in all resource facets. Next, instructor assignment is explicitly modelled, requiring a model adaptation in terms of instructor assignment and role assignment. Furthermore, the model is adjusted to schedule standard and nonstandard sets of training events, as opposed to only allowing for assignment sets of two captains as done by Holm (2008). All changes are captured in the sets, parameters, decision variables, objective function and constraints of the model. The resulting formulation is presented below.

$$\begin{aligned} \text{minimize} \quad & \sum_{k\in K}\sum_{t\in N}\Bigg[\Bigg(\sum_{s\in S} c_{sk}^{simulator} + \sum_{j\in J} c_{jk}^{instructor} + P_{kt}\cdot \mathbb{E}[c_{kt}^{recovery}]\Bigg)\cdot a_{kt} + \sum_{h\in I} c_{hk}^{helpout}\cdot b_{kt} \\ & + \sum_{i\in I} c_{ik}^{trainee}\cdot (n_k^{max} + (n_k^{max} - \sum_{p\in P} x_{kt}^{p})) - (\sum_{i\in I} p_{it}^{trainee}\cdot y_{ikt} + \sum_{j\in J} p_{jk}^{instructor}\cdot (z_{jkt} + h_{jkt}))\Bigg] \end{aligned} \tag{1}$$

$$\text{s.t.} \qquad \sum_{i\in I} y_{ikt} \geq 1 \qquad \forall k\in K, t\in N \tag{2}$$

$$\sum_{k\in K}\sum_{d=0}^{min(t,l_k)} dem_{sdk}\cdot a_{ks(t+d)} \leq min(ns_{std}) \qquad \forall t\in\{1,2,...,N\} \tag{3}$$

$$\sum_{p \in P} x_{kt}^{p} \leq cap_s \cdot a_{kt} \qquad \forall k \in K, \forall t \in \{1, 2, ..., N\} \tag{4}$$

$$a_{kt} - b_{kt} \leq x_{kt}^{p} \qquad \forall p \in P, \forall k \in K, \forall t \in \{1, 2, ..., N\} \tag{5}$$

$$\sum_{i \in I_{pk}} y_{ikt} + b_{kt} \geq cap_s \qquad \forall k \in K, \forall t \in \{1, 2, ..., N\} \tag{6}$$

$$\sum_{i \in I_{pk}} y_{ikt} = x_{kt}^{p} \qquad \forall p \in P, \forall k \in K, \forall t \in \{1, 2, ..., N\} \tag{7}$$

$$\sum_{j \in J_k} z_{jkt} = nj_k \cdot a_{kt} \qquad \forall k \in K, \forall t \in \{1, 2, ..., N\} \tag{8}$$

$$\sum_{j \in J_k} z_{jkt} \geq nj_{k_q} \cdot a_{kt} \qquad \forall k \in K, \forall t \in \{1, 2, ..., N\} \tag{9}$$

$$\sum_{j \in J} h_{jkt} = nh_k \cdot b_{kt} \qquad \forall k \in K, \forall t \in \{1, 2, ..., N\} \tag{10}$$

$$\sum_{k \in K} z_{jkt} + h_{jkt} + y_{jkt} \leq 1 \qquad \forall j \in J, \forall t \in \{1, 2, ..., N\} \tag{11}$$

$$\begin{aligned} a_{kt} &\in \{0, 1\} && \forall k \in K, \forall t \in \{1, 2, ..., N\}, \\ b_{kt} &\in \{0, 1\} && \forall k \in K, \forall t \in \{1, 2, ..., N\}, \\ x_{kt}^{p} &\in \{0, 1, 2\} && \forall k \in K, \forall p \in P, \forall t \in \{1, 2, ..., N\}, \\ y_{ikt} &\in \{0, 1\} && \forall k \in K, \forall i \in I, \forall t \in \{1, 2, ..., N\} \\ z_{jkt} &\in \{0, 1\} && \forall k \in K, \forall j \in J, \forall t \in \{1, 2, ..., N\}, \\ h_{jkt} &\in \{0, 1\} && \forall k \in K, \forall j \in J, \forall t \in \{1, 2, ..., N\} \end{aligned} \tag{12}$$

The objective function (Equation 1) captures the (first term) course costs, consisting of, per presented order, simulator cost, mandatory instructor cost and the estimated recovery cost of that course, (second term) costs associated with the use of helpout instructors to nonstandard courses, and (third term) offset costs to account for trainee costs of a course assigned to a standard crew. The fourth term in the objective function represents a priority factor that rewards consecutive instructor assignment, promotes compliance with rules on mandatory rest periods, and give preference to trainees with upcoming due-dates for their training (Sohoni et al., 2003). For a more detailed discussion on the objective function, model formulation, and variables definition, the reader is referred to van Kempen (2019), Section 5-2. The first set of constraints (Equation 2) forces at least one trainee to be scheduled at every simulator slot to initiate the scheduling part of the model. Then, Equation 3 ensures that simulator capacity is not exceeded. For courses stretching beyond a single session, future simulator capacity is also restricted. Equation 4 limits the training course capacity in the number of trainees. Whenever the number of trainees between ranks is not the same, a nonstandard course is scheduled. The model identifies this via the nonstandard course constraints of Equation 5, which are added for each rank. With the above-mentioned constraints, the model schedules courses based on interdependencies with demand, but it does not yet assign individuals. Equation 6, Equation 8, and Equation 10 forces trainees, instructors and helpouts to be assigned respectively in the correct number based on the scheduled courses. The correct rank is ensured via Equation 7. Furthermore, Equation 9 ensures that the assigned instructor is sufficiently qualified and Equation 11 allows each individual to be assigned in one role only (i.e. trainee, instructor or helpout). There is no qualification requirement on the helpout assignment, other than the crew member having to be an instructor. Lastly, Equation 12 display the integer bounds of the decision variables. The decision variables can be described as follows:

a_{kt}: 1 if course k starts at time t, 0 otherwise.
b_{kt}: 1 if the course k that starts at time t is scheduled with a nonstandard crew, 0 otherwise.
x_{kt}^{p}: number of trainees of position p assigned to course k at time t.
y_{ikt}: 1 if trainee i is assigned to course k at time t, 0 otherwise.

z_{jkt}: 1 if instructor j is assigned to course k at time t, 0 otherwise.
h_{jkt}: 1 if instructor j is assigned as helpout to course k at time t, 0 otherwise.

To be able to simulate the disruptions and learn the expected recovery costs, this linear model has to be solved in a matter of minutes. This is not compatible, for instance, with the run times of 18 hours for a one-year training schedule at SAS Scandinavian Airlines reported by Holm (2008). So we proposed an adaptation of the Construction Heuristic (CH) presented by Xiangtong Qi (2004). The heuristic optimizes locally instead of globally by means of a rolling horizon to solve the scheduling sub-problems sequentially. The implemented approach in this paper differs from the heuristic proposed by Xiangtong Qi (2004) as it considers h classes per iteration of a single simulator slot with the objective of scheduling one. The adapted algorithm proved to be able to solve large problem sizes, involving 5,000 annual training events and 1,000 crew members, within five minutes. The faster run time is expected to come at little expense of solution quality.

3.3. Disruption Generator

The robustness of the output schedules was demonstrated using a repeated stochastic simulation of disruptions. The model mimics the dynamic nature of illness and leave by accounting for historical disruption probabilities on crew illness and crew leave across the year. The model also caters for dynamic disruption lengths. A Monte-Carlo Simulation (MCS) approach was applied to randomly generate disruption scenarios given the roster. MCS allows to extensively test robustness on the full spectrum of the empirical distributions and combinations of disruptions, which is needed to prove the robustness of a schedule.

3.4. Training Schedule Recovery

The repetitive nature of the simulation framework requires a fast recovery model. For these reasons, we proposed a rule-based recovery (RBR) algorithm, as proposed in Ionescu et al. (2011) and Bayliss (2017). The first authors showed that rule-based recovery methods outperform the re-optimization approached in terms of run time (a couple of seconds as opposed to a couple of minutes) with only a limited impact on the solution quality. Because a rule-based recovery algorithm is non-existent for the recovery of disrupted training events, a novel algorithm is developed. This algorithm uses a fixed order based on efficiency in the various possible recovery actions. Once all conditions are met for one of the recovery actions, the action is applied. Recovery options such as using reserve crew, swapping instructors and trainees, and cancellation are included. The application of each recovery action and associated cost are output per disruption and disruption scenario. Next to its speed, a rule-based method is suited to mimic the decision-making process of an airline, increasing the validity of the research.

3.5. Learning Feedback

The results of the DG and RBR model are used by a Neural Network (NN) algorithm, which uses the same set of features. The algorithm learns over multiple iterations the nonlinear relationships between the features and the recovery costs. At each iteration, it feeds back the expected recovery cost to the TS&AM, in order to generate more robust training schedules. To estimate these costs, it uses features related to the disrupted training activity and roster states, such as the day of the week and the time of the day at which the disruptions take place, and the minimum instructor qualification required for the course. The algorithm is composed of two hidden layers with 50 neurons, it uses a Rectified Linear Unit (ReLU) activation function.

3.6. Output and Evaluation

The first time the process layer is entered, the research model will output a reference roster based on deterministic training schedule cost alone and the roster obtained after the estimation of the stochastic recovery costs, obtained after finishing the disruption simulation and recovery model. The output layer is then comprised of two different rosters and associated simulation results containing information on the recovery cost and what recovery actions are applied for each disruption.

Table 1. Normalised mean and standard deviation of the cost per assignment, where AR = Airline Roster and RR = Robust Roster.

	AR	RR
Mean recovery cost per assignment	1.21	1
Standard deviation recovery cost per assignment	1.50	1
Mean total cost per assignment	1.03	1
Standard deviation total cost per assignment	1.49	1

Table 2. Normalised number of allocated instructors per annual roster, where SR = Standard Roster and RR = Robust Roster.

	SR		RR	
	mean	σ	mean	σ
Total instructors	1	0.265	1.14	0.197
Senior	1	0.343	1.11	0.461
Examiner	1	0.283	1.27	0.285
Instructor	1.06	0.456	1	0.413
Courses per instructor	1.10	0.154	1	0.150
Overqualified instructors	1	0.668	1.01	0.502
Overqualified helpouts	1	0.403	1.02	0.348

Finally, the evaluation layer compares the two different rosters to derive and quantify ways of introducing proactive robustness in the crew training rosters.

4. Case Study

4.1. Experiment setup

The proposed modelling framework was calibrated, tested, and demonstrated in a simulation environment developed using four years of historical crew training data from a major European airline. The data was analysed to find empirical distributions of illness and leave to estimate the monetary value associated with the risk of missing due dates.

4.2. Results

The comparison of the average mean and standard deviation of the costs per assignment between the proposed approach roster, the Robust Roster (RR), and the Airline Roster (AR) is presented in Table 4.2. Due to data confidentiality, the costs are presented in relative values. The AR refers to three months of data and each roster was assessed according to 200 simulations of illness and leave events randomly generated based on historical data. The results show that the RR outperforms the AR in both recovery and total costs per assignment. On average, the RR is 21 percent more robust while decreasing the total assignment costs by 3 percent. Also in terms of results stability, the RR roster has a standard deviation of the costs about 50 percent lower than the standard deviation from the AR.

To better understand the way that the roster robustness can be increase, the allocation of instructors in the RR was compared with the allocation from a roster obtained using the TS&AM model without using the estimated recovery costs, to which we called the Standard Roster (SR). Table 4.2 presents the normalised mean number of different type of instructors used in the 200 simulated annual rosters. Instructors are classified into Senior, Examiners, and (basic) Instructors. The latter is the less experienced instructor, which can only run routine type of training programs, while Senior is the most qualified instructor. The RR roster learns that an increase in the number of instructors, in particular high qualified instructors, decreases the expected recovery costs. This results from higher flexibility to reschedule training programs, increasing the swap possibilities between trainees and between instructors. To compensate for the additional costs, the number of (basic) instructors is decreased in the RR roster. Furthermore, the total costs are reduced with having less training scheduled, on average, per simulated year. Another observed effect in the RR roster is the decrease in the number of courses allocated, on average, to each instructor. This can be explained by the fact that it results in having instructors with more distributed training duties, increasing their availability to replace unavailable instructors.

5. Conclusion

This paper contributes to the reduced literature dedicated to airline crew training schedules. In particular, the paper proposes a robust cockpit crew training schedule optimization framework. The framework consists of a Training Scheduling & Assignment Model (TS&AM), a Disruption Generator (DG), a Rule-Based Recovery (RBR) model, and a feedback loop using a Neural Network (NN) to compute the expected recovery cost. This is the first work to present such a detailed pilot schedule optimization model under disruptive operating conditions while considering flight schedule feasibility and labour agreements.

To test the effectiveness of the proposed method, both the airline roster and the rosters produced with our approach were disrupted and recovered using the data-driven disruptions impact simulator. The experiment showed that our approach outperformed the roster produced by the airline. The recovery costs can potentially be reduced by more than 20 percent. Future research should address the dependency with the flight schedule, both for resource dependencies and disruption propagation, chaining of activities and accurate modelling of crew employment.

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