**« Optimouv » :**

**Optimisation des déplacements dans l’organisation des rencontres sportives**

1. **Description générale**

**Généralités**

Dans le cadre de la COP21, le dispositif « Optimouv » a été lancé officiellement le 4 décembre 2015 par le Secrétaire d’Etat aux Sports, Monsieur Thierry BRAILLARD.

L’objectif recherché de cet outil est la réduction du nombre de kilomètres parcourus par les clubs et les pratiquants sans réduire le nombre de rencontres sportives. Il s’agit d’un outil d’aide à la décision permettant de proposer des scenarii d’organisation des rencontres sportives optimisant les déplacements.

Avec plus de 2,5 millions de rencontres sportives chaque année soient 50 000 par semaine, l’économie possible est loin d’être négligeable et permettrait ainsi une démarche économique avec la baisse des frais de transport, une démarche de santé avec la baisse de la fatigue liée au transport, une optimisation du temps de pratique par rapport au temps de transport et enfin une démarche environnementale avec la baisse des émissions de gaz à effet de serre.

1. **Présentation de l’outil applicatif**

Le logiciel **Optimouv** propose des solutions d’organisations des compétitions par des choix du lieu de rencontres optimisés au regard des déplacements tout en tenant compte des contraintes sportives. Cet outil informatique est un outil d’aide à la décision à disposition de l’ensemble des instances sportives organisant les compétitions et les rassemblements, les fédérations, les ligues régionales, les comités départementaux notamment.

La Fédération Française de Basketball (FFBB) et le Ministère chargé des sports, en partenariat avec l’ADEME et le WWF, ont collaboré à l’étude et au développement de cet outil. Découvrez la vidéo de présentation sur <http://www.ffbb.com/video-optimouv-quest-ce-que-cest>

1. **Algorithme Optimouv**
2. Texte de remplacement généré par une machine :
   Stochastic Optimization for Pool Assignrnent 
   Problem statement 
   Let D 1 be the number of pools and M be the size of each pool. 
   Supposc wc havc N M x D teams indcxcd by l, 
   N, the distance 
   (in km Say) between teams i and j being denoted by ô, 
   O for any 
   N F (obsewe incidentally that ô, i 
   These numerical values are stored in the N x N (Symmetric) distance matria; 
   Parametrization. Any pool assignment of the team population (1 
   is described by a N x N (symmetric) matrix P — 
   defined as 
   follows. E (1, 
   pi o +1 if i and belong to the same pool and pi o 0 otherwise. 
   Equiped With this notation, for 1 i, j N, we have p, o and we set 
   0 by convention. Obscrw also that a.ny pool assignment matrix fulfills 
   the following propert.y: Vi E (l, 
   Morc gencrally, the constraints sat'sficd by any pool assignmcnt matrix can 
   be formulated by means of notions perta.ning to Graph theory: the teams 
   N forming the nodes of an undirected graph G, team i is connected 
   to team J if i and j belong to the same pool. The matrix P is then the 
   adjacencv matri:r of G, ench node has degree M — 1 so that the degree 
   matrix Ap of P is 
   (M - 1)1dN, 
   denoting by IdN the N x N identity matrix. The graph G can be partitioned 
   in D cliques (i.e. fullv connected or complete subgraphs, a subgraph G' being 
3. Texte de remplacement généré par une machine :
   said to be Jully connected if there a vertex connecting any pair of nodes of 
   G') Of size AI _ The normalised Laplacian matrix L related to P is then given 
   In tcrms of spectral pmpcrtaes, thc condition stipulating that thc graph G 
   Of adjacency matrix F' Can be partitioned into D connected components 
   Gn is equivalent. to that stipulating that 0 is a singular value of 
   multiplicity D for the matrix V. The distance matrix P can also be viewed 
   as a weight matric for G (ô, ü wcighting thc vcrtcx). wc dcnotc by p thc 
   set of pool assignment matrices. One may easily prove that it is the set of 
   N x N adjacency matrices With (M — 1)IdN as degree matrix and for which 0 
   's a smgular value of multiplicity D for its normalised Laplacian V. Indeed, 
   sinoc — (M — l) IdN, cach component cardinality argcr 
   than M. Since there are D connected components and N DM nodes 
   all connected components have size M exactly and are thus complete (using 
   again that Ap (M — 1)IdN). 
   A straightforward combinat.orial computation also shows that the num- 
   bcr of possible assignmcnt pools (in absence of constraints cxccpt thc sizc 
   contraints (D, M)) is givcn by: 
   x and — m)!) for any nonncgativc 
   whcrc m! —l x 2x 
   integers m q. As D and M become small both at the same time compared 
   to N, becomes rapidly very large (making loops over p hardly feasible 
   in practice). 
   Remark 1 (GENERATING A POOL ASSIGNAIENT) As illustrated by the for- 
   mula above, it is not straight.forward to generate and a sequential procedure 
   is rcquircd in gcncral: sclcct first M tcams among thc N DM tcams by 
   drawing without replacement. Next, in the complementary set, draw without 
   replacement M teams, etc. 
   Optimization problem. For a given pool assignment P p and a two- 
   leggcd tic championshlp, thc total cost (in tcrms of distance travcllcd ex- 
   pressed in km) is given by Texte de remplacement généré par une machine :
   d
   2
   0
   Texte de remplacement généré par une machine :
   P,.k and T, AP). k 
   - for 
   GAP), J -O. 
   This transformation is P.The neighbourhood Of 
   any pool assignment matrix P e p is defined as 
   .V(P) — Ino(P): 
   We have (P) M2D(D — 1)/2 for any P e P and one says that P is 
   a neighbour Of P if P' N (P) (observe that this relationship is symmetric 
   Since P' Tiù(P) P The sequence generated will be such 
   that for all I and will so that its 
   limit distribution coinc.des With the target distribution, i.e. the uniform 
   distribution on argminecp V. 
   Simulated Annealing. The Simu ated Annealing method for building a 
   (time-inhomogeneous Markov) sequence fulfilling (G) involves a (tempera- 
   turc) paramctcr T(n) O, which dccrcxqe.; "s thc nllmbcr Of it.crations n 
   grows. In practice, T(n) decreases in a stepwise mariner. Given a cooling 
   schedule T it Can be implemented by meanS Of the pseudo-code below: 
   • (Initialization) Select at random p (1) in p 
   • (Itérations) for I to 
   1. Draw at random a pair (i, j) s.l. i and pi".) 
   Lhe neighbour 
   2. Compute 
   — — V(PW) 
   0 and consider 
   3. If O (i.e. the cœ;t Of is than that Of the 
   current poo assignment), set 
   If AVn » O (the 
   eurrent configuration is better than draw a r. v. U (n) 
   uniformly distributed on (0, 1). If set 
   T, (PI")) and set P (0+1) p(") otherwise (this happens 
   With probability 1 — Texte de remplacement généré par une machine :
   (Output) Pool assignrnent O. 
   Thc choicc of the initial value p (fi) and that of thc cooling schcdulc have 
   a strong ilnpact on the performance Of the algorithm. ln practice, one runs 
   in parallel the algorithm With varions/nnmerons configurations (adaptative 
   cooling schedules can also be considered). ln addition one may consider an 
   early stopping condition if V (p(n)) stops significantly decreasing after a large 
   number of iterations (to be fixed by the user) 
   Remark 3 (ON THE CHOICE OF THE METHOD) Aletrnative metahenristics 
   could be considered for solving approximately (3) (deterministic approaches 
   in particular). Howcvcr, results of t e type of (6) are not availablc for de- 
   terministic techniques. Exp oring the paramet.er space p in a stochast..c (i. 
   random) manncr is known to bc vcry cfficicnt and widcly uscd in a largc vari- 
   ety of applications (ranginz from mechanical statistics to operations research 
   through network optimization since the eighties. Theoretical foundations 
   for the simulated annealing have been set in the early 90's. For a fixed 
   temperature T (i.e. T independent from n), the algorithm above is known 
   as thc Mctropolis-Hastings algorithm and the (time-homogcncons) Markov 
   chain thlas generated converges to the Gibbs measure: (l/ Z) 
   where Z is a normalization constant. Computation 
   of Z, and thus direct sampling from this distribution, is unfeasible in practice 
   sincc it involvcs a summation ovcr p, This is Why a Markov Chain Montc 
   Carlo (MCMC) procedurc IS requ.rcd. The pool assignmcnts wit louvvst 
   cost are the modes of this distribution and as T decreases t e distribution 
   becomes more and more concentrated around Its modes. The rationale be- 
   hind the change Of the progresive change Of telnperature in the simulated 
   anncaling approach 's to avoid bcing trappcd in local minima: an incrcasc 
   of the cost may occur With a probability increasing With the pararneter T in 
   order to explore the space (if T is very large, a ot of fluctuations are possible 
   whereas V (IX")) is monotonous/decreasing With probability I if T 0), 
   Remark 4 (COOLING SCHEDULE) In practice, one picks a high initial tem- 
   perature 1'(0) and make it decrease in a stepwise manner (the number Of 
   steps and the number of iterations related to cach step are tuning parame- 
   ters Of the schedule). When the output Of the algorithm stops fluctuating 
   convcrgcncc" ) 
   onc stops if, at iteration say and "restarts" thc algorithm 
   With — and the same cooling schedule, and so on and so forth. 