Ecodesign of a 'plus-energy' house using stochastic occupancy model, life-cycle assessment and multi-objective optimisation

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ECODESIGN OF A 'PLUS-ENERGY' HOUSE USING STOCHASTIC OCCUPANCY MODEL, LIFE-CYCLE ASSESSMENT AND MULTI-OBJECTIVE OPTIMISATION

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ABSTRACT

Designing plus energy buildings, at lower environmental impact and lower cost, is a complex optimisation problem. In this context, this paper presents an ecodesign approach of a plus-energy house assisted by multicriteria optimisation. Illustrated by a real case, this approach uses a genetic algorithm to find a set of solutions as close as possible to the theoretical Pareto front, corresponding to the best compromises for the formulated problem. The solutions' performance was evaluated using a dynamic building energy model (*COMFIE*), a life cycle analysis model (*novaEQUER*), and a construction cost database. In order to study the solutions' robustness, the diversity of occupants' behaviour was stochastically modelled. The proposed approach is thus contributing to the decision making process, beyond simple evaluation by simulation.

INTRODUCTION

'Plus energy' buildings (Heinze and Voss 2009) are considered as possible solutions for climate change mitigation. If an official definition is still expected, 'plus-energy' generally refers to a building which produces more primary energy than it consumes in a year, assuming a typical behaviour scenario and meteorological year. Designing such buildings at suitable cost for the market constitutes a challenge. The environmental aspect can be integrated by means of an ecodesign approach (Peuportier 2015). The stake in design phase is thus to explore a large range of solutions in a limited time, in order to optimise the performance of the studied concepts according to several criteria which can be antagonistic. We include in this study the annual energy balance, an environmental criterion evaluated by life cycle assessment (LCA), and construction cost, which is very important for the concerned professionals. Interactions between the building, its environment, and its occupants constitute another element to take into account by designers.

In this context, the traditional approach that tries to encompass the globality of the problem by simple parametric variations is no more sufficient. To address this issue, an ecodesign approach of a plus-energy house assisted by multicriteria optimisation is presented in this paper. Following existing works in this fast-growing research area (Attia et al. 2013; Evins 2013), it uses the concept of Pareto's dominance to look for the best set of compromises in a multicriteria problem (called Pareto front) with a genetic optimisation algorithm.

METHODOLOGY

Selection of the design variables

The optimisation purpose is to explore the most revelant search space within a limited time, in order to find the best possible solutions. Because an optimisation study could be computationaly expensive, selecting suitable design variables is an essential preparatory stage of optimisation (Machairas et al. 2014). Indeed, it allows to reduce the search space's size. This selection stage can be carried out using sensivity analysis, e.g. Morris screening method (Morris 1991). Expert judgment can also be used to simplify the optimisation problem. The two approches are complementary for identifying the most influential design variables in relation to the considered performance criteria. At a first step in this study, we selected the design variables based on an expert judgment.

Optimisation algorithm: NSGA-II

Genetic algorithms, particularly the NSGA-II one (Deb et al. 2002), correspond to a simplified computing transposition of Darwin's theory. Their purpose is to mimic a living organism's population adapting itself to its surroundings over generations. The principle consists of manipulating a population (composed of individuals, each one corresponding to a solution of the considered optimisation problem) using stochastic operators in order to improve it. This evolution is managed on the one hand by selection, linked to population individuals' performance (which corresponds to environment pressure on the population), and on the other hand by genetic operators (namely crossover and mutation operators) which generate the next generation of individuals. The evolving population tends to converge towards the best solution(s) of the problem (according to the number of optimisation criteria).

Genetic information (or genome) is usually binary encoded. It presents the advantage of dealing with crossovers and mutations into genes, emphasising in this way genetic mixing and enlarging search space exploration. Without any condition on the considered function's properties such as continuity and derivability (only the function's evaluation on sampled points is required), genetic algorithms are particularly well adapted to complex functions as the ones arising in building energy models.

The general principle of genetic algorithms is based on a generational loop (Figure 1). After the creation of an initial population of μ individuals, step 1 consists in detecting and selecting λ individuals in the current population (called parents), which are allowed to breed. At step 2, parents generate λ descendants (called children) via crossover and mutation operators. These operators are applied randomly using two parameters, the p_c crossover probability and the p_m mutation probability. Performance of the generated λ descendants are evaluated at step 3. Finally, replacement (step 4) consists in creating the next generation operating a selection between the current population of μ individuals and the generated λ children in order to maintain a constant population size. The process is generally stopped when reaching a given number of generations, but can also be defined regarding the current population's performance. Genetic algorithms require several internal parameters, namely the current population size, the parents' number for reproduction, the crossover and mutation probabilities, and a stopping criterion. Like all metaheuristics, setting these parameters is not trivial and mainly based on values from existing literature and on experience gradually acquired.

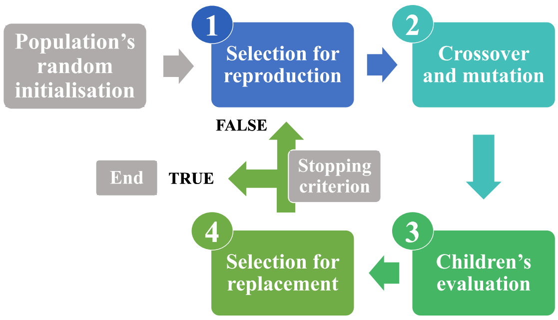

Figure 1 Illustration of the genetic algorithm process

Performance assessment

To design plus-energy buildings, at lower environmental impact and lower cost, several performance assessment models are necessary.

The dynamic building energy simulation software *COMFIE*, created by Peuportier and Blanc-Sommereux (1990), was used in this study. The model is based on the concept of 'thermal zone', considered at homogeneous temperature. The main modelling steps implemented in this tool are the meshing of the building envelop (by a volume finite method), the set-up of a continuous and invariant linear system for each thermal zone, the reduction of the system by modal analysis, and finally the coupling between the different thermal zones. The model simulation requires specifying driving forces, in particular heat gains from occupants and equipment, but also meteorological data (particularly outdoor temperature profile and solar radiation). Phenomena that are non-linear or involving variable parameters (ventilation, thermal resistance due to intermittent use of shutters, etc.) are taken into account through additional driving forces. On top of several validations (Peuportier 2005), the model's reliability was studied in the particular context of a high energy performance house (Brun et al. 2009; Munaretto 2013; Recht et al. 2014).

The building environmental performance was assessed with an LCA software (*novaEQUER)*, created by Polster (1995) and coupled to *COMFIE.* The construction, exploitation, renovation, and demolition steps were taken into account. Life cycle simulation was run using an annual time step, and uses the *ecoinvent* database to establish an inventory of flows from and into the environment. Based on this inventory, 12 environmental indicators, initially proposed by Peuportier et al. (1997), were computed, including the greenhouse gases global warming potential at 100 years as well as human health, biodiversity, and ressources depletion, etc.

As part of the COMEPOS French research and development project (for an optimised design of plus-energy houses), construction cost was chosen as an additional evaluation criterion. Construction cost functions were developped from a database provided by a constructor partner. They take the form of affine or quadratic functions. Due to confidentiality reasons, coefficients associated to these functions cannot be disclosed.

Being more and more insulated, very high energy performance buildings are significantly sensitive to external (meteorological data) and internal (metabolism, electrical appliances) loads. This concerns notably heat gains from equipment and occupants, generally modelled by conventional ratios (e.g. number of persons or kW per m²) and profiles. The Vorger et al.'s (2014) stochastic model for occupancy was applied to achieve a more realistic design. Calibrated on national socio-demographic and time-survey data, but also from measurement campaigns, this model can represent the diversity of inhabitants' behaviours through a probabilistic approach. For each simulation, a different household was generated according to accommodation properties (house or apartment, number of rooms, etc.). Depending on the household socio-demographic characteristics (age, gender, job status, etc.), appliances and activity scenarios were generated, allowing to simulate the occupants' localisation inside the house and the use of electrical appliances and lighting. From several hundred simulations, it was possible to establish average occupancy scenarios (Figure 2 and Figure 3) via the obtained statistical distributions. These scenarios can advantageously replace those generally defined by deterministic ratios and rules. In addition, some model parameters can be manually set, that enables generating customised scenarios corresponding more precisely to the desired study context (accomodation type, household characteristics, range of electrical equipment performance, etc.).

In the COMEPOS project, average statistical scenarios were created for detached houses with high performance appliances and lighting, whose occupants are first-time buyers (S1), specifically a couple of young active people with a young child. From the average profile of activities, we used people's absence time to determine an hourly ratio of presence in the house. Concerning the hourly heating setpoint temperature scenario $T(h)$, we conditioned it from the hourly presence ratio $P(h)$:

$$T(h) = 18 + (21 - 18) \times P(h) \quad (1)$$

The hourly ventilation rates $\dot{V}(h)$ are the sum of a nominal value of 90 m^3/h ($\dot{V}_{nom}$) and an additional air flow of 75 m^3/h ($\dot{V}_{add}$) during n_V (two) hours per day (in accordance with the French regulation). In order to allocate this additional air flow, the two activities which mainly contribute to moisture production were taken into account, namely cooking/washing up (n° 3) and dressing/personal care (n° 8):

$$\dot{V}(h) = \dot{V}_{nom} + [A_3(h) + A_8(h)] \times k_V \quad (2)$$

where A_3 (resp. A_8) is the average hourly rate of activity n° 3 (resp. 8). k_V is the additional air flow per activity rate, averaged over a week:

$$k_V = \frac{\dot{V}_{add} \times n_V \times 7}{\sum_{h=1}^{h=168} (A_3(h) + A_8(h))} \quad (3)$$

The hourly internal heat gains scenario was directly obtained from the occupancy model outputs.

In addition, a retired couple (S2) and a single person (S3) average statistical scenarios were generated, allowing to study the robustness of the optimisation solutions regarding different possible inhabitants along the building's life cycle. Table 1 summarises the annual energy characteristics of the three households. Values are given in final energy. The conversion factor from final energy to primary energy is 2.58 for electricity (French thermal regulation value).

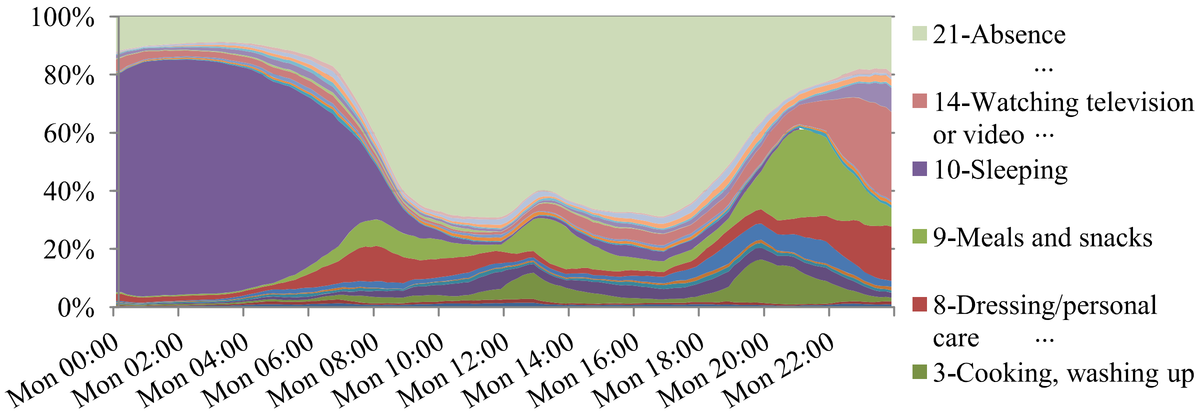

Figure 2 Average daily profile of the activities for a population of 15 441 individuals

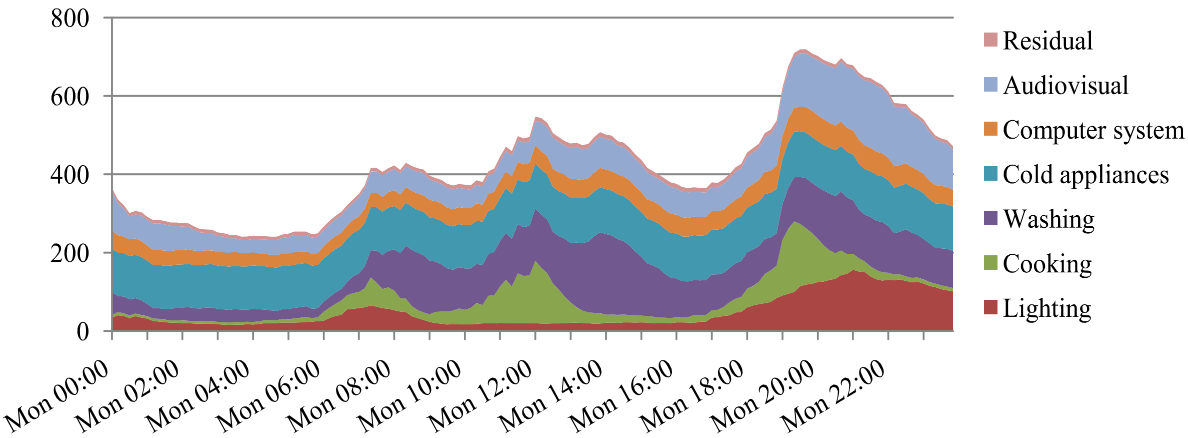

Figure 3 Average daily specific electrical load curve for 100 random young family households

Table 1 Annual final energy characteristics for the three average statistical households (in kWh/m²)

	S1	S2	S3
Metabolic heat	10.2	10.3	3.7
Heating load	22.7	25.3	28.7
Domestic hot water	10.5	8.3	4.2
Electricity for appliances	20.3	17.9	13.0

CASE STUDY

General description and information

The proposed methodology was applied during the design process of a plus-energy house (Figure 4). The target was to elaborate a prototype with a positive annual primary energy balance minimising both construction cost and greenhouse gases emissions (in CO_2 equivalent).

The house has a wooden structure, mainly composed of certified spruce and OSB panels. The walls and the roof are insulated by glass wool, and the floor by polystyrene. Windows are made of PVC with double glazing and are mainly located on south-east and south-west facades. The house surface area is 101 m². It has an electrical heating system, and a thermodynamic water heater with an outdoor air heat pump. The average coefficient of performance (COP) is 2.77. The photovoltaic (PV) modules (1.6 m² each) are made of polycrystalline cells. Concerning LCA simulation, the building's lifetime was assumed to be 100 years. Table 2 presents the life span of the building's elements, according to corresponding environmental product declarations. In order to take into account the variability of energy production during the year (winter/summer, day/night), a dynamic hourly energy mix was used (Peuportier and Herfray 2012).

Design variables

To explore the performance of different concepts of plus-energy houses, 11 design variables were considered in the optimisation problem. This search space was established in collaboration with the architect in order to integrate constraints and degrees of freedom of the project (Table 3).

Algorithm parameters

Specific parameters of the NSGA-II algorithm were set at the following values: 400 for the current population size μ, 400 for the number λ of parents individuals for reproduction, 0.80 for the p_c crossover probability, 0.15 for the p_m mutation probability and 20 generations for the stopping criterion.

Figure 4 3D model of the case study house near Orléans, France (source: Fousse Constructions)

Table 2 Lifetime of materials and equipment

MATERIALS	LIFETIME (IN YEARS)
Doors and windows	30
Coating	10
Greywater recovery system	50
Hot water tank	20
Ventilation system	20
Photovoltaic system	30
Other materials	100

RESULTS

The optimisation process results are a source of diverse information that cannot be totally synthesised in this paper. We propose firstly to display the compromise surfaces between the construction cost and the global warming potential at 100 years, then to evaluate the algorithm convergence and to analyse observed trends regarding the design variables, and finally to study the robustness of the solutions.

Pareto fronts

The base case, the initial population and rank 1 Pareto front at the final 20th generation are plotted in

Table 3 Optimisation problem's search space

DESIGN VARIABLES	UNIT	BASE VALUE	LOWER BOUND	UPPER BOUND	NUMBER OF LEVELS
Thickness of glass wool (walls)	cm	22	15	36	8
Thickness of polystyrene (roof)	cm	22	15	36	8
Thickness of glass wool (floor)	cm	26	12	28	8
Area of window 1 (south-east)	m²	3	2	5	4
Area of window 2 (south-east)	m²	1.46	1.46	2.92	2
Area of window 3 (south-west)	m²	6.88	0	10.50	4
Area of window 4 (south- west)	m²	2.71	2.71	5.42	2
Type of glazing in north-east facade*	-	DG	DG	TG	2
Ventilation system*	-	DF	SF	DF	2
Greywater heat recovery system	-	No	No	Yes	2
Number of photovoltaic modules*	-	12	1	28	16

*DG: double-glazed, TG: triple-glazed, SF: single-flow, DF: dual-flow, PV module surface area: 1.6 m²

Figure 5. The majority (three-quarters) of the initial solutions do not have a positive annual energy balance (see off-peak points in Figure 5), that is why the final Pareto front is located in a limited region of the search space that respects this constraint. Regarding the base case, an additional economic cost is necessary to reach a positive annual energy balance that may on the other hand yield a reduction of greenhouse gas emissions.

Figure 6 presents the rank 1 Pareto fronts evolution over successive generations. Graphically, a clear progression of the Pareto front is observable during the first generations, which slows down around the 10^{th} generation. Up to the end of the process, the front gets denser without really progressing.

Algorithm convergence

In order to evaluate the genetic algorithm performances, the theoretical Pareto front was computed in a 4 194 304 combinations search space. In practice, a reduced number of dynamic thermal simulations were necessary because some variables do not influence the annual heating load. The results concerning the PV modules (16 levels) and the greywater heat recovery system (2 levels) can be obtained by independent and quick calculations. Using a computer with an Intel® Xeon® E5-1650 (3.20 GHz) processor, a 35 h computation time is required to perform the 131 072 thermal simulations.

A comparison between the theoretical Pareto front and the approached Pareto front found by the genetic algorithm is plotted in Figure 6. It took two hours approximately to compute the latter which consisted of 8 000 evaluations of the model. These were enough for the algorithm to effectively converge near to the theoretical Pareto front. However, the approached front is less dense particularly on the edges. Optimisation by metaheuristics being a balance between intensification and diversification of the exploration research space, the relatively quick convergence observed in the case study suggests that a higher mutation probability could improve the population diversity, and thus widen the Pareto front.

Trends about design variables

Figure 7 illustrates the statistical analysis of the characteristics of this 90 solutions set for the equipment. The levels of the photovoltaic system correspond to the number of modules. The upper bound (28) was mostly represented, and no solution had less than 22 modules (the case base: 12). Concerning the greywater heat recovery system, it appears in half of the cases. In contrast to these two systems, there is no compromise for the type of glazing and ventilation. Results highlight privileged solutions, namely only triple-glazed windows on north-east façade and a dual-flow ventilation system with an 80 % efficiency heat exchanger. It is a significant result in the sense that all solutions with double-glazing are dominated by others with triple glazing even for the cheapest ones. The same conclusion could be drawn for the type of ventilation.

Another interesting information is the evolution of the characteristics solutions following the ranking of one of the two criteria, for instance decreasing GHG emissions. As we can see in Figure 8, a compromise exists for the insulation thicknesses. Firstly, the thicknesses increase slowly because the primary lever of the reduction of GHG emissions is mainly the number of PV modules. When its number reaches the upper bound, increasing the insulation thicknesses become a more pertinent action to implement in order to further reduce GHG emissions.

Robustness of the solutions

In order to evaluate the robustness of the obtained solutions, the optimisation process was repeated with the S2 (retired couple) and S3 (single person) behaviour scenarios. The approached Pareto fronts are plotted in Figure 9. Obviously, GHG emissions are different for each household at equal construction cost. The front corresponding to the single person's scenarios was the lowest one, mainly due to its low hot water and specific electricity consumptions. Despite an additional person (a child), the Pareto front of the young couple was relatively close to the retired couple's. That can be explained by higher heating loads due to a more important occupancy ratio and a higher temperature setpoint for the retired couple. In terms of equipment characteristics, results are almost the same for the type of glazing (between 99 % and 100 % of triple glazing) and the type of ventilation (between 98 % and 100 % of double flow). The cheapest two solutions in the S2 Pareto front have single-flow ventilation, contrary to S1 for which all theoritical solutions have a dual-flow ventilation system. For S3, either the genetic algorithm did not capture these solutions, or they do not exist. Because S3 presents relatively high heating loads combined to low internal gains, we believe that the simple-flow is not a feasible solution of the problem. On the other hand, differences are observable for the number of PV modules and the greywater heat recovery system (see Figure 10): the higher the global consumption, the higher the number of PV modules. Similarly, the lower the hot water consumption, the less relevant the greywater heat recovery system is. After obtaining these three Pareto fronts, we recalculated the 90 unique solutions of the S1 front with S2 and S3 behaviour scenarios in order to assess if these solutions would still be performant with different types of inhabitants. In Figure 9, results show that S1 solutions are globally robust, in particular with S2 scenarios, which are closer to S1's than S3's. When we compare S3 (resp. S2) Pareto front with S1 solutions calculated with S3 (resp. S2) scenarios, we observe that the cheapest solutions are lost. They mainly correspond to solutions with simple-flow ventilation for S2 and solutions with a lower number of PV modules for S3. The linear part

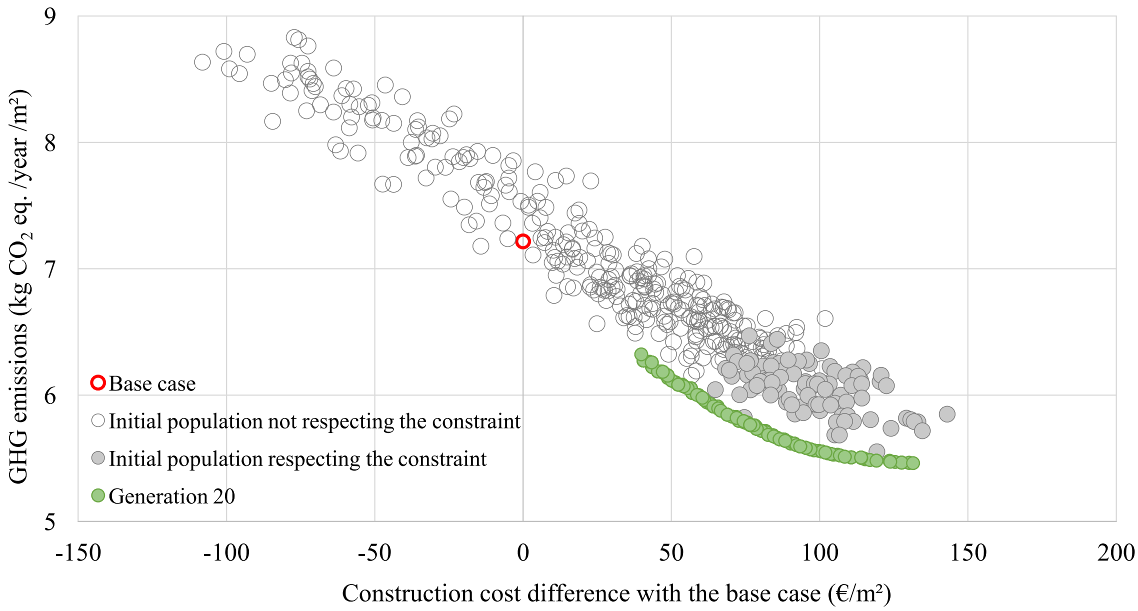

Figure 5 Base case, initial population and final rank 1 Pareto front

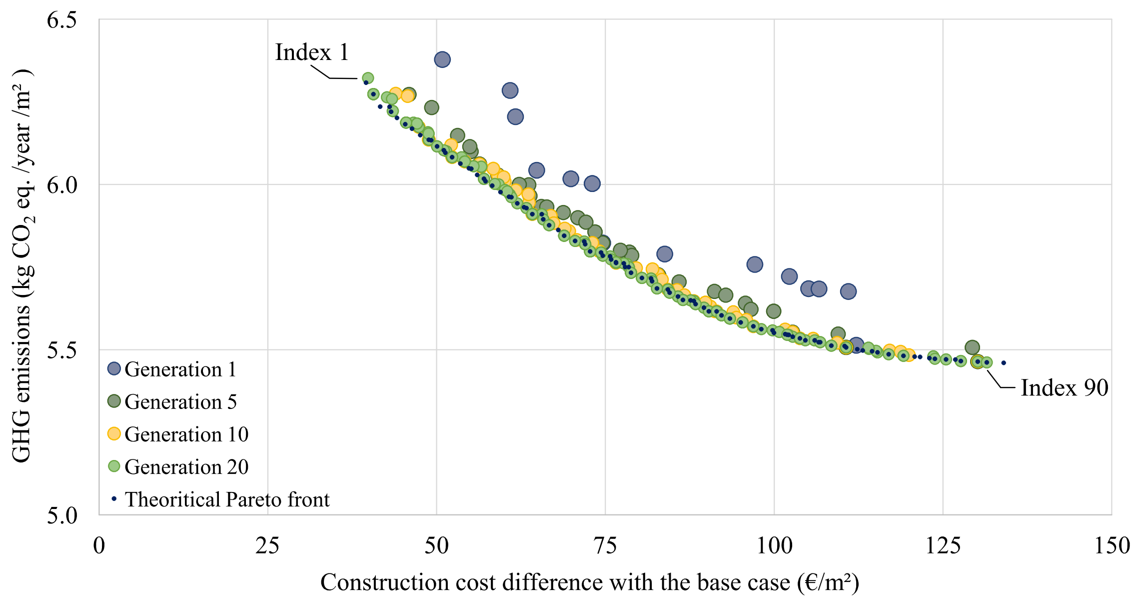

Figure 6 Evolution of rank 1 approached Pareto fronts and theoretical Pareto front, zoom

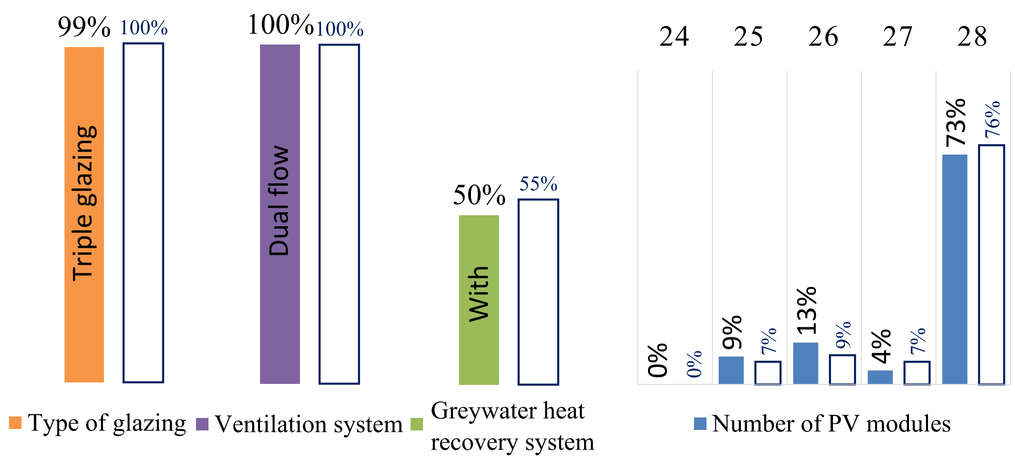

Figure 7 Equipment characteristics of approached and theoretical (blue contour rectangles) Pareto fronts

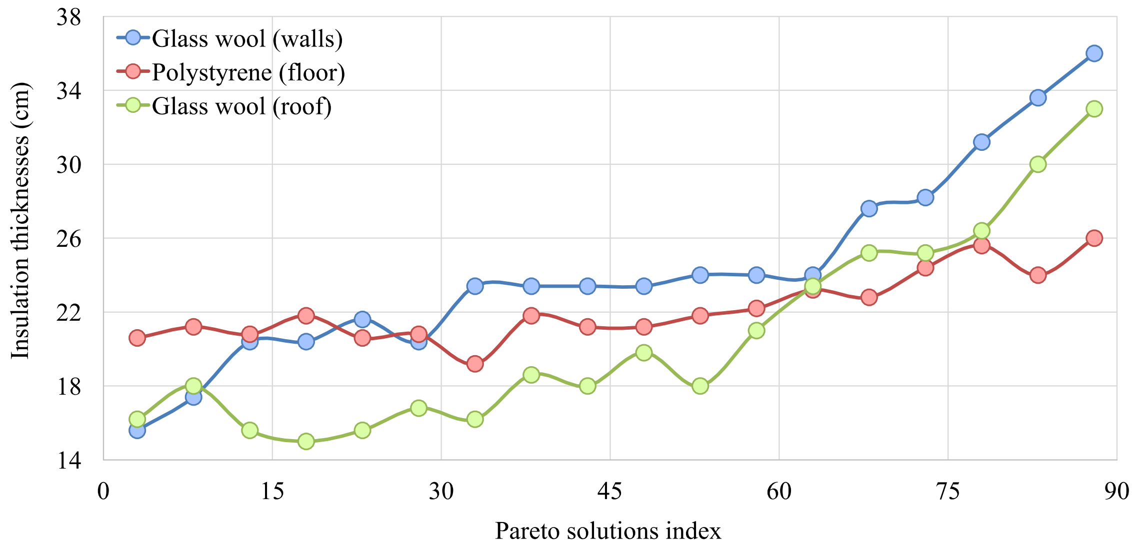

Figure 8 Evolution of the insulation thicknesses for decreasing GHG emissions (Pareto solutions)

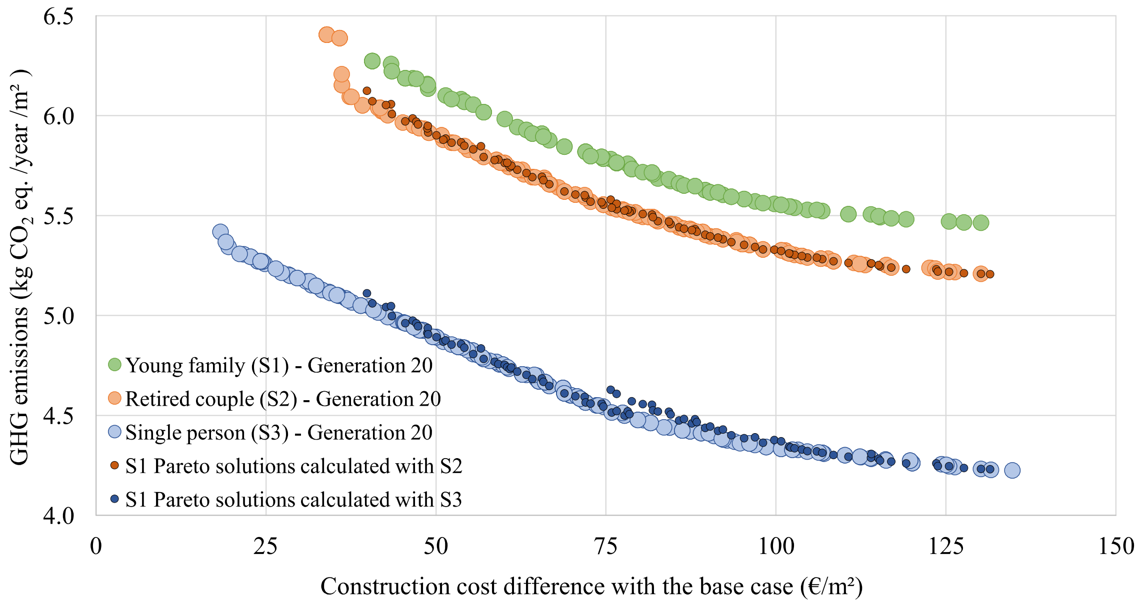

Figure 9 Comparison of the approached fronts for the three considered households

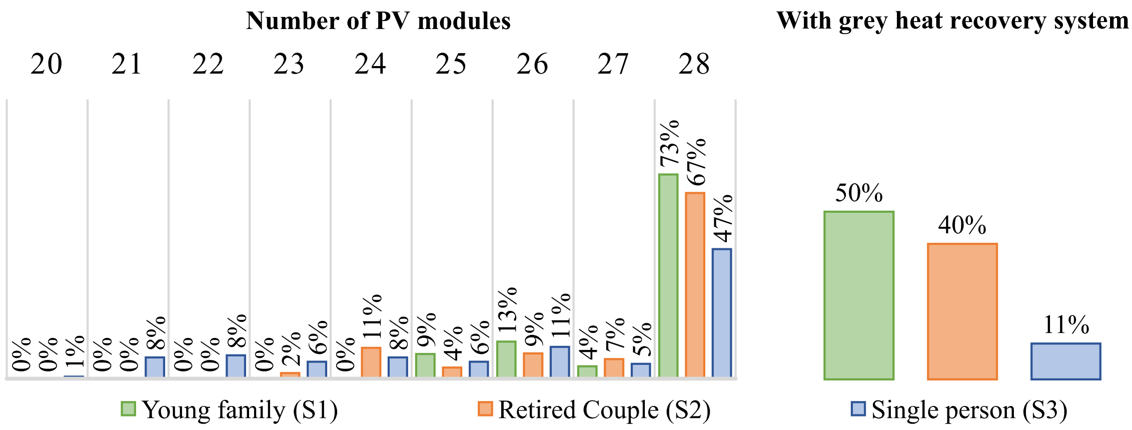

Figure 10 Comparison of Pareto front's characteristics for the three households

of the Pareto front is mainly due to a variation of the number of PV modules which yields a linear variation of the cost and GHG emissions. For S3, some solutions appear distant from the approached Pareto front. They correspond to solutions with a greywater heat recovery system, which is not always pertinent. However, most of the solutions are very close to the S3 Pareto front. Therefore, in this case, the optimisation procedure appeared to be robust.

CONCLUSION

An ecodesign approach of a plus-energy house assisted by multicriteria optimisation was developed using a building energy model including a stochastic occupancy model in order to have more realistic scenarios (*COMFIE*), and an LCA model (*novaEQUER*). NSGA-II genetic algorithm was implemented to identify the best compromises in a multicriteria problem,. The proposed methodology was applied in the French research project COMEPOS, in order to design plus-energy house prototype. For illustration purposes, optimisation results aiming at minimising jointly the construction cost and greenhouse gas emissions, under a positive annual energy balance constraint, were presented showing a compromise surface whose characteristics' analysis allowed to extract useful information to help in the decision making process. In a reasonable time (two hours), the algorithm identified a solutions set near the theoritical one, confirming its acknowledged performance and outlining perspectives for future more ambitious explorations, in terms of number of design variables, number of discretisation levels, but also number of performance criteria. In addition, the robusness of the solutions was studied comparing optimisation results for two other occupancy scenarios. In the case study, the optimisation process looks fairly robust inviting to ascertain its robustness on other similar cases.

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