Multi-Agent Cooperation for Optimizing Weight of Electrical Aircraft Harnesses

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Abstract. This paper deals with minimizing aircraft electrical system weight. Because of technological advances that are spreading, electrical system of aircraft is more complex to design and requires new way to be conceived in order to reduce its weight. This paper describes how to optimize weight of harnesses thanks to the Adaptive Multi-Agent System approach. This approach is based on agent cooperation which makes global function of system emerge. Communication between agents is the focus of this approach. We will develop this approach and apply it to the weight optimisation problem. The developed software provides results that are either equivalent or better than those of classical approaches. Moreover, this software may be a precious help to engineer in charge of designing harnesses as it enables to make different tests in a quasi-real time.

1 INTRODUCTION

The development and the use of new technologies as well as the increase of cabin space imply important changes in the field of aeronautics as aircraft have to integrate new characteristics to improve flight comfort. As part of the electrical system becomes larger in aircraft, cables routes are denser and electrical wiring intensifies.

As a consequence, defining new routes guaranteeing aircraft security becomes harder. Constraints are numerous and interdependent, and mainly concern environmental, electrical and thermic constraints (such as temperature, voltage drop, electromagnetic compatibility or EMC ...). They also depend on the flight phases: landing, parking, flying and taking off. Until now far margins taken to oversize cables ensured respect of constraints. The number of oversized elements is important as the structure of a cable harness is a complex electrical system. A harness is an assembly of cables being themselves an assembly of wires which transmit signals or electrical power through aircraft. Each element (harness, cable, wire) has several constraints to respect and an aircraft has a large number of harnesses: it implies an explosion of the number of elements and thus of constraints to respect. Indeed, as an aircraft may contain up to one thousand harnesses, each of them may contain dozens of cables having themselves up to four wires, there are about fifty thousand interdependent variables. For instance the A380 has about 350 km of cables. Cables'diameter over-estimation leads to increase the weight of the harness (and thus the aircraft's one) implying an increase of operational costs (a more important fuel consumption for ex.) while current trends impose to reduce them.

The present challenge consists in decreasing harnesses weight: cables must be sized at their best while all constraints are not violated. As this problem is a first study in the framework of a French project, this paper will not take into account all constraints neither all elements of an aircraft. Since classical approaches of optimization lack performance to solve such problems, we tackle it by using Multi-Agents Systems. This approach is based on cooperation between agents in order to make global function of the system emerge. We focus our study on the cooperation between agents and the way they communicate.

The rest of this paper is divided into the following parts. Section 2 describes the structure of an electrical system and its constraints and gives a formalisation of this optimization problem. Section 3 gives an overview of meta-heuristics and develop the Adaptive Multi-Agents System (AMAS) approach. In section 4, the AMAS approach is applied to the harness weight optimization problem. In this section the behaviour and the communication of agents are detailed. Section 5 gives some results and analyses them before concluding in section 6.

2 Description of the Harness Weight Optimization Problem

Before formalizing this optimization problem, we give a detailed description of the harness architecture which has physical and functional points of view, as well as the constraints of its elements.

2.1 Electrical System Architecture

Electrical distribution in aircraft consists in bringing energy from production heart towards several consumer systems. Designing electrical systems must take into account the aircraft topology, pressure and non-pressure areas, electrical devices location within aircraft and possible routes for harnesses. Harnesses use paths reserved for electrical distribution in the aircraft structure. Moreover, for security reasons harnesses connecting sensitive equipments must be duplicated and follow different routes. Designing electrical system is a very complex task because of the harness structure which is an aggregation of several elements.

Electrical harness architecture is twofold: a physical point of view and a functional one. According to the physical point of view, equipments are at the lower level connected by *wires*; they are themselves aggregated into *cables* in order to reduce both weight and cost of cladding and shield. Cables are themselves gathered within a *harness*. A harness (connecting several equipments) forms an arborescence whose unit element is a *branch*. A branch, corresponding to space located between two nodes has homogeneous environmental conditions of temperature and pressure. Figure 1 shows a schematic representation of the harness physical view.

According to the functional point of view, production system is connected to consumer equipments via *links* going through the whole harness. A link is represented by wire succession: it has no physical reality but a functional one. The complexity of the problem also came from the fact that a link may run through several interlinked harnesses. Figure 2 shows a schematic representation of the harness functional view.

To sum up, a harness is composed of cables, wires and links. Wires are at the intersection of cables and links as they are related to these two elements.

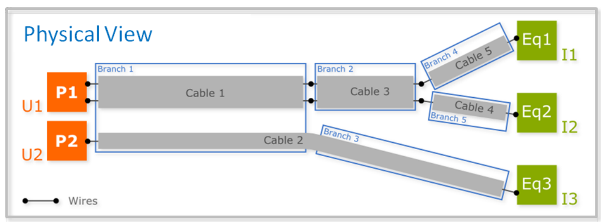

Fig. 1. A harness physical view

Fig. 2. A harness functional view

2.2 Harness Constraints

Besides structural constraints related to its architecture, the design of an electrical system has to take into account functional constraints which are numerous, manifold and interdependent in order to enable a secure functioning of an aircraft during its operation life. In the addressed problem we focus on electrical and thermal constraints detailed below.

A maximal voltage drop is associated with each link and it must not be exceeded at risk of dysfunction of the powered system. A maximal temperature and a maximal overheating are associated with each cable: they must not be exceeded at risk of melting. All of these constraints have to be checked for each flight phase (landing, parking, flying and taking off). Moreover, all wires that are gathered in a cable must have the same gauge. A gauge is a standardized measure representing section of a wire and in a cable (being an assembly of wires) all the wires must have the same section or gauge). Considering the harness sizing rules, increasing a cable gauge(denoting decreasing the cable diameter) means increase of its temperature and of its voltage drop. Thus selecting minimal diameter of cables to minimize harness weight does not mean respecting electrical and thermal constraints: this is not a solution!

Respecting those constraints is difficult task due to the data number (elements and constraints) to be processed. Indeed, in addition to the large number of interdependent variables (about fifty thousand), aircraft harness design has to consider voltage drop, overheating and temperature constraints and the objective of minimizing the electrical system weight. This optimization problem to solve is multi-constrained and mono-objective.

2.3 Formalization of the Harness Weight Optimization Problem

Different formalisms have been developed for solving complex optimization problems under constraints, the most widely studied being the Constraint Optimization Problem (COP) formalism. In this formalism, a set of variables (problem entities) must be assigned a value of a given domain in order to minimize or maximize an objective function. Solving such problems consists in exploring search space and finding the best assignment to those variables.

A COP is a triplet $\langle X, D, C \rangle$ where $X = \{x_1, \ldots, x_n\}$ is the set of variables to instantiate which take values in the specific domains $D = \{D(x_1), \ldots, D(x_m)\}$, and are restricted by the set of constraints $C = \{c_1, \ldots, c_k\}$.

Applying to the harness weight optimization, this problem is described as follows:

- Variables are wires $W =\{ w_1,\ldots, w_m \}$ with $m \in \mathbb{N}$;
- Sets of domains are $\mathbb{R}^+$ for a range of diameter (continuous values) and a set of gauges $G = \{g_1, \ldots, g_{10}\}$ (discrete values); the gauges are standard cross sectional areas.
- Sets of constraints are:
  - A set of links $L = \{l_1, \ldots, l_n\}$ with $n \in \mathbb{N}$;
  - A set of connections $O = \{o_1, \ldots, o_j\}$ with $j \in \mathbb{N}$; a connection is a point connection between several wires belonging to the same links.
  - A set of cables $C = \{c_1, \ldots, c_p\}$ with $p \in \mathbb{N}$;
  - Let $ConnectedTo$ be a function giving connections of the considered wire : $ConnectedTo : W \longmapsto O$.
    Let $BelongToLink$ be a function giving links containing the considered wire $BelongToLink : W \longmapsto L$.
  - $\forall s \in [1..m]$, $\forall l_i \in L$ and $\forall w_s \in W \mid BelongToLink(w_s = l_i)$, $VoltageDrop(w_s) < MaxVoltageDrop$: terminal voltage drop of wires forming a link must be less than the authorized maximal voltage drop;

- $\forall k \in [1..p]$, $\forall c_k \in C$, $Temperature(c_k) < MaxTemperature$ and $Overheating(c_k) < MaxOverheating$: each cable has to check temperature and overheating constraints;
- Let $BelongToCable$ be a function giving the cable containing considered wire: $BelongToCable : W \longmapsto C$.
  Let $Gauge$ be another function giving the gauge value of considered wire : $Gauge : W \longmapsto G$.
  $\forall r \in [1..m]$ and $\forall s \in [1..m]$ with $r \neq s$, $w_r \in W$ and $\forall w_s \in W$ | $BelongToCable(w_r) = BelongToCable(w_s)$, then $Gauge(w_r) = Gauge(w_s)$ (Gauge of each wire belonging to the same cable has to be identical);

The problem to solve is:

$$S = Min(\sum_{i=1}^{m} Weight(w_i))$$

with $Weight : W \longmapsto \mathbb{R}^+$ be a function giving the wire weight.

3 Optimization Methods

Complexity of optimization problem addressed in this paper is due to the number and interdependence of involved parameters. It is practically impossible to predict long-term consequences of the choice of a parameter value on the choice of values for others. Current applications having an important number of elements and constraints to be respected imply a combinatorial explosion of search space. Finding optimal solution of such applications becomes difficult even impossible or requires prohibitive computation times. If we consider n links and if each link has to choose a gauge among g gauges, the number of possibilities is g^n. Considering n = 1000 and g = 10, there are $g^n = 10^{1000}$ combinations. Some domain experts work on strategies to reduce this combination number but despite this, it remains large. Several methods have been developed among them Meta-heuristics, an approximated one, which we will focus on.

3.1 Brief Overview of Meta-heuristics

Meta-heuristics, the most important class among approximate methods, are uncertain and often non-deterministic solving algorithms. Their aim is to efficiently explore search space in order to find a solution close to the optimal one. Their strategy is to alternate between an exploration phase (which consists in discovering new zones of the search space) and an exploitation one (which consists in concentrating search in promising zones). Meta-heuristics are divided in two groups: trajectory meta-heuristics (such as Tabu search [6] or Simulated Annealing [10]) and population-based meta-heuristics (such as Genetic Algorithms [7], Particle Swarm Optimization [9] and Ant Colony [4]).

Those methods, based on a centered approach have shown their limits to cope with growing complexity of current applications because of system dynamics produced by unpredictable changes of events, and also by necessity to have a well-defined objective function that is sometimes missing. Furthermore those methods failed in resolving real problems with so many data because of required prohibitive computation time [11], [13].

Hybrid meta-heuristics increase solving performance of problems with growing complexity as they combine trajectory meta-heuristics during exploitation phases and population-based ones during exploration phase. This association introduces parallelism (through computation distribution) and cooperation between several meta-heuristics (through control decentralisation).

Thus some solving methods, based on computation distribution and on control decentralisation were defined to bring these improvements to problems, and among them the Distributed Constraint Optimization Problem also called Multi-Agents Systems. In those MAS, each variable is managed by an autonomous entity called *agent*. Those agents have to cooperate by coordinating their choices and their actions, in order to satisfy global objective function. This global objective function is modelled as a set of constraints known by agents in which its variables are involved.

Multi-agent technology is pertinent for environments relatively dynamics (constraints and local objectives may evolve) and where search time is constrained (user waiting time). A comparative study realised in [8] shows scalability performances of MAS with regard to classical algorithms.

We propose to use the Adaptive Multi-Agent System (AMAS) approach [2] [3] to solve harness weight optimization. This approach is based on cooperative self-organization of agents, and whose system's aim is to reach adequate collective function. For each agent the self-organization principle consists in satisfying its local criteria thanks to its skills and beliefs, and without being conscious of the global objective to reach. Thus each agent has its own local function and has to cooperate with its neighbour agents, thus enabling self-organization [12] to achieve its own local goal. Cooperation is defined as a social attitude of the agent.

3.2 The Adaptive Multi-Agent System Approach

The Adaptive Multi-Agent System (AMAS) approach is based on cooperative self-organization of agents of the system whose aim is to reach adequate collective function. Cooperation between agents having a local aim leads to emergence of the function at global (i.e. system) level. This emerging global behaviour is only visible by an observer outside the system. Explicitly defining the global function is not needed but it is necessary to lead agents to make this function emerge thanks to their cooperation.

This approach is based on the *functional adequacy theorem* [5] stating that: *For any functionally adequate system, there exists at least one system with cooperative internal medium that fulfils an equivalent function in the same environment.*
A cooperative internal medium system is a system having none Non Cooperative Situation (NCS): for this purpose each agent interacts with agents of its neighbourhood in a cooperative way. Life cycle of an agent being perception, decision

and action non-cooperation is defined as follow:

$$NonCoop = \neg C_{perception} \vee \neg C_{decision} \vee \neg C_{action}$$

It means that an agent is in a NCS if i) the signal it perceived is ambiguous or not understood, ii) perceived information does not produce any new decision and iii) consequences of its actions are not useful to others. An agent detecting a NCS should be able to solve it in order to come back into a cooperative state. During its life cycle an agent may face one or several of the seven types of NCS. During perception phase:

- *ambiguity*: the agent interprets the perceived signal in several ways;
- *incomprehension*: the agent does not understand the perceived message.

During decision phase:

- *unproductiveness*: the agent does not produce any conclusions from perceived information;
- *incompetence*: the agent is not able to exploit the perceived information.

During action phase:

- *uselessness*: the agent thinks that its action will neither help another agent nor come closer to its own objective;
- *conflict*: the agent thinks that its action and the one of another agent are antinomic;
- *concurrency*: the agent thinks its action and the one of another agent will end up in same result.

Solving NCSs may be regarded as learning adequate functionality and it represents the critical point of adaptation process. Besides its nominal behaviour related to its local objective, each agent needs a cooperative behaviour to detect and solve an NCS, or even to anticipate it.

3.3 Solving Non Cooperative Situations

In the AMAS approach, an autonomous agent owns a local objective that influences the function of decision of its life cycle. The agent has the capability to evaluate its non-satisfaction degree depending on its current situation with regard to its local aim. This non-satisfaction degree also called **criticality** represents the distance from its current situation to achievement of its local objective. Thus the further from its local objective an agent is, the more critical it is.

Cooperative attitude of an agent consists in achieving its local objective without increasing -but rather decreasing- criticalities of neighbourhood agents. It may even deteriorate timely its own situation, in order to help a neighbour agent with a too high criticality, thus offering a (temporary) discharge of constraints. The best solution is obtained when criticalities of all agents are minimum within the system. This cooperative attitude represents reorganization dynamics as it guarantees that the system will reach a functionally adequate state aimed by designer.

4 APPLYING THE AMAS APPROACH TO MINIMIZE HARNESS WEIGHT

Designing and sizing harness cables by minimizing their weight is a complex problem of combinatorial optimization under constraints. Since problem becomes more complex optimization tools come up against exponential increase of calculation times(see section 3). This difficulty narrows use of these tools for sizing subsets of aircraft wiring and poses issue of coherence of the whole.

The AMAS approach leads to a strictly local resolution of problem. Thus search space is not totally explored but is guided by the cooperative principle. This paradigm change enables to break free of practical limits met by classical approaches of optimization such as increase of computation times. Thus cooperation between agents has to make the adequate function, i.e. minimizing the harness weight, emerge.

We now specify the different types of agents composing the system and their behaviours.

4.1 Agent, Local Aim and Nominal Behaviour

AMAS approach proposes a bottom-up analysis of the problem, the ADELFE methodology [1]. This methodology is based on *Unified Modelling Language* (UML) and *Rational Unified Process* (RUP) and uses Agent-UML to express interaction protocol between agents. Its aim is to guide complex system designers through development phase of systems based on AMAS approach and emergence concept. From domain and data model analysis, several Non Cooperative Situations (NCS) were identified and for each agent type encountering one of these situations, its behaviour has to be cooperative. Thus each agent type is endowed with a nominal behaviour and a cooperative one.

Applying ADELFE methodology to the harness weight problem, *agentification* phase has enabled to define four types of agents: the *Link*, *Cable*, *Wire* and *Connection* agents.

- the *Link* agent represents functional aspects of electrical system and its local goal is to respect voltage drop constraints.
- the *Cable* agent represents a cable and its local goal is to uniform diameter of its wires and to expose a current diameter. It also has to respect temperature and overheating constraints.
- the *Wire* agent represents a wire and it binds functional aspects (links) and physical ones (cables). Its local objective is to stabilize its diameter (whatever its initial value).
- the *Connection* agent represents a connection point between several wires belonging to a same link. Its local objective is to balance criticalities of *Wire* agents connected to it.

As constraints differ according to the four flight phases (landing, parking, flying and taking off) and as they must be respected at each of these phases, all *Link*, *Wire* and *Connection* agents were cloned four times, once per flight phase. Only the *Cable* agent is not cloned as it is the central element which integrates all additional constraints of *Wire*, *Connection* and *Link* agents related to flight phases. Indeed, a *Cable* agent is the physical element shared by all flight phases and it seeks the optimized gauge value satisfying all its *Wire* agents, themselves constrained by *Connection* and *Link* agents.

For instance a cable made of three wires in a physical real system is thus represented by a *Cable* agent having three *Wire* agents for each flight phase, so twelve *Wire* agents in all. The *Cable* agent has to converge towards a common gauge satisfying constraints of all its *Wire* agents, and indirectly those of *Link* and *Connection* agents related to previous *Wire* agents. As each *Wire* agent is in relation with *Link* and *Connection* agents, a modification of its gauge perturbs voltage drop, criticalities balance etc. implying adaptation of other agents (chain reaction) but it also means that other agents may perturb it.

4.2 Steps of Resolution and Cooperative Behaviour

Problem resolution seeks the optimal diameter value and so is carried out on continuous values. For that purpose, *Wire* agents are at the heart of algorithm. Their own goal is to stabilize their diameter with *Link*, *Cable* and *Connection* agents satisfy electro-thermal and charge balance constraints.

First each *Wire* agent estimates its criticality degree according to its current diameter thank to a local computation. This criticality is then communicated to *Connection* agent to whom it is connected. Each *Link* agent checks that voltage drop between ends of *Wire* agents that form it is lower than the authorized one. When voltage drop exceeds the maximal authorized one the *Link* agent is in a Non Cooperative Situation (NCS) and more precisely an *incompetence* one since it is not able to change itself this situation. To become again cooperative, it informs the *Connection* agents connected to it. Each *Connection* agent retrieves criticalities of the *Wire* agents to whom it is connected to and it deduces which *Wire* agent may act in order to i) solve *Link* agent NCS and ii) make criticality degree decrease.

Each *Cable* agent checks that no temperature or overheating constraint is violated. Otherwise, incriminated *Wire* agents (the most critical contained by *Cable* agent) are informed and have to increase their current diameter. If none constraint is violated, the *Wire* agent decreases its criticality by reducing its diameter. The *Wire* agent ends up determining its optimal diameter through this play of modifications (successive increases and decreases) and through an internal learning mechanism. The selected diameter underlies the choice of the wire gauge.

During this solving phase, the notion of minimizing weight is not explicitly nor directly tackled. Weight of harness or of its elements is never computed. This is the succession of changes and the propagation of modification among agents that lead the system to have its global function that emerges. To show this clearly we will have a focus in the following section on communication between agents.

4.3 Focus on Communication between Agents

Communication between agents is the crucial point that enables them to cooperate. To show how the cooperation occurs, we detail exchanges between agents by giving the algorithms of communication for each agent type. We consider here the first step of resolution, that is to say search of the optimal diameter of cables (continuous part). We clarify that the resolution has two steps: first computation of all diameters of cables (which are continuous values) and then once this first step achieved, gauges (which are discrete values) of cables are selected (according to the computed diameter) to size harnesses at their best. *Link* agent has to respect voltage drop constraints and it communicates with *Connection* agents connected to it.

```
if (voltage drop > Max. Voltage Drop) then
  send request to the Connection agents to reduce voltage drop
else
  send to them request to reduce weight
end
```

Connection agent has to balance criticalities of *Wire* agents who belong to it.

```
receive at least one query
if (request to decrease voltage drop) then
    send request to the Wire agents on less critical side to reduce
     voltage drop
else
   if (request to reduce weight) then
    send request to Wire agents on most critical side to reduce weight
   end
end
```

Wire agent has to stabilize its diameter according to the respect/non-respect of constraints and it may send a request to *Cable* agent to whom it belongs to.

```
receive at least one query
if (request to decrease  voltage drop) then
    send request to the Cable agent to reduce voltage drop
else
   if (request to reduce weight) then
      send request to the Cable agent to reduce weight
   end
end
```

Cable agent has to respect temperature and overheating constraints and to uniform diameter of its wires.

```
receive at least one query
if (request to decrease voltage drop, temperature or overheating) then
    increase its diameter
else
   if (request to reduce weight) then
     reduce its diameter
   end
end
```

First we could notice that during resolution step, the weight value is never used or calculated or exchanged between agents. Weight optimization is carried out indirectly by increasing or decreasing diameter of cables. This point shows that global objective is not explicitly *computed* but *emerges* from local actions of each agent achieving its own goal.

Second we notice that there is no *random* during algorithm execution as opposed to classical algorithms such as Ants Colony, or Tabu Search. An agent tries only to reduce its degree of criticality or the one of its neighbourhood. We also see in this algorithm that each agent decides at most one action during a cycle and may act in opposite way between cycles.

In this section we have detailed the problem solving process based on agent cooperation. This cooperation enables to find the smallest diameters (and gauges) of cables satisfying all addressed constraints and thus it entails an optimised weight of harnesses.

5 RESULTS AND ANALYSIS

This work has been achieved within the French project SMART-HARNESS. As it was a first study on weight optimisation, addressed problem only considers few harnesses (up to 52). Data used to validate our solution were provided by expert Company. We have developed a software platform called Smart Harness Optimizer that implements AMAS approach using processes of local decision. Its interface may be visualized in Figure 3 and shows the structure of a harness (center) and its elements and characteristics (below).

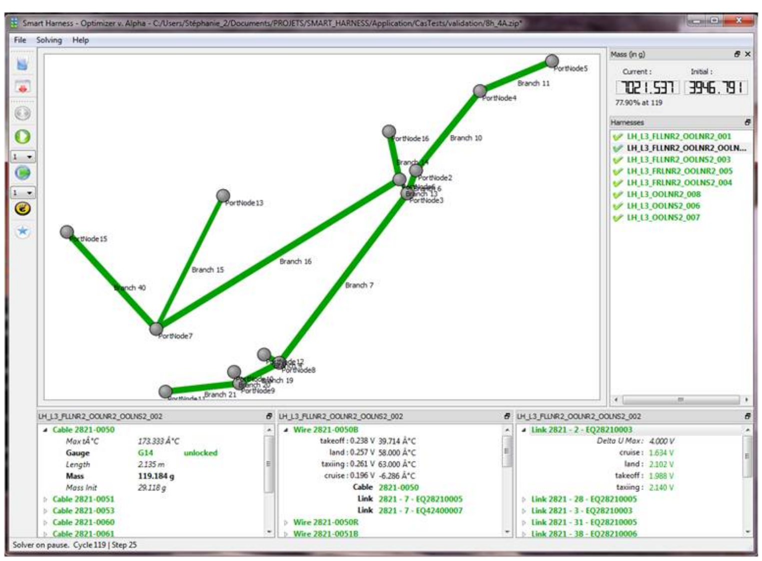

Fig. 3. The Interface of the Smart Harness Optimizer

5.1 Outlines of Test Cases

Three categories of test cases were used to evaluate the developed tool. They correspond to three electrical systems constituted of respectively 3, 8 and 52 harnesses. Each category comes in several instances where charge required by equipments was changed. The two first instances are amperage uniformed loaded for all links in all flight phases with 1A, 4A and 20A (10A for the second case). The last instance has amperage modifications depending on flight phases. The 52-harness case has only one instance. Moreover we consider that there are 10 possibilities of gauge available per cables for all the instances and cases.

The first and simplest case contains 3 harnesses and is constituted of 9 cables crossing 9 branches and grouping together 18 wires realizing 6 links. Search space size of this case is 10^9.

The second case contains 8 harnesses and is constituted of 25 cables crossing 40 branches and grouping together 50 wires realizing 22 links. links. Search space size of this case is 10^{25}.

The third case contains 52 harnesses and represents an ATA (Air Transport Association). It is constituted of 404 cables crossing 406 branches and grouping together 643 wires realizing 200 links. links. Search space size of this case is 10^{404}.

We remind that size of these search spaces is huge but it is possible to reduce them by eliminating impossible values determined by experts. For instance, experts exclude from the search, all gauges being not eligible on ad-hoc problems considering constraints cables.

5.2 Results

Results with Smart Harness Optimizer tool are obtained on a laptop. The 3-harness case resolution lasts between 1600 and 4700 milliseconds and requires between 60 and 160 cycles with 153 agents and according to instances. The 8-harness case resolution lasts between 2100 and 4700 milliseconds and requires between 90 and 200 cycles with 425 agents and according to instances. The 52-harness case resolution, with 5548 agents, lasts about 2 min in 754 cycles.

All these cases were also tested by the expert company which provides us those test cases. The used tool first reduces search space (according to an experiment plan) and then finds the optimal solution. This enables to verify the relevance of solutions obtained with the Smart Harness Optimizer Tool.

Table 1 sums up results obtained with the Smart Harness Optimizer tool compared to ones of the expert company. Besides optimized weight, this tool is able to show each element violating a constraint and its characteristics.

5.3 Analysis

We compare here results of the Smart Harness Optimizer Tool with those obtained by the expert company using their own methods based on classical optimization algorithms. The main advantage with our tool using AMAS approach

Table 1. Test Case Results

	Agent Number	Resolution time (ms)	Cycle Number	Classical methods of optimization
3 harnesses	153	1600 to 4700	60 to 160	1000ms
8 harnesses	425	2100 to 4700	90 to 200	2 min
52 harnesses	5548	about 120000	754	more than 2h

is the significant time saving particularly for the 52-harness case. Smart Harness Optimizer tool found a solution in a few minutes, while expert company methods require several hours. We underline that 52 harnesses represents an ATA and in an aircraft there may be more than 10 ATA. This first study is promising as time resolution is really short. Increasing the harness' number (or ATA) is now conceivable. Nevertheless we mention that for smaller cases (3 and 8 harnesses) results between our tool and expert company methods are quite similar, even better for the latter concerning the 3-harness case.

The second advantage is that our tool enables a fast adaptation in a real time to take into account dynamical changes and disruptions during resolution time or once a solution is provided. This is particularly interesting when an engineer needs to change a value to make tests or comparisons. For instance he may decide to block a gauge value, or to change another one. Once this modification is applied, resolution process does not start again from beginning, but from the current solution, i.e. from current computed values of variables. As the problem resolution is based on local objectives and on cooperation between agents, this value change has a direct impact on neighbourhood of agent whose value is modified is concerned and adapts itself to this new configuration. In other words the initiator agent of modification propagates around its neighbourhood change to other agents. This also leads to obtain new solutions in a quite short time.

The third advantage, consequence of the second one, is that our tool enables an analysis of obtained results. It is possible for engineer to visualize elements (it may be just one element) that prevent the problem to be solved because of constraint violation. An engineer is also able to test several versions for a harness: short time of response got with the tool facilitates such studies.

6 CONCLUSIONS

This paper addresses the weight optimization problem of aircraft harnesses. Minimizing harness weight consists in optimizing cable gauge: increasing gauges gives decreasing diameters and so lighter cables. An electrical system is mainly composed of harnesses, functional links, cables and wires of cables and lots of dependencies exist between these different elements. Additionally some environmental, electrical and thermal constraints must be respected and they depend on the four flight phases.

We show that considering the growing complexity of current applications, Adaptive Multi-Agent Systems enable to get systems being flexible, addressing scalability and being able to quickly adapt to the environment dynamics, thanks to the computation distribution and the control decentralization. The AMAS approach requires the implementation of local interactions between agents enabling them to coordinate locally their actions in order to produce a solution at the global level. In the used resolution techniques, we underline that cooperation is a fundamental notion that rules interactions and enhances quality of obtained solutions.

We have developed a platform to solve optimization problem using the AMAS approach. This tool enables harness designer i) to obtain a solution in a relatively short time, ii) to improve harness sizing by optimizing wire diameter and iii) to focus on elements that do not satisfy constraints. Thus the optimized weight of harnesses enables to reduce operation costs of aircraft.

This work offers numerous perspectives for industrials. By improving and enriching this software, this tool may help designers to reconfigure harnesses by inverting or changing cables from their harness. For instance if one cable poses problem because of constraints imposed on its harness, moving it to a new harness may decrease its constraints as its nearby environment has changed.
Going one step further, the tool could help designers to co-design harnesses. This co-design may assist them to specify in real time the most appropriate characteristics and make designers save design time by avoiding going back and forth between services. Going one more step further, this kind of tool could help in routing harnesses within aircraft structure, by choosing the most appropriate way and it could also be coupled with assignment of cables within harnesses.

Considering performances of operational tool, we think that a commercial software may help designers to co-design harnesses. This co-design may assist them to specify in real time most appropriate characteristics like voltage drop.

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