A study on the multi-objective optimisation of district energy system performances

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Abstract

The design of sustainable district is a recent subject which is motivated mainly by environmental, energy and economy aspects. The DIMOSIM (DIstrict MOdeller and SIMulator) platform allows to investigate this research field by modelling and simulating an entire district. A complete procedure, based on direct search and the NSGA-II genetic algorithm, was developed to solve this multi-objective optimisation problem. The aim of this study is to prove that it is perfectly suitable for this type of complex problem. The solutions obtained show satisfactory results compared to the real Pareto solutions which confirms the choices made to elaborate this optimisation procedure.

Introduction

Research carried out in the building research community conducted to enhance performances of buildings resulting in a new generation of efficient constructions: passive buildings, eco buildings, low or zero energy buildings among others. Even if there are still possible improvements at the building level, the district scale perspective offers significant potential. Particularly, the energy design of district helps to foster synergies and to obtain a suitable global concept for urban planning.

For this purpose, it is essential to consider the dynamic behaviours and phenomena of the district, in particular buildings, local or centralised systems and also the urban environment. These elements are linked, mainly dependent of the district properties and must be well modelled because they can definitely affect the relevance of choices made.

Using the DIMOSIM (DIstrict MOdeller and SIMulator) platform developed by Riederer et al. (Riederer et al., 2015), a district can be numerically simulated using physical models and its performances can be analysed. Moreover, this tool allows to launch large parametric studies accurately and quickly. The results obtained are useful to identify the most suitable configurations of a district energy system.

The optimisation of a district energy system is a complex multi-objective problem: the parameters taken into consideration can be discrete or continuous, the research space is almost infinite and the objective functions are undefined because of the use of a simulation platform which is considered as a black box. The processes to solve this multi-objective optimisation problem must be especially dedicated to overcome all these scientific obstacles.

Therefore, the purpose of this study is to highlight the problems encountered in the optimisation of district energy design. The solutions deployed to solve them are integrated into a single optimisation procedure which is multi-level and multi-objective. In a first section, this article presents a state of the art about similar energy based problems. Relying on identified methods, a complete optimisation procedure has been developed. It is presented and applied to a case study of a small district with 25 buildings. Finally, the results obtained are compared and analysed to ensure that this multi-objective optimisation problem is well solved.

State of the art

The optimisation of district energy system performances is a recent field of study, especially when using a simulation tool. Even if several studies on optimisation methods concerned with complex optimisation problems in the domain of civil engineering, only few of them use multi-objective methods and even less at a district level.

A work on the optimisation of building refurbishment has been published by Pernodet Chantrelle et al. (Pernodet Chantrelle et al., 2011). Several optimisations were conducted based on one, then two and finally three objectives considered simultaneously from the following list: energy consumption, economic cost, life-cycle environmental impact and thermal comfort. The authors used TRNSYS to simulate the building and the NSGA-II genetic algorithm (Deb et al., 2002) to solve the problem. This study highlighted the benefits of multi-objective considerations and the NSGA-II algorithm but it has been applied only to one single building.

Verbeeck and Hens (Verbeeck and Hens, 2007) presented an interesting approach for the multi-objective optimisation of low-energy houses. Three objectives were taken into account: net present value, primary energy consumption and global warming potential during the building life cycle. The authors used TRNSYS for the simulation of the houses and MATLAB to perform the optimisation. The development concerned a multi-level optimisation methodology decomposed in sub-problems and a Pareto-based evolutionary algorithm for the global optimisation. The application was simple but enough detailed to prove that the methodology is well adapted to solve multi-objective optimisation problem for single houses.

Armand Decker et al. (Armand Decker et al., 2014) developed a methodology to design multi storey timber buildings. Based on a meta-model generated from EnergyPlus, the building has been simulated and optimised thanks to the Particle Swarm Optimisation algorithm. This dedicated process, used to find the Pareto-optimal solutions on several objectives, has been used on the example of a three story building with two objectives for this application: energy demand and summer comfort. The use of a metaheuristic has allowed reducing significantly the computational time to solve this simple problem.

Salminen et al. (Salminen et al., 2012) also combined energy simulation and multi-objective optimisation on a case study: a two-storey shopping centre. By using the simulation tool IDA-ICE and the Pareto-archive NSGA-II algorithm, the authors optimised two different objective functions: energy savings and investment costs. The prospective case study was restricted in research space but the results obtained were satisfactory and may be integrated in the planning process to help decision making.

The references listed above are well-suited optimisation processes for the building level but their application on a district scale needs major adaptations and improvements. Indeed, the limited domain size simplifies the nature of the problem and the choices made to solve it. More, the combinatorial explosion is huge at the upper scale.

Kämpf and Robinson (Kämpf and Robinson, 2009) have studied an optimisation problem at the district scale. They have developed a mono-objective optimisation process that uses a hybrid evolutionary algorithm based on CMA-ES and HDE algorithms. A simple case study using the CitySim district simulator software was performed to show the potential of such investigation but limited to a restricted research space. In conclusion, it is functional but it is complicated to conclude on the adaptability of this optimisation concept for a complete and multi-objective problem.

To date, no research has been found that addresses the problem of a district energy system optimisation with an extended parametric set and a multi-objective approach. However, the most suitable methods may be conserved and modified to fit with the optimisation problem, in particular the use of an evolutionary algorithm and the multi-level approach. That is still a convenient base for developing the optimisation process dedicated for the design of the entire energy concept at the urban scale.

Development

The optimisation of district energy system performances is a complex problem requiring dedicated optimisation processes. The developed procedure is based on a multi-level approach and composed of several methods designed to take into account multi-objective considerations. Developed in MATLAB, the procedure has been integrated into the DIMOSIM software as a plugin.

Definition of the optimisation procedure

The optimisation procedure detailed by three principal levels is described by the flowchart showed in Figure 1.

First of all, the initial definition of the research space is provided by the DIMOSIM database. Once it has been defined and structured, there are still too many alternatives to solve the problem in a reasonable time with a direct search (i.e. brute force search also called exhaustive search). Thus, all parts of the problem that can be optimised separately are dealt with independently. In a first step, the Pareto-optimal configurations for the envelope of all buildings are determined individually by calculating their loads without systems (1^{st} level or 1). After a selection, the optimal solutions retained are used in the second level of the procedure where systems are added. Then, two major branches have to be investigated separately and are treated differently:

- Local production: The configurations from the first level are directly used and combined with the complete parameters set to find optimal configurations for all entire buildings (i.e. with systems) (2^{nd} level/Local/1^{st} step or 2.1.1). Afterwards, the selected configurations are used to define the optimal configurations, including sizing, of district with only local production (2^{nd} level/Local/2^{nd} step or 2.1.2).
- Central production (district heating): The configurations from the first level are combined to obtain optimal configurations of building's envelopes for the district (2^{nd} level/Central/1^{st} step or 2.2.1). The goal of this step is to reduce drastically the number of configurations to simulate and thus to avoid the combinatorial explosion. Then, the solutions retained are combined with the complete parameters set to obtain the final district configurations with central production (2^{nd} level/Central/2^{nd} step or 2.2.2).

Finally, the optimal configurations from the two parts of the second level are aggregated to form the final results (3rd level or 3) that they are presented later on.

Before each step, a hypervolume selection is applied to reduce the number of solutions retained. Furthermore, an energy constraint can be associated. Two different methods are deployed for each step of the second level: brute force search and NSGA-II genetic algorithm. The first one is extremely time-consuming but gives the real Pareto front and the second one is faster but solutions are approximations.

The first level of the optimisation procedure is always done with the brute force search. The differences appear for the second level because the number of combinations is much larger:

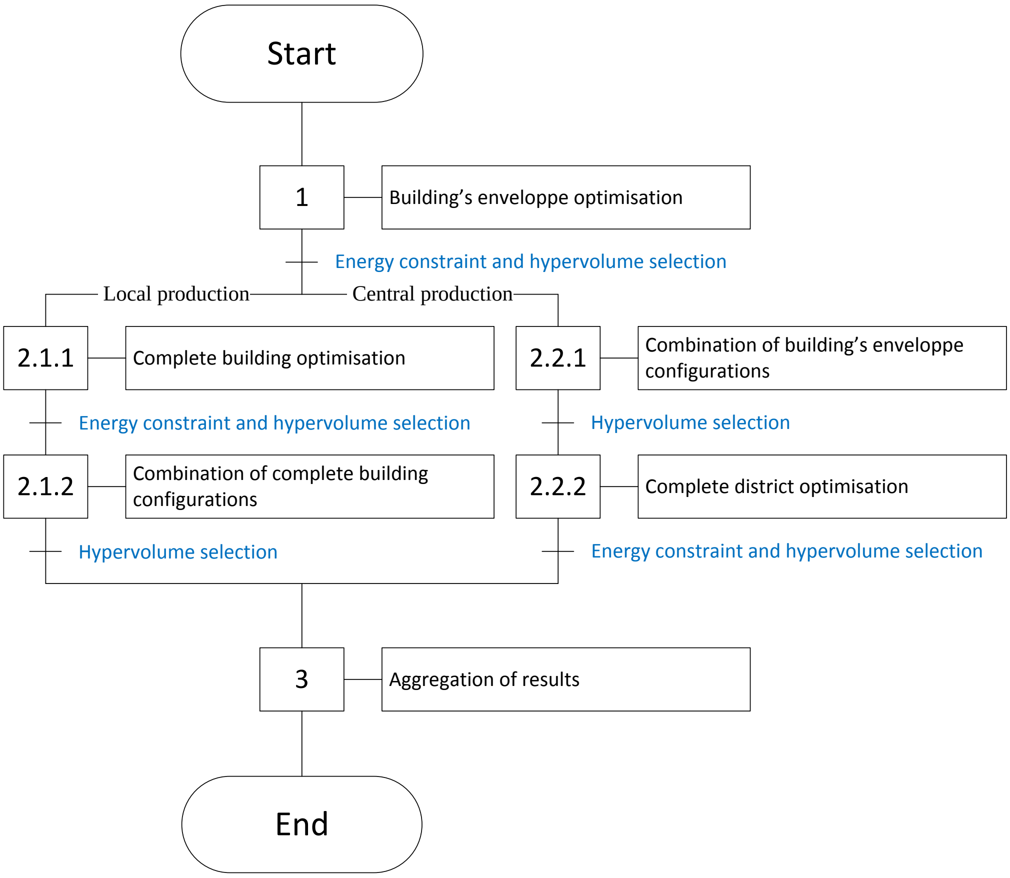


Figure 1: Flowchart describing the optimisation procedure.

- For the combination steps (i.e. 2.1.2 and 2.2.1), incremental brute force search (i.e. the Pareto fronts are found successively by gradually combining the elements of the active front with the configurations of a new building) or genetic algorithm is used.
- For the simulation steps, the "central production" branch is done with brute force search or genetic algorithm. But the "local production" branch is only performed with brute force search. By using DIMOSIM software, the time consumption by buildings is decreasing with the number of buildings simulated simultaneously. It is thus preferable to simulate all the configurations with all buildings together rather than parallelize the processes.

The comparison between the two methods will allow validating the use of the NSGA-II genetic algorithm for this optimisation problem.

Objectives

This optimisation procedure is developed to operate with three objectives which evolve with the level of the process. In any case, they are linked and are widely used for this type of problem.

For the first level, only the energy needs can be calculated and the operational concerns are not available. So the first three objectives are:

- Energy demand per unit area for a year (kWh/m²/year)
- Global warming potential ($kg_{eq}CO_2$/m²/year) related to the envelope during the district life cycle calculated within standard EN 15804 (CEN, 2012), per unit area for a year
- Investment cost per unit area (€/m²)

For the second level, the simulation can be performed with operational aspects. The three final objectives are:

- Total final energy building consumptions per unit area for a year (kWh/m²/year)
- Total global warming potential during the district life cycle ($kg_{eq}CO_2$/m²/year) calculated within standard EN 15804, per unit area for a year
- Global cost (€/m²) for 20 years per unit area defined as follows:

$$Global\ cost = \frac{1}{S}\cdot\left(I_0 + \sum_{i=0}^{N}\frac{(1+ie)^i}{(1+a)^i}\times Ce_i + \sum_{i=0}^{N}\frac{(1+im)^i}{(1+a)^i}\times Cm_i\right) \quad (1)$$

with S the surface; I_0 the initial investment; Ce and Cm the costs of energy and those of servicing and the costs

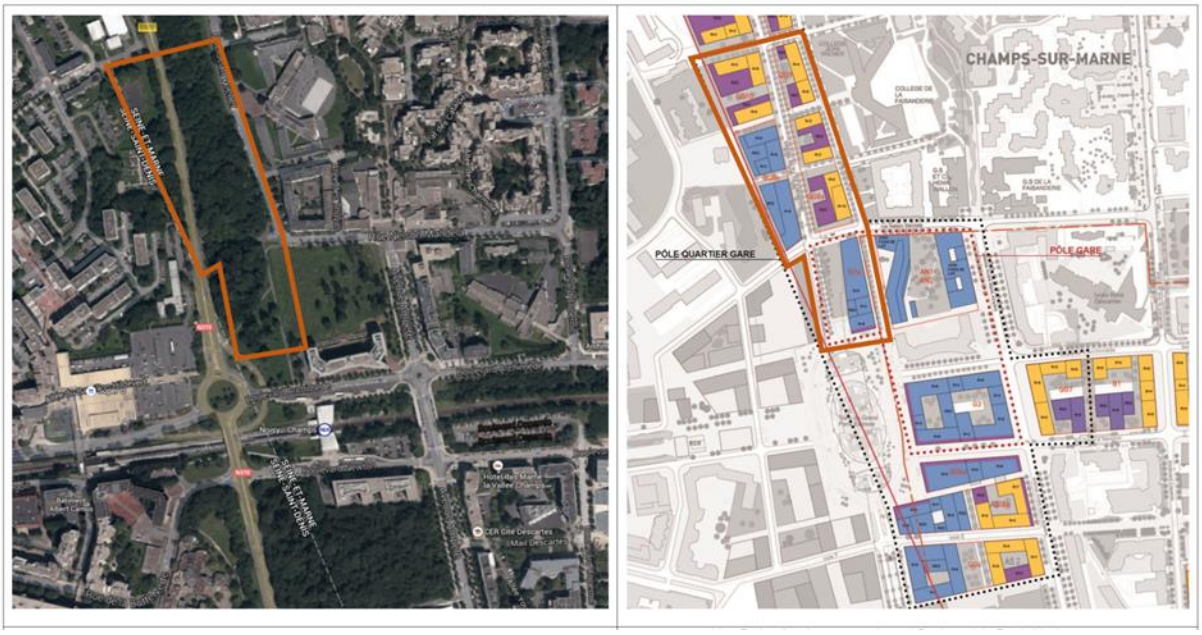


Figure 2: Spatial planning of the RU de Nesles Boulevard (left side: satellite view of the study area at the current state via Google Maps, right side: block plan of the project).

of energy and those of servicing and maintenance respectively; ie and im the inflation rates of energy and that of servicing and maintenance respectively; a the discount rate fixed at a value of 3%; and N the period of calculation of the global cost.

Case study definition

RU de Nesles project

The developed procedure has been applied to a real case study: the development project of the RU de Nesles Boulevard (Champs-sur-Marne, France), planned in parallel with the Grand Paris project for 2030. Figure 2 gives an overview of the current area and the future block plan where the red zone represents the part studied. This new district is composed by 25 buildings: nine residential buildings (in yellow), six commercial buildings (in purple) and ten office buildings (in blue), spread over eight urban islands. It must be effective on several criteria and especially on the three final objectives described previously. Therefore, to support future decisions of the project owners, this detailed study is carried out to design an efficient and sustainable district concept.

Table 1: Sets of parameters

Level	Parameter	Value
1st	Structure material	Concrete, Brick
	Insulation material	Mineral wool, Synthetic wool, Natural wool
	Insulation position	Indoor, Outdoor
	Insulation thickness (wall)	0.1 m, 0.16 m, 0.2 m
	Insulation thickness (roof)	0.1 m, 0.2 m, 0.3 m
	Window type	Double glazing, Triple glazing
2nd	Production system	*Local*: Condensing boiler, CHP (internal combustion engine), Heat pump (air/water) *Central*: Condensing boiler, CHP(internal combustion engine), Heat sharing network (source: aquifer) with local heat pumps (water/water)
	DHW system	Electric hot water tank, Gas (instantaneous)
	Ventilation system	Mechanical extract, Mechanical balanced with heat recovery
	Area ratio for photovoltaic on roof	0%, 10%, 20%, 40%
	Building configuration	N_b configurations from the 1st level optimisation

N.B.: If the energy production system is centralised, it obviously implies that a thermal network is deployed.

Table 2: Population retained for each step

Step	Solutions retained
1	20 per building (N_b=20)
2.1.1	20 per building (L^0=20)
2.1.2	**100 for the district (L=100)**
2.2.1	$3{\cdot}N_b$ combinations from the first level for the district (C^0=60)
2.2.2	**100 for the district (C=100)**
3	**≤ 200 for the district (D=L+C=200)**

Parameters

To conduct this study, a set of 11 discretised parameters is considered, including 6 parameters for the first level and 5 plus 1 parameters are available for the second level, because the configurations retained from the first level become obviously an additional parameter for the second one. Those are described in Table 1. The DIMOSIM database is used to provide information on economic and environmental costs.

Without the multi-level approach and the simplifications from the optimisation procedure, the number of configurations to simulate is over 10^{100}. Now, 216 simulations are needed for the first level with a selection of N_b configurations by building and for the second level:

- For the local production branch, $48{\cdot}N_b$ simulations must be launched for the first step and just calculations are required to find the final combinations because the configurations are already simulated for the second step.
- For the central production branch, after the combinations of the already simulated configurations, a fixed number of $3{\cdot}N_b$ solutions for the district are selected from the first step. Then, $48{\cdot}(3{\cdot}N_b)$ simulations are done.

So, only $216+192{\cdot}N_b$ simulations need to be completed for the entire procedure by considering direct search with, in addition, 2 combination and 6 Pareto searching sub-processes.

Methods configuration

To focus on configurations which can be selected after the complete optimisation procedure, a consumption constraint is taken with the value of 60 kWh/m²/year.

The populations composed by all the solutions retained at each step, are described in Table 2. Their values have been set in order to have a good compromise between computational time and accuracy. Finally, a maximum of 200 Pareto-optimal solutions were preserved for a final decision.

For the NSGA-II genetic algorithm, the parameterisation influences the performances. Thus, parameters have to be properly selected in order to get acceptable results. According to the recommendations of Deb et al., (especially by taking a high value for the crossover rate and a value for the mutation rate close to 1/n with n the number of decision variables) the parameters taken have been tuned depending of the step and the characteristics of the research space associated. They are given in the Table 3. More, only middle single point crossover is used.

Concerning the simulation, the time step is set to 1 hour resulting in a computational time of less than 4 seconds for the thermal needs simulation and less than 20 seconds by complete simulation for this district including the energy system (computer specifications: 2.60 GHz CPU and 8.0 GB RAM).

Table 3: Description of the NSGA-II parameters used for each step

Parameter	Step		
	2.1.2	2.2.1	2.2.2
Population	$3{\cdot}L$	$3{\cdot}C^0$	$1.5{\cdot}C$
Generations	10 000	10 000	7
Crossover rate	0.85	0.85	0.75
Mutation rate	0.10	0.10	0.20

Results

The aim of the approach is to compare the results obtained using brute force search to those of the NSGA-II genetic algorithm on the example of the RU de Nesles project. The results are analysed in order to evaluate the performance of the metaheuristic method to manage this kind of optimisation problem.

Comparison of the methods results

For the comparison between the results from the two different algorithms, a quality criterion for the intensification has been created: Ic. It is the relative distance of the solutions from the genetic algorithm compared to the closest solutions of the real Pareto front from the direct search algorithm. Equation (2) describes this relation which is closed to the normalized root-mean-square deviation formula.

$$\mathrm{Ic} = 1 - \sqrt{\left(\frac{x-x_{ref}}{x_{ref}}\right)^2 + \left(\frac{y-y_{ref}}{y_{ref}}\right)^2 + \left(\frac{z-z_{ref}}{z_{ref}}\right)^2} \quad (2)$$

With (x,y,z) the results on the three objectives of the solution resulting from the genetic algorithm and (x_{ref},y_{ref},z_{ref}) the closest reference results from the direct search algorithm before the selection.

The mean value of this indicator (Equation (3)) is calculated for all steps.

$$\overline{\mathrm{Ic}} = \frac{1}{nPop} \sum_{i=1}^{nPop} \mathrm{Ic}_i \qquad (3)$$

with nPop the number of solutions retained for the step considered (i.e. the population).

To define the quality of the diversification, another criterion is created based on hypervolume, which is the main indicator used for multi-objective optimisation (Zitzler and Thiele, 1998). The hypervolume of a set of points with respect to a reference, denoted as Hv, is the union of the volumes covered between each points and the reference.

The criterion developed Hvr_{method} consists in comparing the real hypervolume of the Pareto front (Hv_{pareto}) to that of the method used to find the solutions retained (Hv_{method}). The relation is given by the Equation (4). The reference point for the calculation is composed by the worst value reached by the complete Pareto front on the three objectives.

$$Hvr_{method} = 100 \cdot \frac{Hv_{method}}{Hv_{pareto}} \qquad (4)$$

The value of Hvr_{brute} is then the goal to reach (maximum value for a fixed number of solutions selected) for the Hvr_{nsga2} criterion.

The first level is a simple brute force search which gives one Pareto front for each building. Figure 3 shows the results obtained for a single building: all the alternatives and the N_b solutions selected on the Pareto front for the next steps. A first constraint for the building thermal needs (i.e. heating and cooling) is taken at a value of 45 kWh/m²/year to filter the initial results.

Two distinct clusters of alternatives can be seen in the Figure 3: the upper one is only composed by alternatives with concrete for the structural material and the lower one with brick. Buildings made with brick almost completely dominate the other ones. The solutions based on brick are slightly less energy efficient than those using concrete, but they are better for the two remaining objectives within an equivalent configuration. On the complete and constraint Pareto front, just few alternatives with concrete for the structural material are present and they are not selected for the next step. Otherwise, the solutions selected would have diversified configurations.

For this level, the maximum value of the density criterion is extremely high for the selection of N_b solutions. These results are almost the same for all buildings: $Hv_{brute} \in [98.88\% ; 100\%]$ with the mean value at 99.69%.

For step 2.1.1, the distribution of the alternatives is relatively homogeneous in the performances space. It is provided by the Figure 4. The alternatives including heat pump appear clearly on the Pareto front, followed by condensing boilers. The Combined Heat and Power (CHP) systems are almost missing. Concerning the other parameters, no particular value takes over. The distribution is almost uniform except for the solutions retained from the previous step because solutions with low energy needs are preferred. Moreover, the constraint fixed initially is not exceeded by the solutions of the Pareto front for this particular example building. For some buildings, it restricts the field of possible solutions.

Proportionately to the complete Pareto set, almost the same number of solutions is chosen compared to the first step. The density criterion is close to the maximum: $Hv_{brute} \in [98.84\% ; 100\%]$ with the mean value at 99.70%.

For the last step of the “local production” branch (i.e. 2.1.2), the NSGA-II is used in parallel with the brute force search. The results obtained are presented by the Figure 5.

The complete Pareto-optimum set forms a convex slick. Although each building has its own particularities in terms of optimal configurations, no particular property can be deduced about complete district solutions. Indeed, the singularities of the buildings create diversity at the district level.

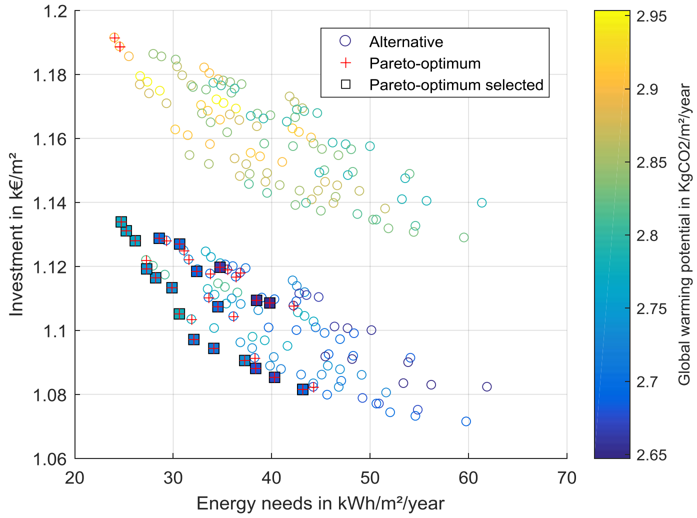
The intensity criterion is nearly maximal, that means the NSGA-II solutions are extremely close to the real Pareto-optimum. The two quality criteria for both methods are significant and this criterion is completely admissible by using the NSGA-II genetic algorithm.

The results of the step 2.2.1 are given in Figure 6. The combinations of building envelope configurations are very varied. It constitutes a convex slick which is narrow on the environmental (from 1 215 to 1 255 €/m²) and economic (from 3.06 to 3.14 $kg_{eq}CO_2$/m²/year) objectives mainly because of the structural material impact.

The intensity criterion is again extremely high. On the other hand, the value of the density criterion for the selection after the brute force search is lower than this of step 2.1.2 which is also a combination step. Actually, more Pareto-optimum solutions and fewer sectioned solutions explain these differences. The density criterion for the genetic algorithm is almost 8 points below the reference value for C^0 solutions selected. The coverage of the performances space by the results obtained with the NSGA-II algorithm can still be considered enough significant, even if the diversity could be improved.

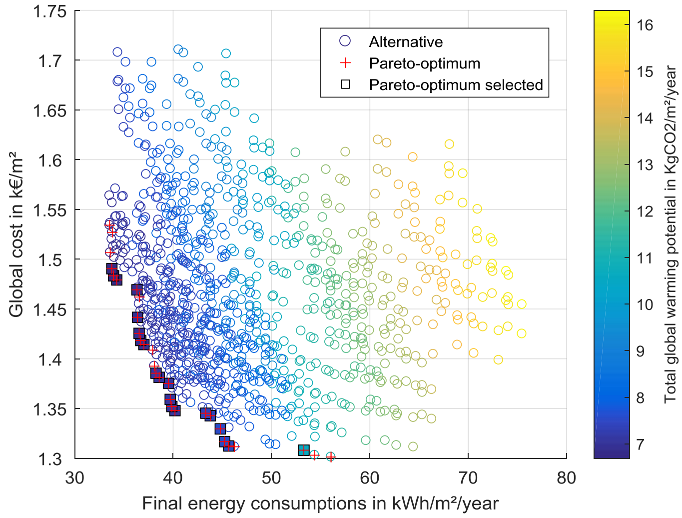
The solutions obtained with a given method, at the previous step (2.2.1), are used as input to solve the sub-problem of the step 2.2.2 with the same method. Figure 7 shows the results.

On the Pareto front, two groups of solutions are clearly identified and form two narrow silks.



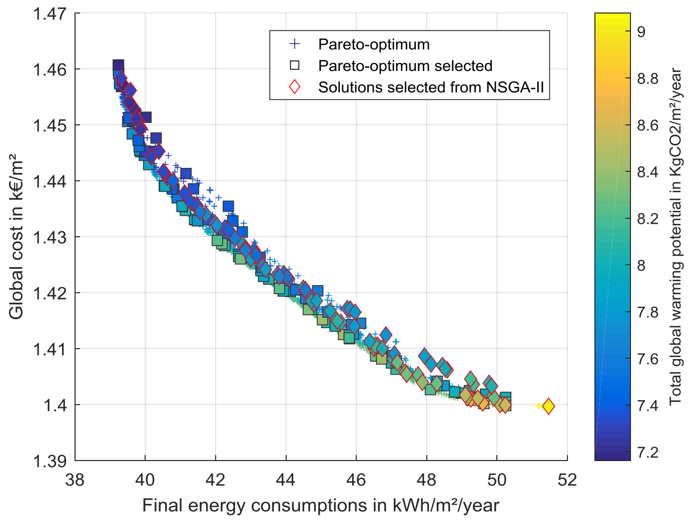
$$Hvr_{brute} = 99.75\ \%$$

Figure 3: Example of a building envelope optimisation (step 1).



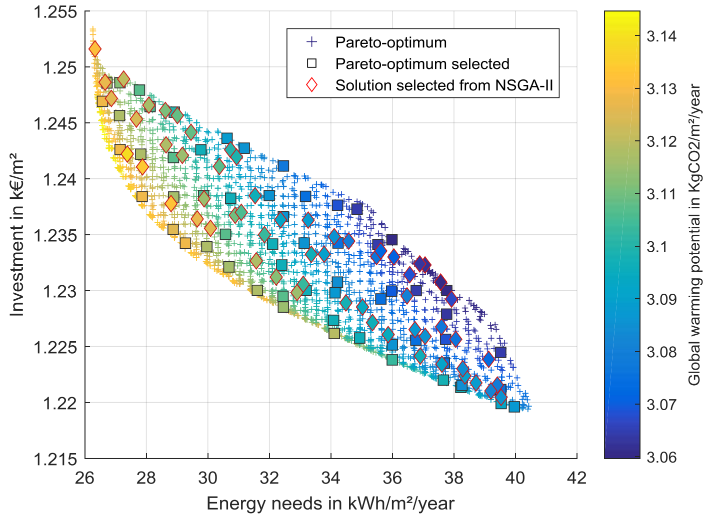
$$Hvr_{brute} = 99.95\ \%$$

Figure 4: Example of a complete building optimisation for the local production (step 2.1.1).



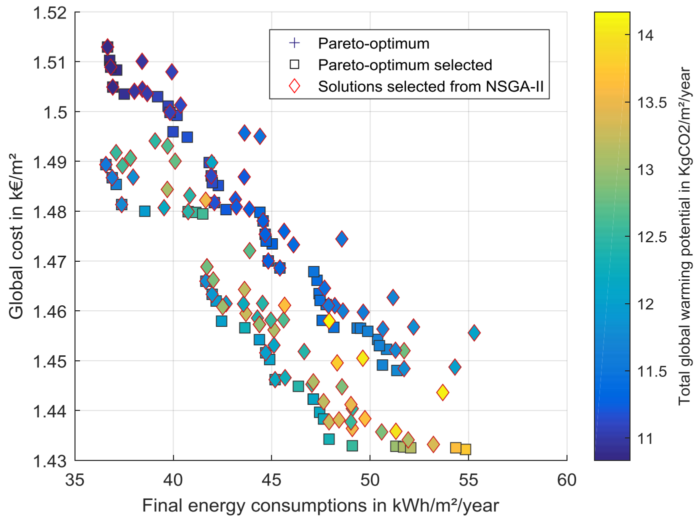
$$Hvr_{brute} = 97.21\ \%$$
$$Hvr_{nsga2} = 94.51\ \%$$
$$\overline{\mathrm{Ic}} = 99.76\ \%$$

Figure 5: Combination of complete building configurations optimisation for the local production (step 2.1.2).



$$Hvr_{brute} = 92.02\%$$
$$Hvr_{nsga2} = 84.88\%$$
$$\bar{\text{I}}\text{c} = 99.78\ \%$$

Figure 6: Combination of building's envelope configurations optimisation (step 2.2.1).



$$Hvr_{brute} = 99.97\%$$
$$Hvr_{nsga2} = 95.08\%$$
$$\bar{\text{I}}\text{c} = 97.32\ \%$$

Figure 7: Complete district optimisation for the central production (step 2.2.2).

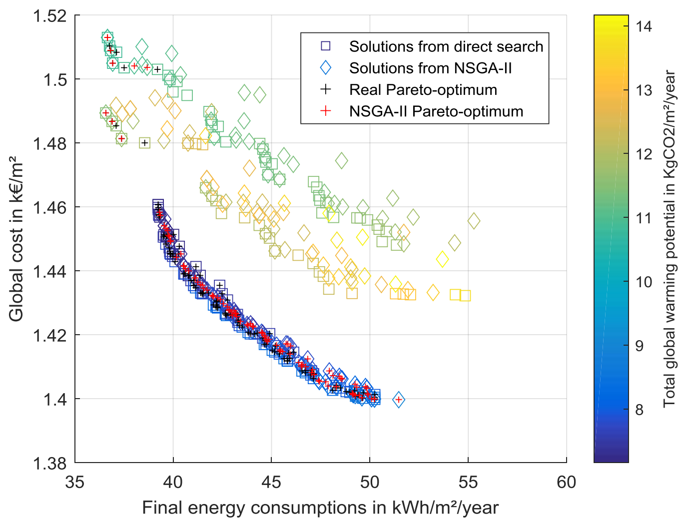


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Figure 8: Aggregation of the results (step 3).

They correspond to: the lower one is districts with condensing boiler production system and the upper one is districts with heat sharing network (aquifer). No configuration with CHP is present on the Pareto front. The distribution on these two clouds is mainly dependant on the surface retained of photovoltaic panels: energy performances are increased with this specific surface but the economic performances are lowered.

The values of the criteria are once again very acceptable. Moreover, the difference between the two methods on the diversity criterion is reduced compared to the previous step. The choice of genetic algorithm is thus reinforced.

Finally, Figure 8 presents the solutions retained at the end of the optimisation procedure (step 3) which correspond of the solutions from the steps 2.1.2 and 2.2.2. The final Pareto front is composed by 113 solutions: 100 with local production and 13 with central production. It forms also a convex slick but disrupted because it is composed of those previously selected.

The procedure including the NSGA-II genetic algorithm allows easily obtaining solutions of the real Pareto front. Concerning the diversity, the performances can be improved but they are amply adequate to justify its usefulness.

The main reason for the use of a metaheuristic is the low computational time in comparison with other methods. The Table 4 makes the summary for each step of the optimisation procedure. Finally, the solving of this problem took 165 681 seconds (i.e. 46 hours and 2 minutes) with only the direct search processes and 39 128 seconds (i.e. 10 hours and 52 minutes) using the NSGA-II genetic algorithm.

Table 4: Computational time for each step depending on the method used

Step	Computational time (sec)	
	Brute force search	NSGA-II
1	796	-
2.1.1	16 214	-
2.1.2	49 742	2 997
2.2.1	51 633	1 729
2.2.2	47 296	17 392
3	0	-

Analysis of the global results for the case study

The diversity of the combinations in the final results proves that it is clearly not obvious to find the preferable alternatives without this type of solving methodology: physical simulation coupled to dedicated optimisation strategies and processes.

Several trends can be observed with the results analysis. The alternatives with a low investment cost are almost all dominated at the end of the optimisation procedure. In fact, their relative high energy demand results in additional economic and environmental costs if the whole cycle life is considered (operation).

Concerning the energy systems, solutions with CHP are always dominated and there is a predominance of 3 different systems: heat pumps for local production, condensing boiler and heat sharing network (aquifer) for central production. Globally, the final set of solutions is mainly composed of local energy solutions (88.5%).

The great thermal performances obtained for all the buildings imply that a low energy demand is required for the district. Therefore, the relative part of the grid losses for district heating systems must be compensated by the efficiency of the production systems to make these centralised configurations competitive compared to the local ones. For the configurations with central production, only solutions with 40% of the roof surface covered by photovoltaic panels are kept in the final results.

This case study concerns a new construction program and thus the important cost of the envelope materials has to be taken into consideration. This particularity explains why the investment cost takes a major part in the global cost and also why the range of the final results is tightens for the economic objective.

A complete analysis by studying precisely each configurations can be carried out to define other trends than general ones and then get the last elements to support the future decision making.

Discussion

This study illustrates the use of a genetic algorithm and its capabilities when dealing with district multi-objective optimisation

For this small district, the computational time difference between the procedure with only direct search and the second one with the NSGA-II is significant. And the more there are buildings, the more beneficial the use of NSGA-II algorithm will be. That is a great advantage especially when the research space will be extended. Nevertheless, the goal is to find the acceptable compromise between calculation time and the accuracy of the results, which is also an optimisation problem. There are four major elements that can be adjusted: initialisation, population, generations and genetic parameters (i.e. crossover and mutation rates).

• The random initialisation of the NSGA-II genetic algorithm, used for this case study, can be enhanced by selecting the configurations of the first population. For example, a clustering of the research space can be considered. That allows to cover wisely the research space and thus to converge quickly.

• The increased number of solutions selected at each step improves the diversity while it rises the computational time. It is indeed critical to keep all configurations of each step but the selected population may be further tuned.

• Less generations may be used to further reduce the computational time. However, the results need to be still acceptable in terms of diversification and intensification because this parameter will lower them.

• The tuning of the NSGA-II parameters can be refined thanks to supplementary case studies in order to gain experience. The performances of the algorithm are directly linked to them, so they have to be finely adjusted. For this study, these elements were fixed a priori and edited multiple times to find a suitable parameterisation.

In addition, to the choices made to solve the optimisation problem, the settings of the simulation platform also condition the results. For example, the database must be as accurate as possible and therefore updated regularly to obtain exploitable results. For the energy objective and constraints, a choice has to be made between final and primary energy and it influences certainly the results. Only final energy is considered in this study and that explains the preponderance of configurations with electrical systems, especially for the local production.

One of the most typical attentions to be paid concerns the sensitivity of the input data of the simulation platform. They must be carefully selected (i.e. weather, geometrical specifications…) due to the uncertainty they can generate.

Finally, the utility of such a procedure combined to a simulation platform are the possibility of exploring a very important research space in a limited computational time and to keep a versatile set of potential configurations. Eventually, the final results should be analysed to extract the most representative or interesting solutions. A multi-criteria decision analysis can be applied to highlight the preferential solutions of the decision makers (Perez et al., 2016).

Conclusion

A new optimisation methodology for district energy design has been developed and applied to a case study in order to illustrate its abilities to solve this singular problem. The main scientific obstacles were overcome and this study illustrated the utility of such procedure (computational time, accuracy…), especially by using of the NSGA-II genetic algorithm.

The application of the complete procedure leads to a large variety of possible configurations. It also highlights general trends as predominated production systems depending of the type: local or central; or the envelope layout according to the buildings.

However, it may require some improvements to look at mixed production systems (i.e. local and central productions considered in the same district), to broaden the range of choices available for parameters or to enlarge the size of districts studied while maintaining a reasonable computational time.

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