Genetic Optimisation for the Positioning of Openings in Natural Ventilation

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RESUME. La ventilation naturelle peut être un moyen efficace de rafraîchir les bâtiments. L'optimisation du placement des ouvrants pour la ventilation naturelle peut se faire par un algorithme génétique discret. La méthode est cependant coûteuse en calcul car basée sur la taille de la population. On s'intéresse donc ici à l'influence d'un choix judicieux de la population initiale à partir des différences de pression entre éléments de façade.

MOTS-CLÉS. ventilation naturelle, optimisation

ABSTRACT. Natural ventilation may be an efficient means of cooling the build environment. The optimal place for openings may be found using a discrete genetic algorithm, however the method is computationally intensive, as it is based on the population's size. Therefore we study here the influence of an appropriate initial population, selected using the pressure differences between facade elements.

KEYWORDS. natural ventilation, optimisation

1 Introduction

Energy in buildings is a major concern of the current times. More specifically, the rise of cooling expenses is likely to be a challenge in the coming decades and hence providing tools for a better operation of natural ventilation may be of some interest.

Natural ventilation is driven by pressure, height and temperature differences. Common sense offers a good start with positioning openings : for buoyancy-driven ventilation, inlet and outlet shall be positioned respectively in the lower and upper parts of facades. Nevertheless, wind-driven ventilation is more challenging : wind patterns are changing and pressures may be heterogeneous, especially when exotic shapes of buildings are involved.

Using algorithms coupled to Building Energy Simulation (BES) in order to select openings appears to be a promising perspective. Different procedures have been explored to optimize natural ventilation in buildings : genetic algorithms (Hamdy et al., 2011b,a) and particle swarm algorithms (Hasni et al., 2011, 2009; Wei et al., 2015; Stephan et al., 2009). The aforementioned works chose various cost functions aiming at maximizing comfort, air quality, or minimizing financial costs and energy consumption. To the best of the authors' knowledge they did do not address the position of structural elements such as openings, but rather quantities such as ventilation rates.

Positioning openings on a given facade is a discrete problem which search space is often too large to be explored thoroughly. Indeed, considering facades with numerous layout possibilities for openings (*e.g.* glazed facades), the very high number of combinations is a challenge in terms of computational expense : selecting the position of 10 openings out of 100 possibilities yields roughly 10^{13} options, which is a hundred times the estimated number of stars in our galaxy. In the present work, we expose a method allowing for the determination of the optimal number and position of openings in buildings with the help of a genetic algorithm. We mean to use the computational effort at its best by an appropriate selection of the initial population with a physical basis. The eventual intention is to provide practitioners a tangible method for the positioning of openings on complex facades.

2 Discrete genetic algorithm

Genetic algorithms are widely used in building energy simulation. Starting from a given set of solutions (called "parents"), such algorithms generate other solutions (called "children") and evaluate them versus an objective, determining their "fitness". The fitnesses of the children are then compared to their parents' ones, and the best individuals are kept, following Darwin's principle of selection. This new set of individuals (called a "generation") is used to generate new children and so on. At each generation, the population is better or equivalent to the preceding one, which is the reason why the algorithm converges. Such methods are particularly adapted for problems where the cost function is not regular or where the data that needs to be optimized is discrete, as is the case for natural ventilation.

As the goal of the study is to select the openings for natural ventilation, the model we used is the following : each solution of the problem (called an "individual") is represented by a list of bits ("true" or "false", also called "genes" in the sequel), each of which being associated with a window of the building. If the bit's value is "true", the window is open, otherwise it is closed. In the present work, we used the NSGA-II algorithm (Fortin et al., 2012) that enables multi-objective optimization without preferred objective. The selection is based on a partial order between individuals called domination enabling to build Pareto fronts.

The creation of two children from two parents happens in two steps. First, the genes of the parents are split into fragments and randomly distributed to their children, as in chromosomal crossover, using a "crossover function". Random modifications are then made to the genes of the children using "mutation functions". Both will be explained in the following sections.

2.1 Crossover function

The crossover function was designed to allow for the control of the level of mixing between the genes of the parents, and to satisfy given constraints on the number n of open windows (*e.g.* if $n_{min} \leq n \leq n_{max}$). The function takes as variables two lists of bits representing two parents, and it generates two lists of bits representing the children, by random permutations between the bits of the parents. Below is the simplified algorithm of the crossover function, which is illustrated in Figure 1 :

- Initialization of children 1 and 2 identical to parents 1 and 2.
- Search for the windows which status (closed or open) is different for parent 1 and parent 2. They are divided into two lists : $\mathcal{F}_1$ contains the windows that are open for parent 1 and closed for parent 2, and can thus be given from parent 1 to child 2, *vice versa* for $\mathcal{F}_2$.
- Selection of the number n_1 of open windows given by parent 1 to child 2, and the number n_2 of open windows given by parent 2 to child 1. The mean number of chosen windows

is based on a geometric distribution, so that small numbers are more common. n_1 and n_2 also have to satisfy the given constraints on the number of openings.

— Selection of n_1 windows in $\mathcal{F}_1$ (based on a uniform distribution) which are given from parent 1 to child 2. Reciprocally, n_2 windows are chosen in $\mathcal{F}_2$ and given from parent 2 to child 1.

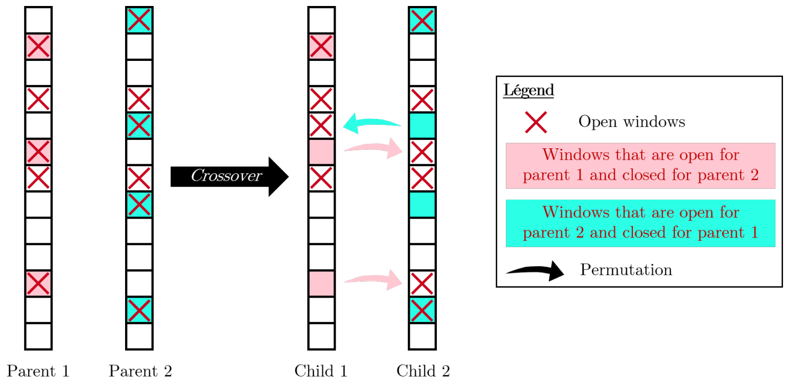


FIGURE 1. Illustration of the crossover function. In this example, child 1 gives $n_1 = 2$ open windows to child 2, and child 2 gives $n_2 = 1$ open windows to child 1.

The level of mixing between the genes of the parents can be adjusted with two parameters : the probability of crossover $p_{crossover}$ (if there is no crossover the children are the same as their parents), and the mean rate of modification $\tau_{crossover}$.

2.2 Mutation functions

Three genetic modifications are possible on an individual : opening windows, closing windows and/or swapping open and closed windows. Each of these modifications is coded by a mutation function as follows :

— Selection of the number of modifications (or permutations) to be made on the individual. The mean number of modifications is based on a geometric distribution, fostering small mutations.

— Selection of the windows to be modified (or swapped) amongst the possible ones, followed by modifications.

These three functions are then applied to the individual in a random order. For each mutation, the probability p_{mut} of modification can be independently adjusted to control the frequency of mutations at the scale of the population. At the scale of the individual, the mean rate of modification τ_{mut} is controlled by the mean of the geometrical distribution used to chose the number of modifications per individual.

2.3 Choosing the initial population

The number of combinations of n open windows among N windows is given by the binomial coefficient $\binom{N}{n}$. Given the shape of this function when N increases, the combinations of open windows rapidly get too numerous to be exhaustively tested, even with parallel high-performance computing. In such cases, the number of tested combinations is negligible compared to the solution space and the algorithm exhibits a slow convergence (most likely the best combinations are not evaluated at all).

An interesting strategy to overcome this problem is to couple the genetic algorithm with an artificial neural network (Gossard et al., 2013; Hamdy et al., 2011b). Here we have implemented a simpler idea : going back to the physical basis to select an initial population which is already better than the average, ideally with a moderate computational effort.

Intuition would advise to select openings based on wind orientation : Indeed, using windward/leeward positions for openings may be an excellent initial guess. However, for exotic geometries or complex urban environments, the pressure on facades may exhibit more complex patterns, as for instance on Figure 2 showing the pressure coefficient of the case study presented below.

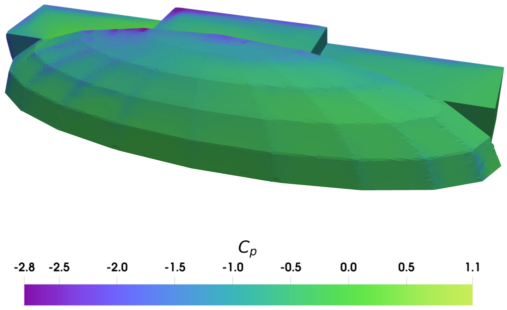


FIGURE 2. Pressure coefficients on facades for a given wind direction on the case study.

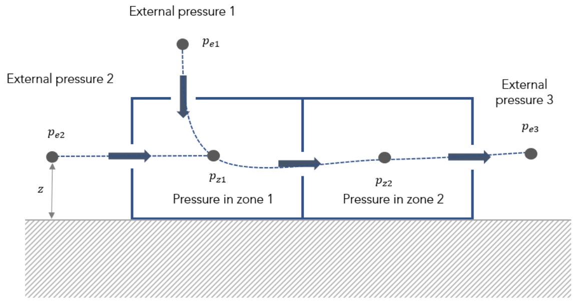


FIGURE 3. Scheme of the pressure nodes in building energy simulation

In BES, wind-driven natural ventilation is function of the pressure differences on external nodes (Dols et al., 2002; Axley et Nielsen, 2008), as represented on Figure 3. Finding the best combination of openings implies solving for the non-linear equation system of size N at a sub-hourly time step, which is is also computationally expensive.

The proposed approach hence consists in selecting the pairs of facade elements (i, j) exhibiting the largest sum of pressure difference during the building's opening hours over summer. This pressure difference $\Delta P(i, j)$ is the straightforward product of wind velocity at building height from the weather data $v(t)$, surface of both openings $S_{i,j}$ and pressure coefficient difference between elements $C_p^{i,j}$:

$$\Delta P(i,j) = \left(\frac{1}{{S_i}^2} + \frac{1}{{S_j}^2}\right)^{-\frac{1}{2}} \times \sum_{t \in \text{opening hours}} \sqrt{\left|C_p^i(t) - C_p^j(t)\right| \times v(t)^2} \tag{1}$$

The amount of calculation is reduced as the sum of pressures is computed only for $\binom{N}{2}$ which is about $\sim 5 \times 10^3$ in the case study (as a reminder, for a given N the function $\binom{N}{n}$ is symmetrical and reaches its maximum for $n = N/2$; values close to $n \sim 0$ are reasonably low).

2.4 Objectives or Cost functions

The choice of cost function is critical as it may be considered the "compass" of the algorithm. In the present case, we aim at improving thermal comfort while reducing the financial cost, therefore following objectives were chosen :

- a metric for thermal comfort : the mean value over summer of the maximal daily difference between the corrected PET comfort index as per Walther et Goestchel (2018) and the center of the PET comfort range, that is $20.5°C$, as in Matzarakis et al. (1999).
- a function measuring the financial cost of openings : in our case study, we opted for a primary dependence on the number of openings n and a relationship with the height of the opening (a proxy for maintenance cost). The financial cost has therefore been defined as : $n + \frac{\sum_{f \in \text{open windows}} h(f)}{\sum_{f \in \text{highest windows}} h(f)}$, where $h(f)$ refers to the height of the centroïd of window f.

The calculation of the comfort metric requires BES over the summer season. The algorithm runs in the Python computer language, according to the diagram presented in Figure 4.

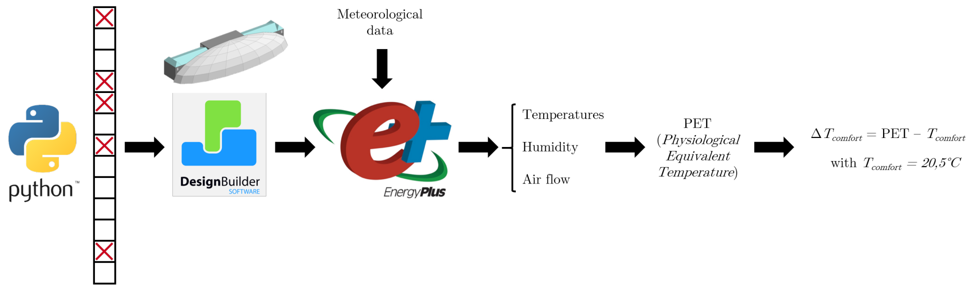


FIGURE 4. Flow chart for the computation of the comfort metric : Data from the genetic algorithm are converted in a *EnergyPlus* file generated with *DesignBuilder* and combined with meteorological data run the building energy simulation. Results are then post-processed to calculate hourly PET values.

3 Application

In this section we try to address the question whether the careful selection of the initial population impacts the convergence of the algorithm with the help of a case study.

3.1 Case study and simulation setup

An *EnergyPlus* model inspired by of Strasbourg's station was setup and the PET comfort index in the hall during the opening hours was computed as presented on Figure 4. As we are interested in natural ventilation, only the season between May and September was simulated. The pressure boundary conditions are determined using the methodology described in Walther et al. (2019), using a windrose discretisation of 24 directions and computing the pressure coefficient for each facade element (see Figure 2). For the sake of the study, every window of the $N = 98$ was allowed to be turned into an opening.

The genetic algorithm described in Sections 2.1 and 2.2 was setup with following parameters :

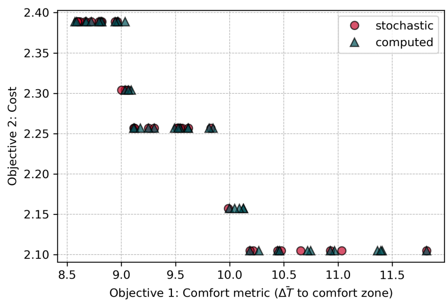
- Crossover parameters : $p_{crossover} = 0.8$ and $\tau_{crossover} = 0.5$
- Mutation parameters : $p_{add} = p_{remove} = 0.08$, $p_{swap} = 0.15$ and $\tau_{mut} = 0.3$.

As a means of comparison between the stochastic and the proposed initial selections, we perform the optimisation using 100 individuals over 10 generations, which is an acceptable trade-off between population size and the accepted computational effort in engineering (that is : the algorithm can run overnight on any computer).

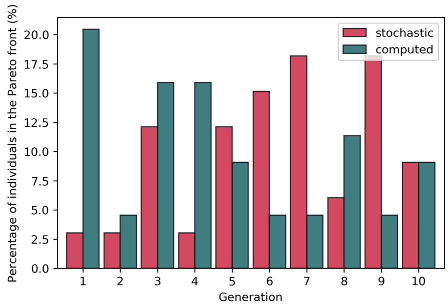
Following sections show the results for both methods, first imposing the algorithm a fixed number of openings and then using a variable one. When trying to compare these methods, a drawback of stochastic selection is obviously its variable nature : the initial population may be more or less close of the optimal solutions. Repeating the comparison a sufficient number of times would allow to determine the performance of the proposed method more reliably. However, time lacked to perform such an analysis and we will have to be satisfied with the preliminary results obtained here, knowing that convergence may well not be attained.

3.2 Fixed number of openings

In this case the number of openings is constant, taken as $n = 2$. The explored fraction of the space of solutions is (10 generations $\times$ 100 individuals)$/\binom{98}{2} \sim 0.2$. One can see on Figure 5a) that the Pareto fronts are very likely. As the cost objective is strongly dependent on the number openings (see section 2.4), in the present case it does exhibit only small variations. The comfort metric however may vary significantly, between ~ 8 to 12 [K]. Figure 5b) shows the percentage of individuals in the Pareto front depending on the generations : for the first generation, it is clearly visible that the computed initial population performs better than the stochastic one with 20% of individuals in the Pareto front. This percentage is favourable for the four first generations, after what no clear trend is visible.



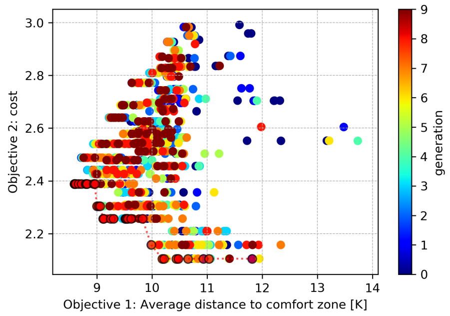
(a) Pareto fronts for both methods.



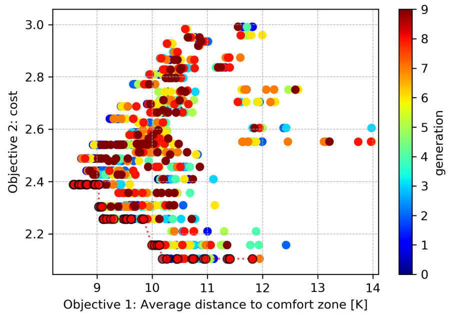
(b) Percentage individuals in the Pareto per generation.

FIGURE 5. Comparison of the results after 10 generations of 100 individuals.

Figure 6 shows the performance of each individual and the Pareto front for both methods. The distribution of individuals is similar and spreads over the same range of abscissa and ordinate.



(a) Stochastic initial population.



(b) Physically based initial population.

FIGURE 6. Pareto fronts after 10 generations of 100 individuals.

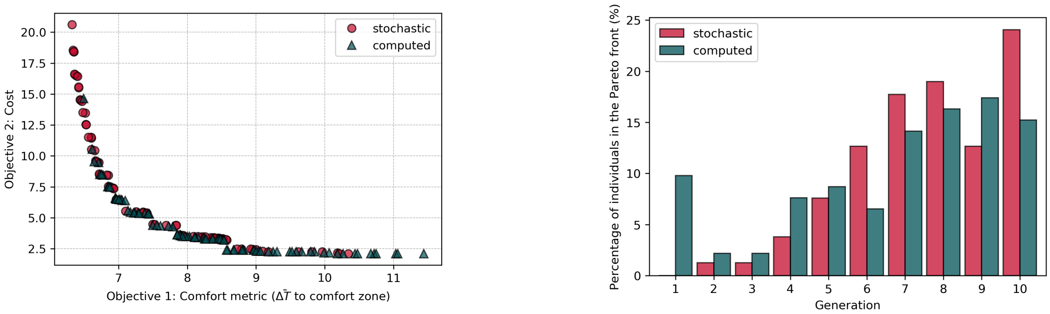
In the studied case, for a fixed, low number of openings, the computation of the initial population seems to provide more disperse results and yields more individuals in the Pareto front during the first generations. The more generations, the less the algorithm is sensitive to the initial population, which suggests that the heuristic choice of the initial population is only beneficial if the algorithm is launched for a small number of generations.

3.3 Variable number of openings

Finding the best combinations for a variable number of openings was the next test for the algorithm. A number such that $2 \leq n \leq 20$. The possible combinations are above 10^{13} and hence the explored fraction of the space of solutions is negligible (in the order of $1000/10^{13}$). After 10 generations, the Pareto fronts are quite similar for the lower values of the cost objective (objective 2), as can be observed on Figure 7a). The algorithm with stochastic selection yields a Pareto front with more individuals having an elevated number of openings (high values of ordinates), whereas the one with computed initial population has more individuals with a smaller number of openings.

Figure 7 b) shows that the computed initial first population provides $\sim 10\%$ of the Pareto front, which is considerable, after what no clear trend is visible compared to the stochastic initial selection.

The performance of each individual of the populations for stochastic and computed initial selections are represented respectively on Figure 8 a) and b), intentionally drawn with identical axis' bounds. Although the Pareto values are similar in the range of $7 \sim 10$ [K] for the comfort objective, one can see that the overall population is less diverse in the case of a pre-computed

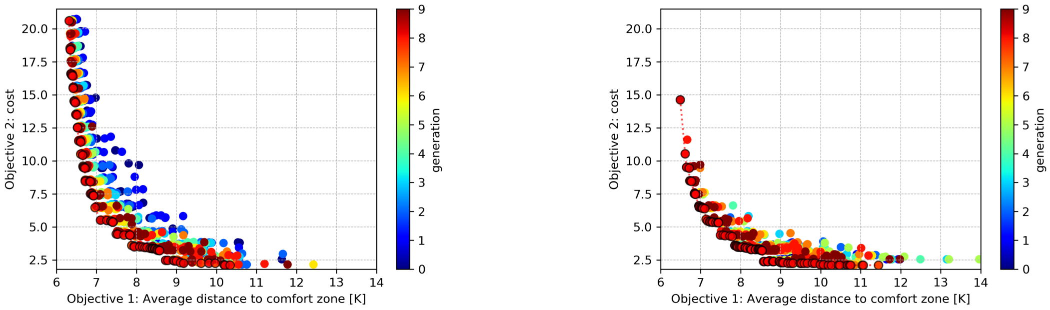


(a) Stochastic initial population versus pre-selected pairs

(b) Percentage of individuals in the Pareto front

FIGURE 7. Results after 10 generations of 100 individuals.

initial population. In this case the Pareto front extends further to the 'right' of the abscissa, after ~ 10 [K] but does not reach the best values for objective 2 (cost) attained by the Pareto front of the stochastic initial selection : the initial selection orientates the algorithm towards optimal solutions with low numbers of openings.



(a) Stochastic selection of initial population

(b) Physically based selection

FIGURE 8. Pareto fronts for a variable number of openings $2 \leq n \leq 20$

3.4 Comparison of the test cases

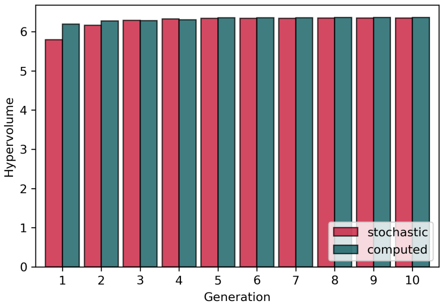
In this section we compare the evolution of the hypervolumes, a metric of the diversity of solutions, for both fixed and variable number of openings.

In the case of a fixed number of openings Figure 9 a) shows that the computed initial population outperforms the stochastic distribution in the first generations, after what the difference vanishes. On Figure 9 b) the hypervolume of the stochastic selection is better, especially for the first generations, after what the difference tends to reduce. In both cases, the extent of the hypervolume is matching after 10 generations, meaning a similar share of the solution space is covered.

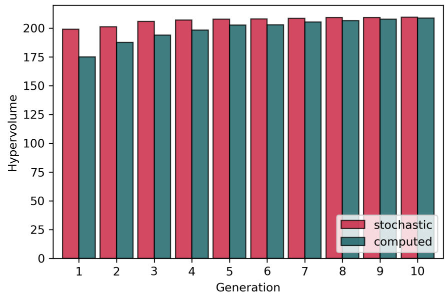
4 Conclusion

In this article a novel approach for the determination of the number of windows and their optimum position on facades was presented. Using the genetic algorithm NSGA-II combined with seasonal building energy simulations may be computationally expensive, the proposed methodology hence consists in selecting an initial population based on heuristic considerations, that is : the couples of openings that have the largest pressure difference over the summer season.

Compared to stochastic initial selection, the obtained solutions have a similar degree of diversity as per the hypervolumes' observation. However, the solutions stemming from the pre-



(a) Fixed number of openings $N = 2$.



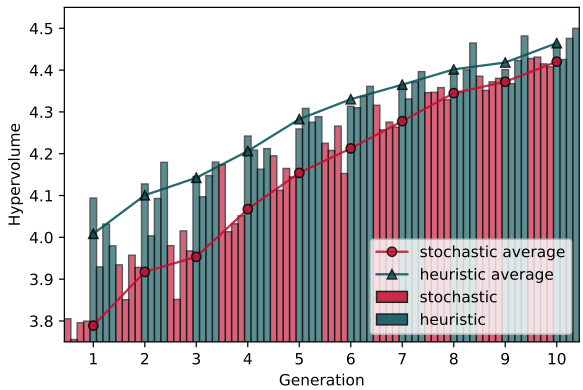
(b) Variable number of openings $2 \leq N \leq 20$.

FIGURE 9. Comparison of the hypervolumes' convergence.

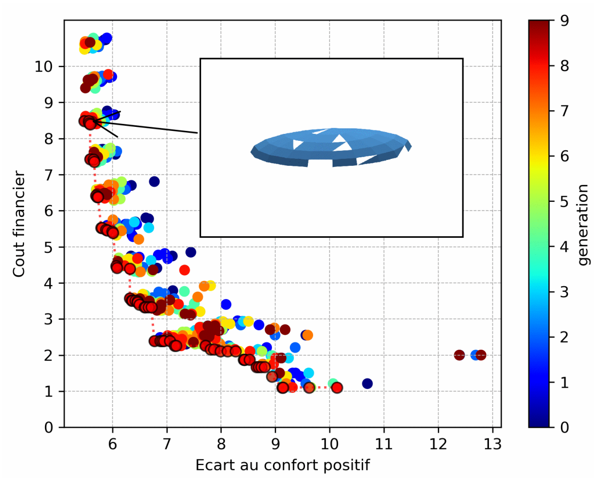
computed initial population generally have a lower number of openings : For an identical computational effort, the method allows to focus on solutions with a low number of windows.

At the time this article was submitted, the initialisation of the population was only possible for $N = 2$ openings. The extension to any number was implemented inbetween and shows promising results (see the evolution of hypervolumes on Figure 10 a) for $N = 10$ openings). It will be included in a future communication.

An example of application is presented on Figure 10 b), exhibiting the position of each ensemble of optimal position on the facade of Strasbourg's train station, showing graphically the diversity of the facade elements.



(a) Comparison of the stochastic and heuristic results for $N = 10$ openings (for 4 simulations for each method).



(b) Animated window positions for individuals of the Pareto front

FIGURE 10

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