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Dynamic airspace configuration by genetic algorithm

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Highlights

- An algorithm to solve a dynamic airspace configuration problem is proposed.
- The considered problem is formulated as a graph partitioning problem and is solved using genetic algorithms.
- Airspace configurations obtained using the developed algorithm, outperform the existing airspace configurations.

Abstract

With the continuous air traffic growth and limits of resources, there is a need for reducing the congestion of the airspace systems. Nowadays, several projects are launched, aimed at modernizing the global air transportation system and air traffic management. In recent years, special interest has been paid to the solution of the dynamic airspace configuration problem. Airspace sector configurations need to be dynamically adjusted to provide maximum efficiency and flexibility in response to changing weather and traffic conditions. The main objective of this work is to automatically adapt the airspace configurations according to the evolution of traffic. In order to reach this objective, the airspace is considered to be divided into predefined 3D airspace blocks which have to be grouped or ungrouped depending on the traffic situation. The airspace structure is represented as a graph and each airspace configuration is created using a graph partitioning technique. We

optimize airspace configurations using a genetic algorithm. The developed algorithm generates a sequence of sector configurations for one day of operation with the minimized controller workload. The overall methodology is implemented and successfully tested with air traffic data taken for one day and for several different airspace control areas of Europe.

Keywords:

Dynamic airspace configuration; genetic algorithm; sectorization

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1 1 Introduction

2 With the continuous air traffic growth and limited resources such as air traffic controllers, there is a need
3 for decreasing airspace congestion by adapting current airspace design to new traffic demands. In order
4 to manage air traffic safely and efficiently, the airspace is currently divided into 3D airspace volumes
5 called *sectors*. An elementary sector is defined as a volume of the airspace within which the air traffic
6 controller can perform his controlling function. Each sector assigned to a team of controllers is called a
7 controlled sector. A set of controlled sectors composes an airspace configuration. An air traffic control
8 (ATC) workload is a way of evaluating an air traffic situation inside the controlled sectors in terms of
9 several factors. The first factor is related to the number of potential conflicts in the sector. The second
10 one is linked to the monitoring workload in the sector. The last factor is a coordination workload, which
11 takes into account all aircraft that cross sector frontiers (in this case pilots and controllers have to
12 exchange information in order to ensure a safe transfer of aircraft between two sectors).

13 During the course of a day, the ATC workload fluctuates based on traffic demands between various
14 origin-destination pairings. As the traffic in the airspace is changing with time, it is necessary to consider
15 dynamic reconfiguration of the airspace for which the number of controlled sectors and their shape will
16 be adapted to the current traffic situation. Initial sectors can be temporarily combined with others into a
17 new controlled sector in order to improve efficiency of the airspace configuration. This process is called
18 dynamic airspace configuration (DAC).

19 In DAC, airspace configurations are generated so as to reduce the coordination workload between
20 adjacent controlled sectors and to achieve workload balancing between them for each time period of the
21 day. The DAC process also has to ensure that configurations are stable over time periods. Other
22 important aspects of DAC concern the reduction of multiple entries of an aircraft in the same sector and
23 the maximization of the average flight time through the sector. The DAC problem is even more critical in
24 the SESAR or NextGen framework. In comparison with a currently used fixed route network, the SESAR
25 program introduces the user preferred routing (UPR) or free routing concept to enable the airspace
26 users to plan freely 4D trajectories that suit them best. Contrarily to a fixed-route network, a free-route

27 environment will produce a much larger number of different trajectories, for which the dynamic nature
28 and flexibility of the DAC process will work most efficiently.

29 Our contribution aims at improving today's airspace management in Europe in a pre-tactical
30 phase. Our research is part of SESAR Programme (Project SJU P07.05.04) co-financed by the EU and
31 Eurocontrol. The aim of this project is to develop research prototype (decision-support tool) to support
32 new sectorization methodologies based on 4D trajectories to deal with the implementation of the free
33 routing concept in the short-term future.

34 In this paper, we present a genetic algorithms (GA) to solve the DAC problem. Our goal is to
35 produce a solution (airspace configurations for several time periods) that satisfies most constraints and
36 minimizes all costs. Our approach is based on a graph partitioning algorithm. The method is able to find
37 a solution even for large problems such as, for example, configuration of the French Airspace for 24 h.

38 This paper is organized as follows: Section 2 presents an overview of related works. In Section 3,
39 a mathematical model of the DAC problem is proposed. Here, the DAC problem is described as a multi
40 periods graph partitioning problem. A pre-processing step is presented in this section as well. In Section
41 4, GA is introduced. Section 5 describes a GA approach for the DAC problem. Results are presented in
42 Section 6. Finally, conclusions are presented in Section 7.

43 **2 Previous related works**

44 Till now, only several works concerning DAC have been produced. In fact, DAC is a quite new paradigm
45 for airspace systems. The DAC concept consists in allocation of airspace as a resource to meet new
46 demands of the airspace users. Further introduction to the DAC concept can be found in Kopardekar et
47 al. (2007) and in Zelinski and Lai (2011). The DAC concept should not be confused with dynamic
48 sectorization. The main aim of dynamic sectorization is to adapt the airspace to changing needs and
49 demands of the airspace users, by creating an absolutely new sectorization for each time period of the
50 day (Chen et al., 2013; Delahaye et al., 1998; Martinez et al., 2007). This means that at each time
51 period controllers can be obliged to work with new sectors that have different design, as they are not
52 composed of static airspace blocks, but built from "scratch". From an operational point of view, this is not
53 desirable, since controllers become more efficient as they become more familiar with airspace, i.e.

54 controlled sectors.

55 Existing approaches on DAC are based on a model in which the airspace is initially divided into 2D
56 or 3D functional airspace blocks (Delahaye et al., 1995; Klein et al., 2008; Zelinski and Lai, 2011) so that
57 the DAC problem becomes a combinatorial problem. Configurations are constructed from controlled
58 sectors, built from pre-defined airspace blocks. Nevertheless, several works are using already existing
59 and operationally valid ATC sectors (Gianazza, 2010) to construct configurations, or even full
60 configurations (Vehlac, 2005) to build an opening scheme.

61 Numerous works on airspace configuration have been produced in USA. A comparative
62 description of 7 works can be found in Zelinski and Lai (2011). In Zelinski and Lai (2011) first three
63 described works proposed methods for the DAC problem. These works were focused mainly on
64 reducing delays and reconfiguration complexity in airspace configurations. Among these works, the
65 most promising one is presented in Bloem and Gupta (2010). This work used as an input a set of given
66 functional blocks (elementary sectors) and the number of open positions at each period. An output was
67 a set of controlled sectors grouped into configurations. The workload of the sector was computed as the
68 maximum number of aircraft in the sector during a given period of time divided by a monitor alert
69 parameter (MAP). The method minimized a workload cost and a transition cost. It also satisfied several
70 constraints (taking into account as soft one): bounded workload, connectivity and convexity of controlled
71 sectors. The uncertainty of trajectory prediction was taken into account as well. The transition cost in
72 this work was computed as the number of new controlled sectors in the successive configuration. The
73 model is solved using a rollouts approximate dynamic programming algorithm based on a myopic
74 heuristic.

75 In Martinez et al. (2007), Chen et al. (2013), Trandac and Duong (2002), Tang et al. (2011),
76 methods for solving the dynamic sectorization problem (which is related to the DAC problem) were
77 presented. These works took in consideration most of the important operational constraints. However,
78 they also contained several weak points from an operational point of view. First, they did not include a
79 3D design of sectors, including some important airspace design aspects, such as sector shapes. Then,
80 these approaches did not take into account the stability of the generated configurations in time. In DAC,
81 generated configurations should have minimal changes from one time period to another, and should be

82 built with operationally workable controlled sectors. As a matter of fact, the more changes between
83 successive configurations there are, the harder it is for controllers to adapt to a new configuration.
84 Considering that the duration time of one configuration can be short (the minimum duration time is equal
85 to 20 min (Eurocontrol, 2015)), too many changes in configurations can induce safety issues.

86 In Klein et al. (2008), instead of using existing sectors, airspace building blocks, called fix posting
87 areas (FPA), were used. FPAs are assumed to be created in advance. For the complexity metric, rather
88 than using absolute occupancy counts, a relative metric is computed, i.e., occupancy count (the number
89 of aircraft in the sector) as a percentage of the sector's MAP value. The dynamic FPA concept is one
90 form of the flexible airspace management. Sectors are built from FPAs. FPAs can be dynamically
91 assigned from one sector to other during scheduled sectorization events. In case the sector is
92 overloaded in a given period of time, algorithm attempts to reassign some of sector's FPAs to a
93 neighboring sector, if it is possible. If sector is not loaded enough in a given period of time and it has a
94 neighbor sector whose metric is small enough, then this sector with all its FPAs can be combined with
95 this neighboring sector. This procedure is repeated for all sectors and all FPAs. The same principle is
96 used for vertical partitioning of sectors into FPAs, arranged by altitude (e.g., flight levels). In Klein et al.
97 (2012), the author expanded this concept to create dynamic airspace unit (DAUs). The DAUs are
98 represented as sector slices near sector boundaries. During pre-defined increments, these units are
99 dynamically shared between sectors depending on the weather and on the traffic demand. Sector
100 boundaries adjustments are used in case the complexity metric in one sector is above a certain
101 threshold.

102 The authors of Gianazza (2010) used existing controlled sectors to create suitable configurations
103 for different time periods. The decision to reconfigure controlled sectors was driven by the prediction
104 made by an artificial neural network. A classical tree-search algorithm was used to build all the valid
105 sector configurations from an initial set of controlled sectors. The tree-search algorithm explored all
106 possible airspace configurations, among which only one was chosen using evaluation criteria. The
107 computed configurations were compared to the actual configurations archived by ATC centers.

108 It should be mentioned that most of the existing approaches have been developed for the fixed
109 airway route network. The main problem of the previous approaches is that they do not include

110 reconfiguration cost. The stability of the generated configurations as well as most important sector
111 design constraints should be included in the solution of the DAC problem. The next section presents a
112 model which has been used in our work to address the DAC problem.

113 **3 Problem modeling**

114 *3.1 Problem description*

115 Given a forecast on air traffic demand, the DAC problem consists in finding a suitable airspace
116 configuration for each time period, built from a given set of airspace blocks, such as to minimize some
117 cost functions. The main objective of the DAC process is to minimize the workload imbalance and the
118 coordination workload in each airspace configuration. Each configuration should consist of a number of
119 controlled sectors best suited for the given time period. Controlled sectors should be built from
120 predefined airspace blocks, such as to be accepted by ATC experts. Therefore, they should satisfy
121 some geometrical and operational constraints. The quality of the airspace configuration can be
122 evaluated according to several criteria. In this work, the cost function includes the following criteria.

- 123 • The imbalance between the workload of the resulting controlled sectors.
- 124 • The coordination workload.
- 125 • The number of flight re-entry events.
- 126 • The number of short transits flight through sectors.
- 127 • The number of controlled sectors in each airspace configuration (should not exceed a given
128 maximum).

129 All those criteria should be minimized during the optimization process. The workload imbalance
130 minimization means that each sector in each configuration should approximately be loaded with the
131 same amount of traffic at each period of time. The minimization of the coordination workload, and thus
132 the controller workload, implies the minimization of the number of traffic flows, cut by sector borders.
133 Then, the aircraft should not enter the same sector several times. Finally, any entering aircraft must stay
134 between each sector a given minimum amount of time. This is an important safety constraint, as it
135 requires a lot of time for the controller to spend on coordination functions. For the controller of the sector,

136 it is hard to manage a conflict between two aircraft in a safe way, if one or both aircraft are passing
137 through this sector too fast.

138 Then, there are several constraints arising from the sector design methodology. Configurations and
139 controlled sectors have to satisfy the following constraints.

- 140 • Airspace blocks combined into one controlled sector should be connected.
- 141 • There should be continuity between resulting configurations.
- 142 • Shapes of sectors (in a lateral view) such as "stairs" or "balconies" should be restricted.

143 Last two constraints are considered as soft ones.

144 The presented list of criteria and constraints is designed according to Eurocontrol requirements and
145 developed in co-operation with operational experts (Eurocontrol, 2015). All those criteria are included in
146 the model described in the next part.

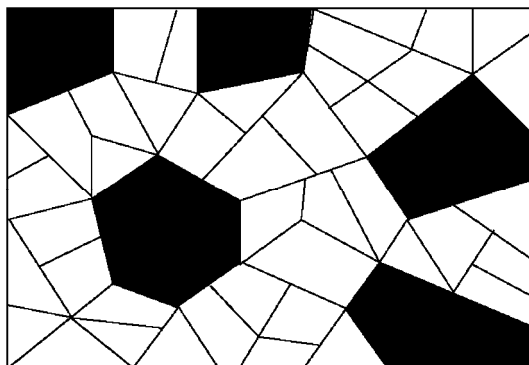
147 3.2 *Airspace modeling*

148 According to Kopardekar et al. (2007) and Zelinski and Lai (2011) in the current DAC concept, sector
149 configurations are constructed by combining existing elementary sectors, provided as an input.
150 Nevertheless, in this work, we introduce a new DAC concept, proposed and developed in cooperation
151 with Eurocontrol for SESAR (Eurocontrol, 2015; Sergeeva et al., 2015). This new concept increases
152 the adaptability of the airspace to the traffic pattern, by delineating from the nominal elementary sectors,
153 to a larger number of new airspace components, that can be easily combined into rather more adaptable
154 control sectors. The idea of this concept is that instead of being trained on a full elementary sectors,
155 airspace controllers can be trained only on a most congested areas, comprised inside smaller airspace
156 blocks. Two types of airspace blocks are specified in this concept (Fig. 1). In Fig.1, the black blocks are
157 non-sharable and the white ones are sharable.

158 (1) Sector building blocks (SBBs) are permanently busy areas with a high traffic load, delineated by
159 recurring traffic patterns. Often, SBBs blocks are small and cannot be sub-divided further. Each SBB is
160 considered as a core of a future control sector. SBBs can be sufficiently large than SAMs, in order to be
161 workable and controllable. It should be noticed that the control sector should include at least one SBB.

162 (2) Sharable airspace modules (SAMs) are built in less busy areas with a temporary high traffic

163 load. SAMs can be re-allocated laterally or vertically between neighboring control sectors within a sector
164 configuration process, in order to equally balance the traffic load among the control sectors. SAMs
165 cannot be used separately in the configuration.



166
167 **Fig. 1** Initial airspace blocks (2D projection).

168 Each controlled sector is supposed to be built of at least one non-sharable block and several
169 sharable blocks. Building of the controlled sector starts from choosing a central block, which can be
170 chosen only among non-sharable blocks. The number of non-sharable blocks is limited; this guarantees
171 that the central part of each controlled sector will be stable between several configurations. Even if the
172 number of controlled sectors is different in two successive configurations, centers of the controlled
173 sectors will be chosen among the same small group of non-sharable blocks. This partly insures
174 continuity between successive airspace configurations.

175 3.3 Graph modeling

176 In this section we describe a weighted graph model of the airspace. Let a graph $G = (N, L)$ represent the
177 airspace, where N is a set of nodes and L is a set of links. In this graph each node represents sharable
178 or non-sharable block and each link represents the relation is neighbor with between two nodes (Fig. 2),
179 it means that when two blocks share a common vertical or horizontal border, a link is built between
180 them. In Fig.2, solid nodes represent non-sharable blocks, and hollow nodes represent sharable blocks.
181 Weight of the node represents the monitoring workload and weight of the link represents the
182 coordination workload.

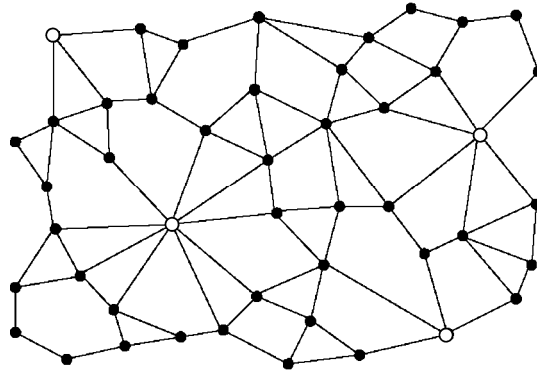


Fig. 2 Example of the initial graph.

183

184

185 The workload assessment is a key requirement for generation of the workable sector
 186 configurations in a context of free route environment. In order to evaluate the monitoring workload, in
 187 each block, an occupancy count is used. The occupancy count metric is computed as the number of
 188 aircraft inside the airspace block at each minute of an associated time period. The weight of the link
 189 (coordination workload) is computed as the number of aircraft crossing the border between two airspace
 190 blocks connected by this link. Both monitoring and coordination workloads of airspace blocks are
 191 computed for each given time period.

192 3.3 A graph partitioning problem

193 Based on the weighted graph described above, our problem consists in finding an optimal multi-period
 194 graph partitioning. For each given time period, we must find an optimal grouping of airspace blocks that
 195 satisfies all the constraints. The time periods (opening scheme) are considered to be an input data.

196 A connectivity constraint on airspace blocks belonging to the same sector means that nodes
 197 belonging to the same component have to be connected. This means that for each pair of nodes
 198 belonging to the same component, there is a path connecting them.

199 For a given time period t_i , the resulting configuration is modeled in the following way: $X_i = \{N_1,$
 200 $N_2, \dots, N_{K_i}\}$, where N_j represents the set of nodes belonging to the component j , K_i represents here the
 201 number of component for time period t_i . K_i value is controlled by the optimization process and has to be
 202 less than S_n , where S_n is the maximum number of available controllers. Having a problem with several
 203 time periods $\{t_1, t_2, \dots, t_p\}$, the associated graph partitioning problem have to be optimized for each

204 period.

$$205 \quad \begin{cases} X_1 = \{N_{11}, N_{12}, \dots, N_{1K_1}\} & \text{for } t_1, K_1 \\ X_2 = \{N_{21}, N_{22}, \dots, N_{2K_2}\} & \text{for } t_2, K_2 \\ \vdots \\ X_P = \{N_{P1}, N_{P2}, \dots, N_{PK_P}\} & \text{for } t_P, K_P \end{cases} \quad (1)$$

206 3.3 Objective function

207 Based on the state space definition, we now model the associated objective function. Five criteria are
208 included in our objective function for evaluation of a solution (resulting configurations).

209 The first criterion measures the total level of the workload imbalance in each configuration,
210 separately for each time period t_i ($i = 1, 2, \dots, T$). The workload of the controlled sector is computed as a
211 sum of the workloads of airspace blocks which are composing this sector. The workload imbalance of all
212 sectors in the configuration for the time period t_i is computed using Eq. (2).

$$213 \quad U_t = \sqrt{\frac{\sum_{k=1}^{K_i} \left(\frac{\|W_{c_{ik}} - c\|}{c} \right)^2}{k_i}} \quad (2)$$

214

215 where K_i is the number of controlled sectors in the configuration for period t_i , $W_{c_{ik}}$ is the total workload of
216 all airspace blocks composing the sector k for period t_i , c is a targeted workload of the sector.

217 c is a user-defined parameter and can be computed, for example, as a capacity of a sector. The
218 capacity of a controlled sector can be defined as the maximum number of aircraft that are controlled in a
219 particular sector in a specified period, while still permitting an acceptable level of controller workload
220 (Majumdar and Ochieng, 2002). The way sector capacity is computed depends on the controller
221 workload definition. Often it is computed as the maximum number of flights that a controller can handle
222 in one hour without breaking a theoretical threshold (Christien et al., 2003). In this work, the
223 maximum sector capacity is taken for 1 min (the workload is computed as occupancy count). The
224 maximum acceptable number of flights per 1 min is equal to 8 (this number was provided by

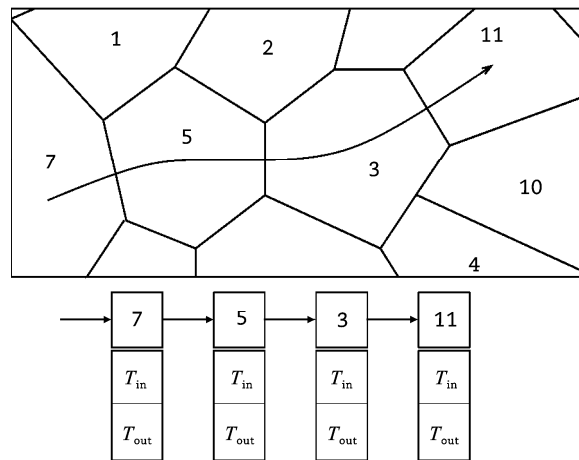
225 Eurocontrol and reflects realistic operational value). Then, the maximum sector capacity for the
 226 time period of 1 h is equal to 8 aircraft multiplied by 60 min. As we would like to obtain controlled
 227 sectors that are not extremely loaded, c is computed as the maximum sector capacity weighted by the
 228 reduction coefficient, which is equal to 75% (value provided by Eurocontrol). Then, for the time period of
 229 1 h, the targeted workload c is equal to 360.

230 The second criterion included in the objective function, measures the transfer traffic between
 231 neighboring blocks (a flow cut). When two neighboring blocks belong to different sectors, the traffic flow
 232 between them is getting cut by the sector's border, increasing the coordination workload of sectors. The
 233 total flow cut for the time period t (FC_t) is given by Eq. (3).

$$234 \quad FC_t = \sum_{\substack{(i,j) \in L \\ i \in N_m, j \in N_m \\ m \neq n}} f_{ij}^t + f_{ji}^t \quad (3)$$

235 where $f_{ij}^t + f_{ji}^t$ is the number of aircraft crossing the border between blocks i and j (in both directions) at
 236 the time period t , computed using a known set of links.

237 The number of re-entries (N_{r_t}) and the number of short transits (N_{s_t}) inside the controlled sectors at
 238 the time period t_i are included in the objective function as well. In order to be able to compute re-entry
 239 events and short transits inside created controlled sectors, we register the list of airspace blocks
 240 crossed by each trajectory with the associated time horizon (Fig. 3). In Fig.3, each element of a list
 241 contains the ID of a block and a crossing time.



242

243

Fig. 3 List of airspace blocks associated to a given trajectory.

244

Then, using this list of airspace blocks associated to each trajectory (list of traversed blocks), it is

245 possible to compute N_{r_t} and N_{s_t} for each time period. It is done in several steps.

246 (1) We first transform a list of associated airspace blocks into a list of controlled sectors associated to
247 each trajectory.

248 (2) To compute the re-entries, we check if in the aircraft's list of traversed sectors there is no situation
249 when the aircraft enters the same sector several times, and if there is, we add one re-entry to N_{r_t} .

250 (3) For computing the number of short-crossings, we check the time that the aircraft stays in each
251 sector, and if this time is smaller than a given value, we add one short-crossing to N_{s_t} .

252 Finally, the last criterion included in our objective function (N_{b_t}) measures the number of "balconies".
253 This type of sector shape (in the lateral view) is not desirable but acceptable, that is why this criterion is
254 included in the objective function. The number of "balconies" is computed during the evaluation process,
255 using the set of links.

256 All those criteria are normalized in order to have values $\in (0, 1)$ and aggregated into one objective
257 function (Eq. (4)) which is used to evaluate each configuration, created during the optimization process.

$$258 \quad \min(y) = \alpha_1 U_t + \alpha_2 Fc_t + \alpha_3 N_{r_t} + \alpha_4 N_{s_t} + \alpha_5 N_{b_t} \quad (4)$$

259 where $\alpha_1 - \alpha_5 \in (0, 1)$ are proportion coefficients.

260 Then, the objective function associated to the whole planning is computed as an average value of
261 the evaluation of each configuration. The proportion coefficients in the objective function enable to
262 obtain optimized results for different scenarios.

263 The number of the controlled sectors in configuration is minimized during the optimization process,
264 due to minimization of the workload imbalance (while trying to keep sectors workload close to a given
265 value, we also optimize the number of sectors in each configuration).

266 3.4 Combinatorial optimization problem

267 Based on the airspace model described above, the DAC problem is formulated as a combinatorial
268 optimization problem, which consists in finding an optimal partitioning of the graph into several
269 connected sub-graphs for each defined time period. Moreover, several operational constraints have to
270 be taken into account during the partitioning process and this makes it difficult to use most common

271 techniques for solving the graph partitioning problem.

272 The proposed formulation of the DAC problem, as a graph partition problem, is highly combinatorial.

273 The size of the state space (the number of states that the problem can be in) depends on the number of

274 blocks N_b , on the number of controlled sectors K_i and on the number of opening time periods N_t . For

275 each time period we must find an optimal grouping among $S_{N_b}^{K_i}$ of possible combinations of N_b blocks

276 into K_i sectors, where $S_{N_b}^{K_i}$ is a second Stirling number. The second Stirling number is computed using

277 Eq. (5).

$$278 \quad S_{N_b}^{K_i} = \frac{1}{K_i!} \sum_{j=0}^{j=K_i-1} (-1)^j \left(\frac{K_i!}{j!(K_i-j)!} \right) (K_i-j)_b^N \quad (5)$$

279

280 The state space of our problem is discrete and its size grows exponentially fast. An example of the

281 number of possible combinations of 16 blocks is shown below.

K_i	$S_{16}^{K_i}$	K_i	$S_{16}^{K_i}$
1	1	9	820,784,250
2	32,767	10	193,754,990
3	7,141,686	11	28,936,908
4	171,798,901	12	2,757,118
5	1,096,190,550	13	165,620
6	2,147,483,647	14	6020
7	2,147,483,647	15	120
8	2,141,764,053	16	1

282

283 The combinatorics of such a problem can become extremely high, especially if we want, for

284 example, to obtain airspace configurations for the whole day and we take one time period equal to 30

285 min.

286 Typically, graph partition problems fall under the category of NP-hard problems (for more details

287 see Kernighan and Lin (1970), Savage and Wloka (1989)). For an NP-hard problem, where

288 state-of-the-art exact algorithms cannot solve the handled instances within the required search time, the
289 use of metaheuristics is justified. Metaheuristics do not guarantee to find optimal solutions, however,
290 they allow to obtain good solutions in a significantly reduced amount of time (Blum and Roli, 2003; Talbi,
291 2009). Their use in many applications shows their efficiency in solving large NP-hard problems.
292 Metaheuristics can be roughly divided into population-based algorithms and non-population-based
293 algorithms (Talbi, 2009). While solving optimization problems, non-population-based metaheuristics
294 improve only one solution, while the population-based algorithms explore the search space by evolving
295 a whole population of candidate solutions. Population-based metaheuristic methods are well adapted
296 for problems that require not a lot of memory to code the state space (in our case, it requires less than 1
297 Mb).

298 The proposed model of DAC can be solved using different techniques (Antosiewicz et al., 2013;
299 Han and Zhang, 2004; Silberholz and Golden, 2010). Non-population-based algorithms, such as
300 Simulated Annealing for example, can allow to converge more rapidly to an optimal solution than
301 population-based algorithms (Kohonen, 1999). Nevertheless, the convergence speed mainly depends
302 on the implementation of the algorithm and on the size of the state space of the problem. In case of the
303 problem with a large state space of feasible solutions (like the DAC problem), it is hard to avoid
304 non-population-based algorithms getting stuck at local minima. On the other hand, in population-based
305 algorithms, solutions are being independently improved at the same time and this makes this type of
306 algorithms less prone to get stuck in local optima than alternative methods (Mukherjee et al., 2015; Nair
307 and Sooda, 2010; Rossi-Doria et al., 2002).

308 The DAC problem can have several different optimal solutions, due to the different possible
309 symmetries in the topological space. As we have several objectives to be satisfied, we can obtain
310 several different solutions with the same value of the objective function. We must be able to find most of
311 the near-optimal solutions, as they have to be evaluated and refined by experts. This last point makes
312 us reject non-population-based algorithms which update only one state variable, i.e. improve only one
313 possible solution.

314 In this work, we aim to obtain a compromise between the quality of the solution and the CPU time
315 required to reach it. Population-based algorithms, such as EAs, maintain and improve a population of

316 numerous state variables according to their fitness and are able to find several optimal solutions. EAs
317 can guarantee stable optimization results even for big problem instances, computed within a reasonable
318 time. EAs are also a good choice if we would like to extend our model to a multi-objective one. Thus,
319 EAs are relevant to solve the DAC problem.

320 **4 Evolutionary algorithms**

321 Evolutionary algorithms (Back et al., 1991; Davis, 1991; Fogel and Owens, 1966; Goldberg, 1989;
322 Holland, 1975; Koza, 1992; Michalewicz, 1992) use techniques inspired by evolutionary biology to find
323 approximate solutions of optimization problems. An individual, or solution of the problem, is represented
324 by a list of parameters, called chromosome. Initially several such individuals are randomly generated to
325 form the first initial population ($POP(k)$ in Fig. 4). Then each individual is evaluated, and a value of fitness
326 is returned by a fitness function. This initial population undergoes a selection process which identifies
327 the most adapted individual. The one which is used in our work is a deterministic (λ, μ) -tournament
328 selection (Miller and Goldberg, 1995). This selection begins by randomly selecting λ individuals from the
329 current population and keep the μ best ($\lambda > \mu$). These two steps are repeated until a new intermediate
330 population (POP_i) is completed. Then, three following recombination operators are applied to individuals:
331 nothing ($1 - P_c - P_m$), crossover (P_c), or mutation (P_m) with the associated probability respectively.

332 The chromosomes of two parents are mixed during crossover resulting in two new child
333 chromosomes, which are added to the next population. Mutation is an operator used to maintain genetic
334 diversity from one population of chromosomes to the next one. The purpose of mutation in EAs is to
335 allow the algorithm to avoid local minima by preventing the population of chromosomes from becoming
336 too similar to each other, thus slowing or even stopping evolution.

337 These processes ultimately result in the next population of chromosomes ($POP(k+1)$ in Fig. 4). This
338 process is repeated until a termination condition has been reached. As a termination condition, we can
339 use the maximum number of generations. In Fig.4, on the first step best individuals are selected from
340 population $POP(k)$. Then, recombination operators are applied to produce the $POP(k+1)$ population.

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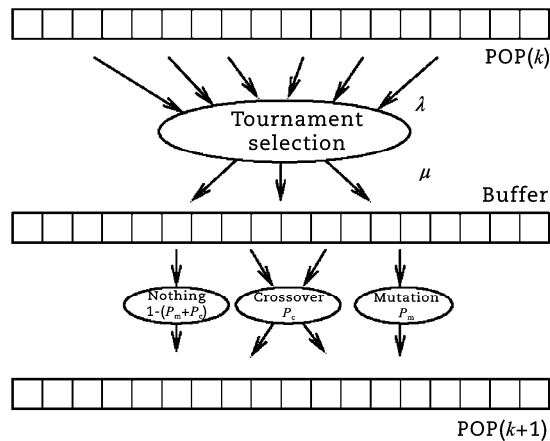


Fig. 4 Genetic Algorithm with tournament selection.

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345 5 Application of GA to the DAC problem

346 5.1 Coding the chromosome

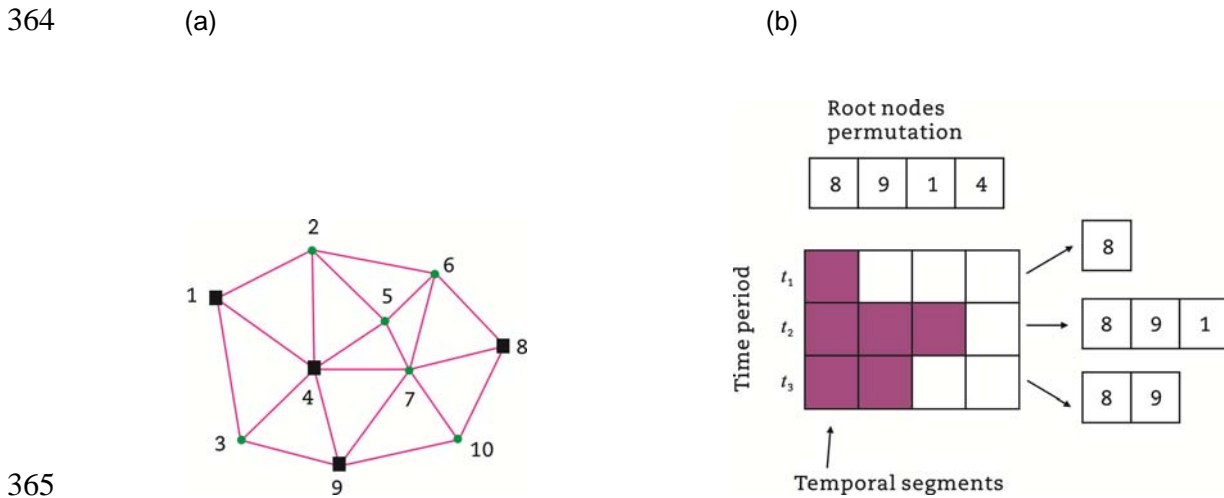
347 Based on the proposed problem modeling, a way of coding configurations for each time period
 348 (chromosome) has to be developed. In the previous section, we have proposed a way of modeling the
 349 airspace configuration as a set of connected components (subgraphs). The coding used for this problem
 350 consists in representing connected components by sub-sets of nodes for each time period.

351 The chromosome used in this work consists of two layers. The first layer controls the number of
 352 opened controlled sectors and theirs centers per each time period. The second layer contains all
 353 sub-sets of connected components obtained for each time period, i.e., the list of all airspace blocks with
 354 the associated number of the controlled sector for each time period. Thus, the first layer controls root
 355 nodes (non-sharable blocks) and consists of two tables. The first table includes all permuted
 356 non-sharable nodes and the second one contains temporal segments for each root node (Fig. 5). In Fig.
 357 5, non-sharable blocks (potential root nodes) are represented as squares and sharable blocks as
 358 circles.

359

360 The temporal segments include the information about the number of the controlled sectors used per

361 each time period. The second layer manages the set of connected components (for each time period)
 362 and is represented as a table that contains all nodes with their associated component number (Section
 363 5.2).

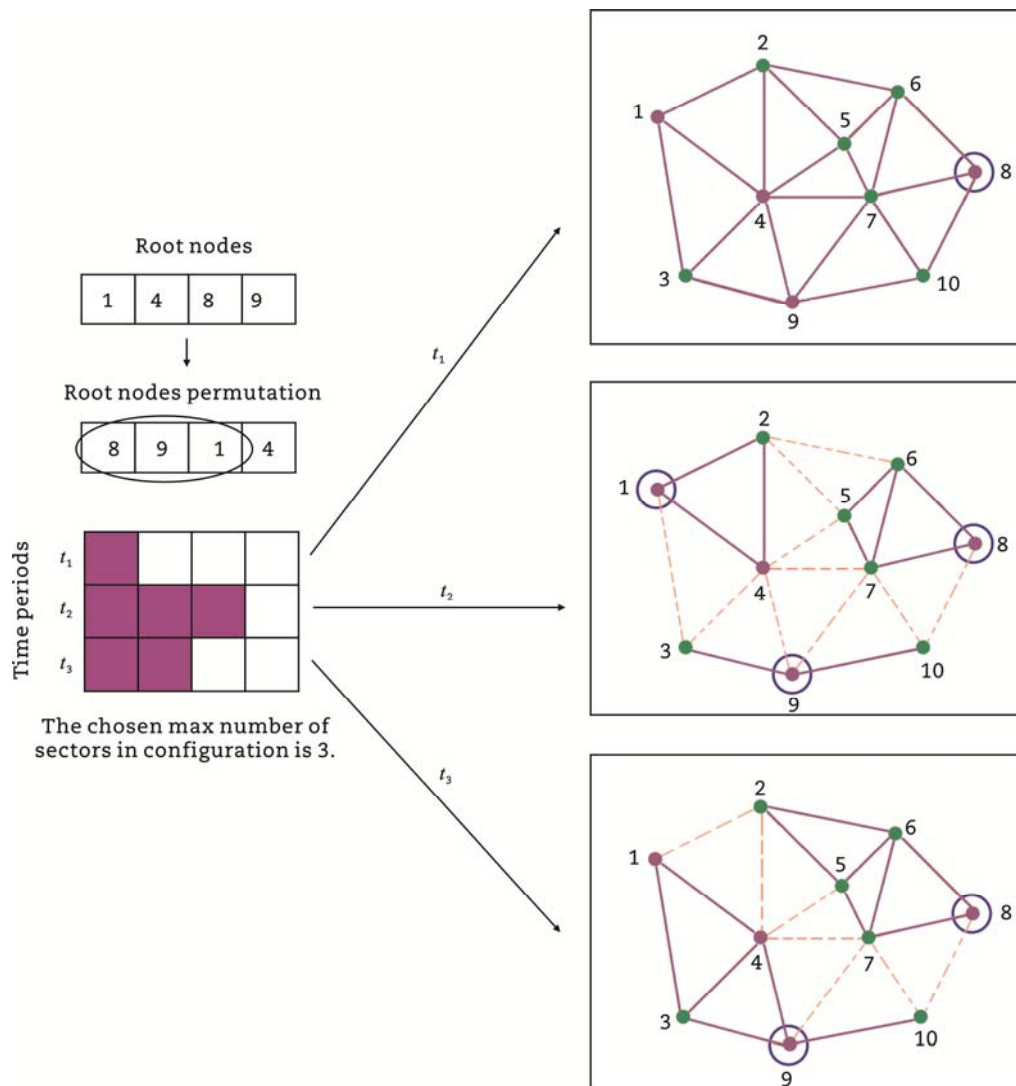


365
 366

Fig. 5 Chromosome structure. (a) Initial graph. (b) First layer of chromosome.

367 **5.2 Initialization of the chromosome**

368 Each solution (chromosome) in a population is first initialized randomly. As our chromosome consists of
 369 two parts, the process of initialization of the chromosome is divided into two steps. On the initial step, for
 370 each time period, several root nodes are randomly selected from the permutation table (initially this
 371 table is randomly generated for each solution in the population) which contains all non-sharable nodes
 372 as shown in Figs. 5 and 6. Those selected nodes are considered as root nodes - central parts of each
 373 subgraph. The minimum number of root nodes that can be selected is equal to 1 and the maximum is
 374 equal to the maximum allowed number of the controlled sectors per configuration, i.e., to the number of
 375 available controllers.



376

377 **Fig. 6** Resulting graph partition for the 3 time periods, obtained using a table of root nodes and temporal time segments.

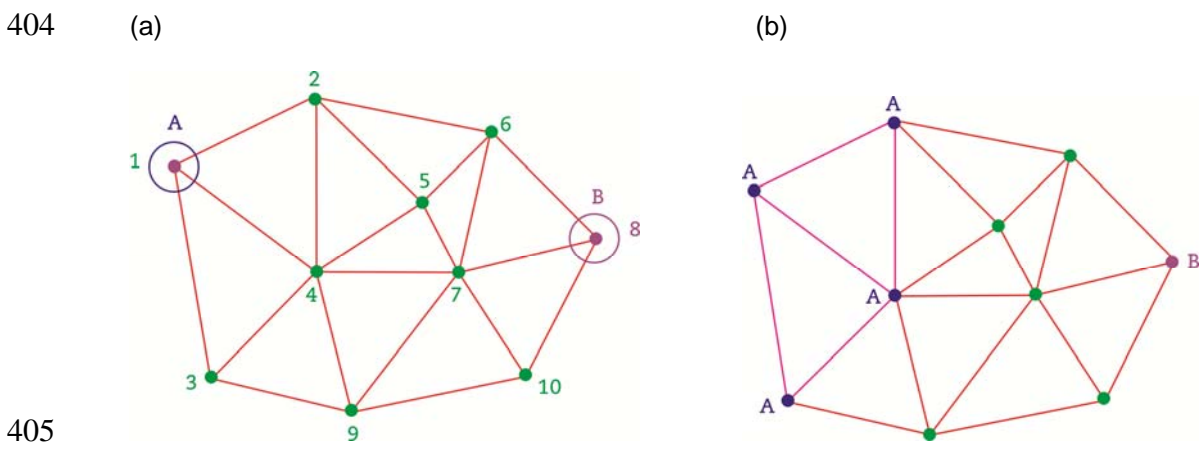
378 On the next step, temporal segments are randomly built. After this, all selected root nodes are
 379 associated with time periods. For each time period, several root nodes can be selected. The number of
 380 the selected root nodes per time period is first chosen randomly and then is optimized in the algorithm.
 381 The first root node in the permutation table participates in the partitioning process for each time period
 382 (node 8 in Fig. 6).

383 In the example illustrated in Fig. 6, the number of non-sharable nodes and potential root nodes is
 384 equal to 4 (nodes 1, 4, 8 and 9) and the maximum number of the controlled sectors per configuration is
 385 equal to 3. Three time periods are considered and three temporal time segments are generated
 386 randomly. Each time segment cannot have a length bigger than 3. At the time period 1 there is one

387 sub-set created with root node 8, and time period 2, with root nodes 8, 9 and 1, and etc. The initial
 388 permutation of the root nodes in different solutions ensures a random mapping between temporal
 389 segments and root nodes (this avoids the same root node to be associated with the first temporal
 390 segment in different solutions).

391 This way of coding the chromosomes with temporal segments ensures the stability in time of
 392 shapes of controlled sectors. For successive time periods, the same root nodes are used as sector
 393 centers, ensuring these volumes of airspace being controlled by the same controllers. As a matter of
 394 fact, compared with the other works on DAC, the main advantage of our method is that the stability of
 395 configurations in time is insured by the proposed model of the configuration process. Most of the
 396 existing methods in the literature, instead, include a reconfiguration cost as one of the objectives. This
 397 cannot always insure the stability of configurations in time, as often the reconfiguration cost is computed
 398 simply as a difference of the number of the controlled sectors in the successive configurations.

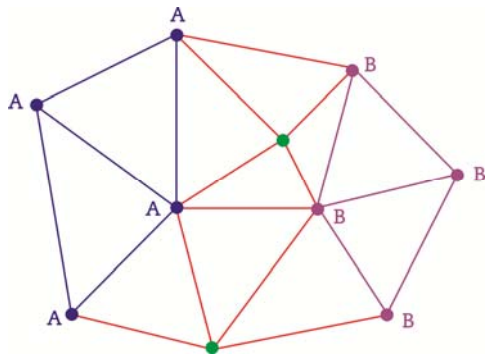
399 After producing the first layer of the chromosome, a graph partitioning algorithm is applied for the
 400 second layer. In the example illustrated in Fig. 6, for 3 time periods, 3 subgraphs are built, using the
 401 associated list of selected root nodes for each time period. The developed graph partitioning algorithm
 402 ensures that nodes of the same sub-set are connected by at least one path. The process of building
 403 connected components using greedy heuristic is illustrated in Fig. 7.



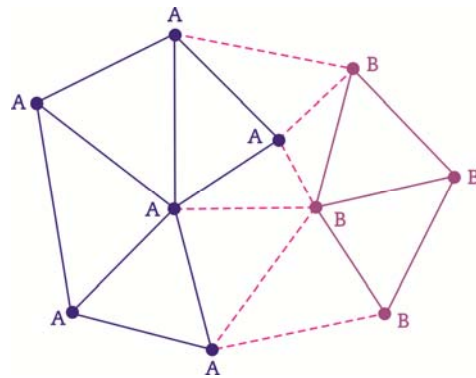
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 406
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 408

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(c)



(d)



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411

Fig. 7 Greedy heuristic is used to create initial partitions. (a) Step 1. (b) Step 2. (c) Step 3. (d) Step 4.

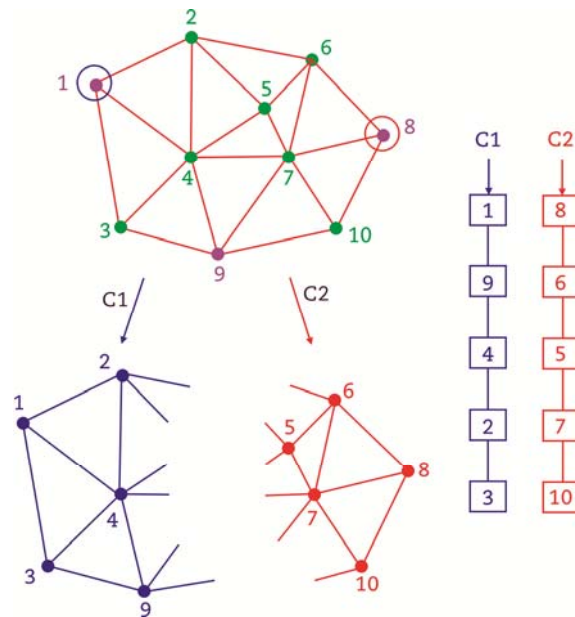
412

This heuristic takes the first root node and propagates it on its neighbours (step 2). Then, the second root node is propagated also on its neighbours (step 3). Then, the algorithm propagates again the first component (step 4) and this process is repeated until all nodes are associated with their components. At the end, each connected component is coded as a list of nodes (Fig. 8).

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Fig. 8 Example of the coding used for one time period. Here, the graph is partitioned into two components using two root nodes 1 and 8.

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419

After creating the first population of solutions, each solution is evaluated using the objective function. Then, after the selection process, the recombination operators are applied resulting in a new population.

420

421

422 5.3 *Recombination operators*

423 5.3.1 *Recombination operators for the first layer of the chromosome*

424 The first layer of the chromosome controls the choice of root nodes used for all time periods.

425 (1) Temporal segment crossover

426 In this crossover operator, two or more solutions (parents) exchange part of their chromosome,
427 resulting in two new solutions. Based on time interval sets from two randomly selected solutions, a
428 crossover has been developed in which, most probably, the individual with the worst performance will
429 receive temporary segments of the second one (i.e., we copy the first layer of chromosome from a good
430 solution to a bad one).

431 (2) Temporal segment mutation

432 The mutation operator starts by selecting a solution from the population. An individual with low
433 performances has more chances to be selected. Then one configuration is selected either randomly or
434 according to its performance. This mutation operator changes the number of the temporal segments in
435 the solution by adding or removing one segment, i.e., adding or removing one controlled sector into
436 configuration for a selected time period. The number of segments has to stay in the following range $[1,$
437 $|N_R|]$ where N_R is the set of root nodes in the network.

438 (3) Root nodes mutation

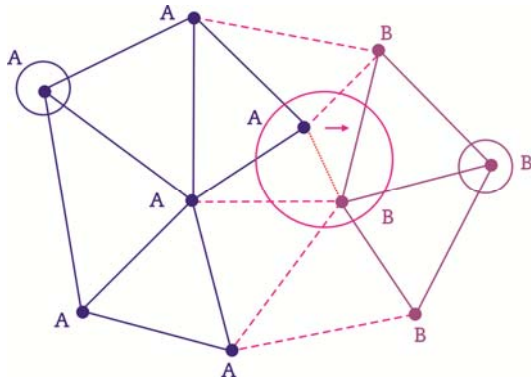
439 The mutation operator starts with randomly selecting a solution from the population. The aim of
440 this operator is to change initial permutation table of root nodes. The operator simply changes the order
441 of root nodes by randomly exchanging two nodes in the permutation table.

442 5.3.2 *Recombination operators for the second layer of the chromosome*

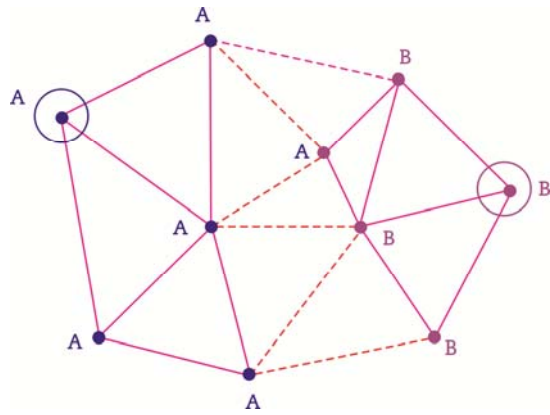
443 For the second layer, we only use one mutation operator. After choosing a solution from the population,
444 the operator selects a time period according to the associated graph partitioning performances,
445 meaning that a bias is added for the period with a low performance. Then the graph partitioning mutation
446 operator is applied (Fig. 9).

447

448 (a)



(b)



449

450 **Fig. 9** Graph partitioning results for the second layer of the chromosome. (a) Before applying the developed mutation operator.

451 (b) After applying the developed mutation operator.

452 This operator begins by statistically selecting the component with the worst performance. Then, in
453 case the selected component is overloaded (sector workload > targeted workload), it seeks the
454 neighbouring component with the least load. In case the selected component is underloaded, the
455 operator searches the neighbouring component with the higher load. This second step is also carried
456 out statistically (introducing a bias into a random selection). We thus obtain a link between the two
457 components. A node is then moved from the most loaded component to the least loaded one, while
458 verifying that the component losing a node remains connected.

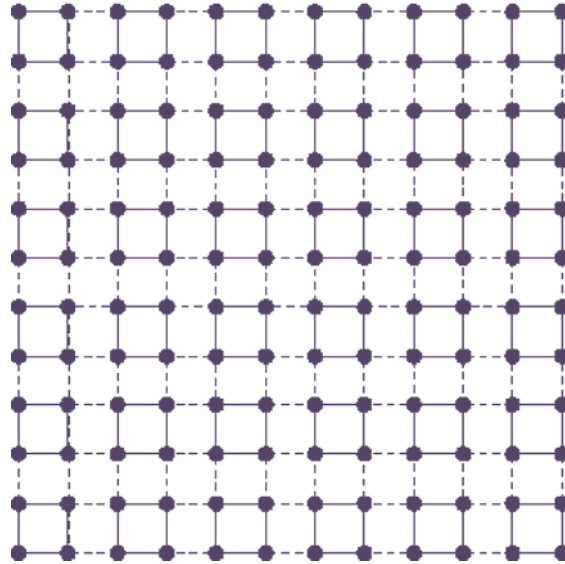
459 6 Results and discussions

460 This algorithm has been tested on several different problems in order to check its efficiency and its
461 future perspective. The algorithm is able to provide different kind of results according to expert
462 requirements.

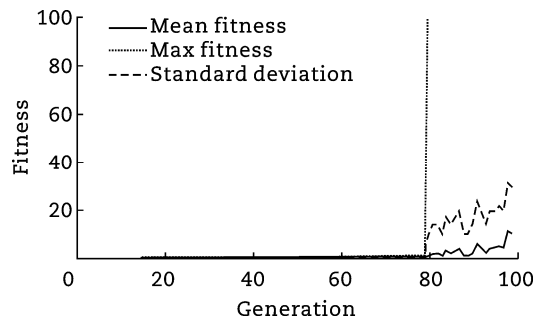
463 6.1 First test: application to a network with symmetries

464 In order to evaluate this algorithm, a network with symmetry has been built for which, a solution is easy
465 to investigate for a human being due to our ability to see such symmetry but which has no particular
466 features for the algorithm. This network is built with 144 blocks which are extended on 10 time periods.
467 Those 144 blocks are symbolized by nodes on the graph in Fig. 10. For this network it is very easy to

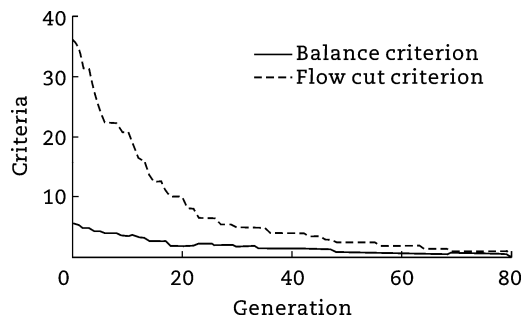
468 identify 36 sectors. With only 100 individual in the population and 100 generation, the algorithm is able
469 to identify the best solution at generation 80 as it can be seen on Figs. 11 and 12.



470
471 **Fig. 10** Graph with symmetries.
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473
474 **Fig.11** Graph with symmetries: fitness evolution (mean, max, standard).



475
476 **Fig. 12** Graph with symmetries: criteria evolution (balance, flow cut).
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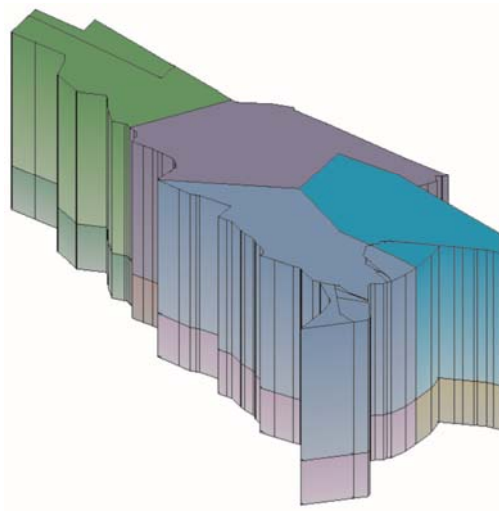
478 Having validated our algorithm on the toy network, we propose now to apply it on a real airspace.

479

480 6.2 Second test: application to a real airspace

481 Our algorithm has been tested on a Maastricht (EDYYBUTA) Area Control Center (ACC). This area
482 initially consists of 8 elementary sectors. For this second test we have prepared two scenarios. In the
483 first scenario, we use existing elementary sectors of today's airspace (Fig. 13). Those sectors are big
484 and not flexible enough, as they are loaded differently during the day. For this scenario, the number of
485 initial sectors is small, and so all of them are considered as non-sharable blocks. In the second scenario,
486 we use 32 sharable and non-sharable blocks (Fig. 14) located on 2 altitude layers and created only for
487 the purpose of our experiments in order to increase the flexibility of new sector configurations (Sergeeva
488 et al., 2015). These blocks are much smaller; as a result, the workload is better distributed between
489 them. Each scenario is based on free route simulated trajectories, which provide a sample of full free
490 route trajectories for the 11th of July 2014 crossing Maastricht/Amsterdam Airspace.

491 Tuning of the controlling parameters of the algorithm (such as generations number, population size,
492 mutation/crossover ratio) is required due to the specific properties of each airspace area. The parameter
493 values are selected after running several tests in order to obtain a required result.



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495

Fig. 13 Eight elementary sectors of the Maastricht ACC (EDYYBUTA).

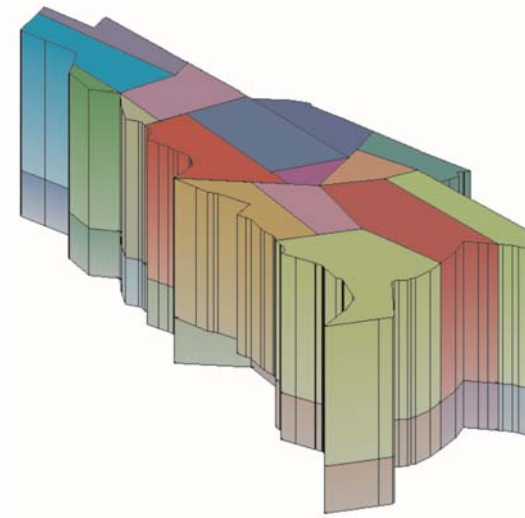


Fig. 14 Thirty-two experimental sharable and non-sharable blocks.

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In this test, the mutation rate is selected to be bigger than the crossover rate, as the mutation operators allow the algorithm to converge faster. The number of generations and the size of the population are chosen according to the size of the network. For example, the first scenario requires smaller number of generations in order to obtain a near optimum solution. The values of proportion coefficients in the objective function are chosen according to interviewed operational experts. The highest priority is given the workload imbalance minimization. The remaining criteria are sorted by priority as follows: short-crossings, re-entries, the number of “balconies” and flow cuts.

The parameters defining the overall resolution methodology for both scenarios are empirically set, and presented in Table 1.

Numerical results from computational experiments for two proposed scenarios are presented in Tables 2 and 3. These two tables include the following data (per each time period): the number of sectors in the configuration, an average workload imbalance per 1 h, the number of re-entries and the number of short-crossings. The execution time for both scenarios is less than a few minutes (1-2 min).

516

Table 1 Values of main criteria of the algorithm.

Parameter	Scenario 1	Scenario 2
Generations	200	1000
Population size	300	1000
Mutation/crossover ratio	0.6/0.2	0.6/0.2
Targeted workload	360	360
Time period (h)	7 – 18	7 – 18
Period size (h)	1	1
$\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$	0.6, 0.05, 0.1, 0.1, 0.2	0.6, 0.05, 0.1, 0.1, 0.2

517

Table 2 Results for the scenario 1.

Time period (h)	Number of sectors	Imbalance	Number of re-entries	Number of short-crossings
7 – 8	4	0.10	0	1
8 - 9	5	0.24	0	6
9 – 10	5	0.30	0	11
10 – 11	5	0.22	0	7
11 - 12	5	0.19	0	9
12 – 13	4	0.20	0	3
13 – 16	6	0.18	0	9
16 – 17	4	0.24	0	8
17 – 18	4	0.10	0	6

518

Table 3 Results for the scenario 2.

Time period (h)	Number of sectors	Imbalance	Number of re-entries	Number of short-crossings
7 – 8	5	0.10	4	7
8 – 9	5	0.14	3	11
9 – 10	5	0.18	2	6
10 – 11	5	0.17	7	8
11 – 12	5	0.13	2	8
12 – 13	5	0.12	5	8
13 – 14	6	0.14	4	8
14 – 15	6	0.08	6	8
15 – 16	5	0.05	2	9
16 – 17	5	0.08	1	5
17 – 18	4	0.06	2	6

519

520 Controlled sectors built by the algorithm for the second scenario are much better balanced in
 521 terms of the workload than sectors built for the first scenario. However, some of the sectors proposed for
 522 the second scenario have undesired shapes like “balconies”. Nevertheless, balanced sectors with only
 523 few “balconies” are considered by operational specialists as an acceptable solution. Then, the number
 524 of re-entries is higher for the second scenario, this is explained by the shape of the initial blocks; they do
 525 not have enough convex shapes, thus, combinations of such blocks are not well adapted to a traffic
 526 pattern.

527 The second scenario proves the idea of using more adaptive blocks instead of those that are
 528 currently used in the airspace management. As a matter of fact, the quality of the workload balance is
 529 mainly linked to the number of input blocks. With a bigger number of input blocks we can obtain less
 530 unbalanced sector configurations.

531 From the provided results we can conclude that the algorithm is quite efficient for the workload
 532 balancing. However, it is hard for the algorithm to remove all defects of sector shapes such as
 533 “balconies” and obtain sectors with convex shapes. The algorithm can later be modified in order to
 534 receive rather convex shapes of the resulting sectors in both horizontal and vertical directions.

535 Next we compare configurations built by the algorithm with the existing configurations (Table 4),
 536 used at the day of operation and also with the solution built by the improved configuration optimizer (ICO)
 537 system tool (Table 5) of Eurocontrol (Vehlac, 2005). The ICO tool uses a limited number of predefined
 538 sectors configurations to construct a full timetable for the day (an opening scheme), based on known
 539 traffic pattern and current organizational framework. ICO provides a limited flexibility, as it uses already
 540 existing configurations that are not well adapted to the traffic. In order to evaluate the workload
 541 imbalance in those configurations, instead of using the same targeted workload as in two solution
 542 scenarios, we use an average workload of sectors in each configuration.

543 **Table 4** Evaluation of existing configurations.

Period	Number of sectors	Imbalance	Number of re-entries	Number of short-crossings
06:30 - 08:00	5	0.37	1	10
08:00 - 09:30	6	0.36	0	15
09:30 - 11:00	5	0.33	0	20

11:00 - 12:00	6	0.42	2	14
12:00 - 13:30	5	0.38	0	20
13:30 - 14:30	6	0.48	0	12
14:30 - 15:00	5	0.35	0	3
15:00 - 15:30	6	0.43	0	4
15:30 - 18:00	5	0.19	2	20

544

545

Table 5 Evaluation of the ICO tool results.

Period	Number of sectors	Imbalance	Number of re-entries	Number of short-crossings
07:11 - 08:10	6	0.28	0	6
08:11 - 09:10	6	0.31	0	6
09:11 - 10:49	6	0.34	0	22
10:50 - 12:06	6	0.39	2	21
12:07 - 14:02	6	0.39	0	15
14:03 - 15:02	6	0.36	1	10
15:03 - 16:43	6	0.30	1	21
16:44 - 18:15	6	0.26	1	18

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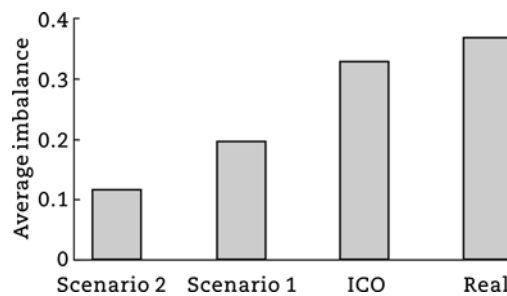
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Fig. 15 shows a significant improvement of the quality of the configurations provided by the solution scenarios, especially in terms of the workload balancing. The results of the ICO tool show worse performance, as this tool does not improve configurations, but it selects for each computed time period one suitable configuration among the existing ones. In the future research, the output of our algorithm can be used as an input for the ICO tool, and a combination of both algorithms could provide better results.



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Fig. 15 An average workload imbalance in configurations proposed by the algorithm (for two scenarios), in existing configurations and in configurations proposed by the ICO tool.

556 It can be seen that configurations from Tables 2, 3, 4 and 5, taken for the same time period, are
557 built of the different number of sectors. ICO aims to reduce overloads in configurations, so it uses the
558 maximum number of controlled sectors per configuration. In the existing configurations, the number of
559 sectors can vary depending on the number of available controllers during the day. Then, our algorithm
560 tries to find configurations with the most suitable number of sectors. This means that the number of
561 sectors in configuration created by the algorithm roughly derives from the chosen value of the targeted
562 workload and the total workload of the ACC for the given time period.

563 Presented results show that our method, which freely combines airspace blocks, enables to
564 propose balanced sectors configuration. The algorithm attempts to keep the value of the workload of
565 each controlled sector close to some given value. The quality of the workload balance is linked to the
566 performance of the algorithm and to the features of the benchmark. Indeed, if there are many input
567 blocks almost equally loaded, it is easy to find a well balanced solution (Table 3). Considered here
568 Maastricht ACC is originally divided into non-equally loaded airspace blocks, which are evidently hard to
569 group into several equally loaded controlled sectors. Airspace blocks used for the second scenario
570 increase the adaptability of the airspace to the traffic pattern, however shapes of these blocks are not
571 enough convex. As a result, controlled sectors in the second scenario are better balanced, but show
572 less performance in terms of other costs. If we want to obtain rather balanced sectors with good shapes
573 and better adapted to the traffic, a new set of initial blocks is required.

574 **7 Conclusions**

575 The algorithm presented in this paper solves the DAC problem. At the first step, a weighted graph of the
576 airspace has been proposed. Based on this initial graph, a method for solving a multi-period graph
577 partitioning problem has been developed. Due to the induced complexity, a population-based
578 metaheuristic optimization algorithm has been chosen for solving the DAC problem.

579 Genetic algorithms give good results on graph partitioning problems, but at some computational
580 cost. The number of criteria and constraints in the DAC problem is highly increasing the complexity of
581 the algorithm. One of the main problems for us was to create suitable recombination operators, which
582 could sufficiently enrich the space of solutions.

583 The developed algorithm, applied to real airspace, has produced realistic and fairly good results.
584 Computed configurations have been compared with the existing airspace configurations and with
585 results obtained using ICO tool, developed by Eurocontrol. The provided results demonstrate that the
586 new solution fits with the requirements of the DAC concept and in some way outperforms the existing
587 ones.

588 Further improvements can be investigated to improve the performance of the algorithm. We can
589 use more advanced workload metric in order to better reflect the associated traffic complexity in the
590 sector. For instance, we could use a metric like convergence rate or Lyapunov exponents (Delahaye
591 and Puechmorel, 2010). Then, in order to obtain operationally feasible sectors, it would require adding
592 more geometrical constraints.

593

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