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Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network

Laurent Magnier, Fariborz Haghighat*

Department of Building, Civil and Environmental Engineering, Concordia University, 1455 de Maisonneuve Blvd. W., BE-351, Montreal, Quebec H3G 1M8, Canada

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A B S T R A C T

Building optimization involving multiple objectives is generally an extremely time-consuming process. The GAINN approach presented in this study first uses a simulation-based Artificial Neural Network (ANN) to characterize building behaviour, and then combines this ANN with a multiobjective Genetic Algorithm (NSGA-II) for optimization. The methodology has been used in the current study for the optimization of thermal comfort and energy consumption in a residential house. Results of ANN training and validation are first discussed. Two optimizations were then conducted taking variables from HVAC system settings, thermostat programming, and passive solar design. By integrating ANN into optimization the total simulation time was considerably reduced compared to classical optimization methodology. Results of the optimizations showed significant reduction in terms of energy consumption as well as improvement in thermal comfort. Finally, thanks to the multiobjective approach, dozens of potential designs were revealed, with a wide range of trade-offs between thermal comfort and energy consumption.

1. Introduction

Energy consumption and indoor environment are two very fundamental yet conflicting objectives of building design. Finding a design that takes full advantage of a situation, while satisfying both of these objectives, is a challenge even for experienced engineers due to the number of parameters and strategies involved. While the classical rules of thumbs or trial-and-error processes may be able to generate acceptable solutions, they are extremely unlikely to achieve near optimal designs. In order to significantly reduce the energy consumption while maintaining a comfortable indoor environment, global optimization techniques such as genetic algorithms can be used [1].

Even using optimization tools though, the handling of multiple objectives remains complex. The classical aggregative method, which combines all objectives into a weighted-sum, only provides singular solutions, according to the set of weights chosen, and a complete understanding of design opportunities is missing. Thermostat settings studies, for instance, generally optimize the energy consumption, considering the thermal comfort only as a fixed constraint [2]. The impact of lowering or increasing the energy consumption on thermal comfort is not studied, and no alternative is proposed to the building operator.

The current study proposed a fast and efficient multiobjective optimization approach, later used to optimize the energy consumption and thermal comfort of a residential building. Variables used in the optimization are related to thermostat programming, HVAC system settings, and passive solar design. While some multiobjective optimizations of thermostats settings have been studied [3,4] in the past, the current work combined passive solar building design and thermostat settings, by included additional variables such as windows sizes and building thermal mass.

2. Optimization approach

2.1. multiobjective Evolutionary Algorithm as the optimization engine

Optimization algorithms can mostly be divided into two main categories: conventional gradient-based methods and gradient-free direct methods. The first school of methods is based on mathematical procedures and suffers from being dependent on initial guess values and being prone to be trapped in local extrema [5] Moreover, these techniques can only be applied to smooth and continuous functions. Since building phenomena are very often nonlinear, which lead to discontinuous outputs [6], gradient-based optimization methods are inapplicable to most building studies.

* Corresponding author. Tel.: +1 514 848 2424x3; fax: +1 514 848 7965.
E-mail address: haghi@bcee.concordia.ca (F. Haghighat).

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Gradient-free methods, in turn, are based on stochastic approaches and are more suitable to building applications. The most well-known and widely accepted one of this category is Genetic Algorithm (GA), developed by Holland [7] in the 1970s. This optimization algorithm, inspired from Darwin's theory of natural selection, has been successfully applied in several building studies, such for online optimization [8], for optimization of HVAC system controls [9] and for optimization of green building design [10]. In those studies, GAs proved to be very efficient even with non-differentiable functions, and enabled significant improvements in the optimization result in comparison with the baseline situation.

A specific class of GAs, named Multiobjective Evolutionary Algorithm (MOEA), is based on Pareto-dominance, which enables the algorithm to optimize all the objectives simultaneously. MOEA can therefore overcome many shortcomings of classical weighted-sum approach [5] as well as providing more solutions from a single optimization problem. The multiobjective algorithm chosen for this thesis is the Non-dominated-and-crowding Sorting Genetic Algorithm II (NSGA-II), developed by Deb [5]. This algorithm uses a specific population sorting based first on dominance, and then on a crowding distance computed for each individual. Due to this selection process, both convergence and spreading of the solution front are ensured, without requiring the use of an external population. NSGA-II is recognized as one of the most efficient MOEA [11]. In this paper, NSGA-II was run with the default parameters of the algorithm [5], as summarized in Table 1.

2.2. Artificial Neural Network (ANN) for RSA

The major limitation of GAs, and especially multiobjective GAs, is that they require hundred or sometimes thousands of evaluations to reach optimal solutions. In building applications, where evaluations are generally performed by time-costly simulations (using TRNSYS, [5], or EnergyPlus, etc.) the time investment associated with optimization can therefore be prohibitively high. Accordingly, building optimization studies using GA generally tend to reduce the computational time by using two methods. The first method is to use very simplified models instead of complete simulation softwares [12]. This method however presents a risk of over-simplification and/or inaccurate modelling of building phenomena. The second commonly used method is to select very small sizes for GA populations and/or relatively small numbers of generations [13,14]. Again, the optimization can be significantly affected and may lead to narrow or non-optimal solutions sets [10].

One very efficient, yet widely unexploited, solution to reduce the computational time associated with GA is to use a Response Surface Approximation Model (RSA) to first mimic the behaviour of the base building model, and then use this RSA inside the GA for the evaluation of individuals. By doing so, the computational time associated with each evaluation becomes negligible, while a good accuracy is maintained in the results. While several RSA techniques exist, there is no common agreement regarding which techniques is the best one [15]. The RSA method used in this study is a multilayer feed-forward Artificial Neural Network (ANN). ANN has been chosen due to two reasons: first, it has proven its efficiency in many building studies [16,17]; also, it is pre-programmed in many languages and calculation softwares.

2.3. Optimization framework

The optimization framework of this study is summarized in Fig. 1. It is divided in three sequential steps. First a model of the base building was created in TRNSYS and validated using measured data. Then, using this model, a database of cases was created and used to train and validate the ANN. After training and validation, the ANN was able to perform fast evaluations of the building performance, with a good accuracy, and without simplifying the problem. Finally, NSGA-II was run by using the ANN to evaluate potential solutions.

Although widely unexploited, the integration of an ANN inside a GA was not a new idea. Such integration can be found as early as in 1993 used by [18] for plant growth optimization. While promising, this methodology has however seldom been used for building applications. The rare studies using it include the optimization of a chiller [19], the optimization of air distribution system operation and design (based on CFD simulations) [1], or the optimization of thermal and visual comfort and energy consumption in a school (based on ESP-r simulations) [20]. These studies confirmed that numerical optimizations using a combination of ANN and GA can be efficient for building applications, which can save a significant amount of computation time. All of these studies were however based on an aggregative handling of multiple objectives and did not fully exploit the GAINN methodology.

3. Design of numerical experiments

3.1. Description and simulation of the base building

The base building of this study is one of the two (identical) residential houses of the Twin House Project on the Campus of National Research Council Canada (NRC). The house is a typical 2-storey wood-frame house, with 210 m^2 of living area, built to meet the R-2000 standard [21]. The HVAC system is composed of a high efficiency condensing gas furnace (80% steady-state efficiency and a rated output of 19,800 W (67,500 Btu/h)), a 12 SEER air-conditioner with a 7000 kW (2 ton) capacity, and a high efficiency (84%) heat recovery ventilator. In the original settings, the thermostat uses a 21 °C set point all year long, with a 1 °C dead-band. Reader is referred to [22] for a more detailed description of the house characteristics.

A computer model of the house was developed in TRNSYS. A special care was taken for the building geometry and materials. The HVAC system and the thermostat were modelled in details to fit the performance of actual ones. Finally, the same occupancies and appliances schedules as in the real building were included. For validation, the TRNSYS model was run using measured weather data for the month January and August 2003, using a 2 min time-step, and simulations results were compared with measured data in terms of energy consumption and indoor temperature. Simulations results were in good agreement with measured data, with relative errors of 3.7%, 3.4%, and 7.3% for heating, cooling, and fan monthly energy consumptions, respectively. A more complete description of the building model and of its validation can be found in [23].

3.2. Design variables

Design variables considered in this study can be divided into two groups: building envelope-related, and HVAC system-related.

Table 1
NSGA-II parameters.

Population size	Crossover type	Crossover probability	Mutation type	Mutation probability	Distribution indices	Termination criterion
100	Simulated Binary Crossover	0.9	Polynomial	0.05	20 in both cases	Maximum generation: 700

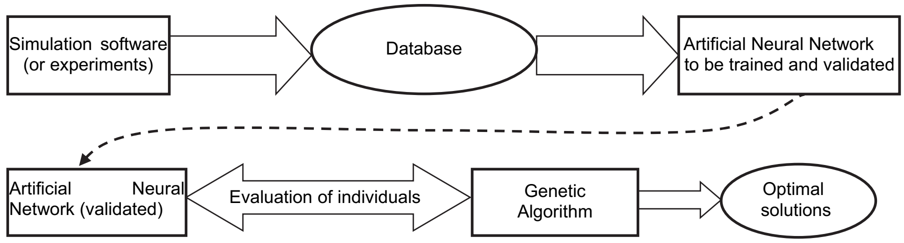

Fig. 1. Optimization framework.

All variables selected were assumed to have impacts on both thermal comfort and energy consumption. Variables ranges are summarized in Table 2.

3.2.1. HVAC system-related variables

The HVAC system-related variables include:

- *Heating and cooling temperature set points* were specified based on ASHRAE comfort ranges [24]. A heating set-back temperature of 18 °C is used at night during inoccupancy. No cooling is provided during inoccupancy;
- *Relative humidity set points* were specified based on ASHRAE comfort ranges [24];
- *Supply air flowrates:* different values were assigned to heating, cooling, and recirculation modes (the amount of fresh air brought in the house is kept to a constant value (0.0302 m^3/s));
- *Thermostat delays:* different values were assigned to pre-occupancy, post-occupancy, and night time; these delays were integrated into design plan to take advantage of the thermal mass of the house in order to reduce the energy consumption while maintaining an acceptable thermal comfort.

3.2.2. Building envelope-related variables

Building envelope-related variables were aimed at taking advantage of passive solar design. Accordingly, the sizes of the five south and north windows were varied, as well as the thermal mass of the house. Window sizes varied between 20% and 60% of the corresponding wall area. The thermal mass of the house was artificially increased in TRNSYS model by modifying the thickness of concrete in the interior floors (5–25 cm).

3.3. Objectives functions

3.3.1. Thermal comfort

The metric used to assess thermal comfort is the Predicted Mean Vote (PMV), based on Fanger's model [25]. PMV is representative of what a large population would think of a thermal environment, and is used to assess thermal comfort in standards such as ASHRAE 55 [24]. It ranges from −3 (too cold) to +3 (too warm), and a PMV value of zero is expected to provide the lowest Percent of People Dissatisfied (PPD) among a population. An absolute PMV value of 0.5 is generally recognized as the limit of the comfort zone [24]. In order to optimize thermal comfort, two parameters were considered in this study:

- Average absolute PMV $|\mathrm{PMV}|_{avg}$: averaged over the whole year and over all occupied zones.
- Number of hours with $|\mathrm{PMV}| > 0.5$ (N_{dis}): representing the cumulative time with discomfort over the whole year. Since discomfort should never occur inside the house, this parameter was used as a constraint. Although several constraint handling methods exist [5], the penalty term method successfully handled the constraint in this study.
- The thermal comfort objective was t_{hen}:

$$F_1 = |\mathrm{PMV}|_{avg} \times (1 + N_{dis}/100)$$

3.3.2. Energy consumption

The annual energy consumption of the building, calculated by TRNSYS, was composed of: the energy consumption of the furnace E_{heat}, the cooling consumption (including dehumidifier consumption) E_{cool}, and the energy consumption of the fan E_{fan}. These consumptions were directly taken from TRNSYS in kJ/h, regardless of the primary energy used. Energy consumptions for domestic hot water, appliances, and lighting were not included because they were not expected to significantly change throughout the optimization. The complete energy consumption objective could thus be written as follows:

$$F_2 = \left(E_{heat} + E_{cool} + E_{fan}\right) \times (1 + N_{dis}/100)$$

Table 2
Ranges of variables used for optimization.

Variable	Lower bound	Upper bound	Unit
Heating set point	20	25	[°C]
Cooling set point	23	27	[°C]
Rh set point (×3)[a]	30	60	[%RH]
Starting delay (×3)[a]	0	30	[min]
Stopping delay (×3)[a]	0	60	[min]
Supply airflow rate (×3)[a]	0.118	0.708	[m^3/s]
1st floor north window	4.76	14.30	[m^2]
1st floor south window	2.20	6.60	[m^2]
2nd floor north window	4.06	12.18	[m^2]
2nd floor southwest window	1.38	4.14	[m^2]
2nd floor southeast window	2.08	6.25	[m^2]
Thickness of concrete	0.05	0.25	[m]

[a] Different variables were used for summer, winter, and shoulder season, respectively.

4. Artificial Neural Network training and validation

4.1. Creation of the training dataset

Based on the variables and ranges summarized in Table 1, a sample of cases was created for ANN training. In order to generate

Table 3
Statistical repartition of relative errors in ANN validation.

Relative error		<1%	<2.5%	<5%	<10%	<25%	Average (%)
Percentage of cases when error falls into the range	E_{heat}	93	100	100	100	100	0.4
	E_{cool}	33	60	89	98	100	2.6
	E_{fan}	58	96	100	100	100	0.9
	$\|\mathrm{PMV}\|$	18	40	78	96	100	3.9
	N_{dis}	13	38	64	84	100	5.2

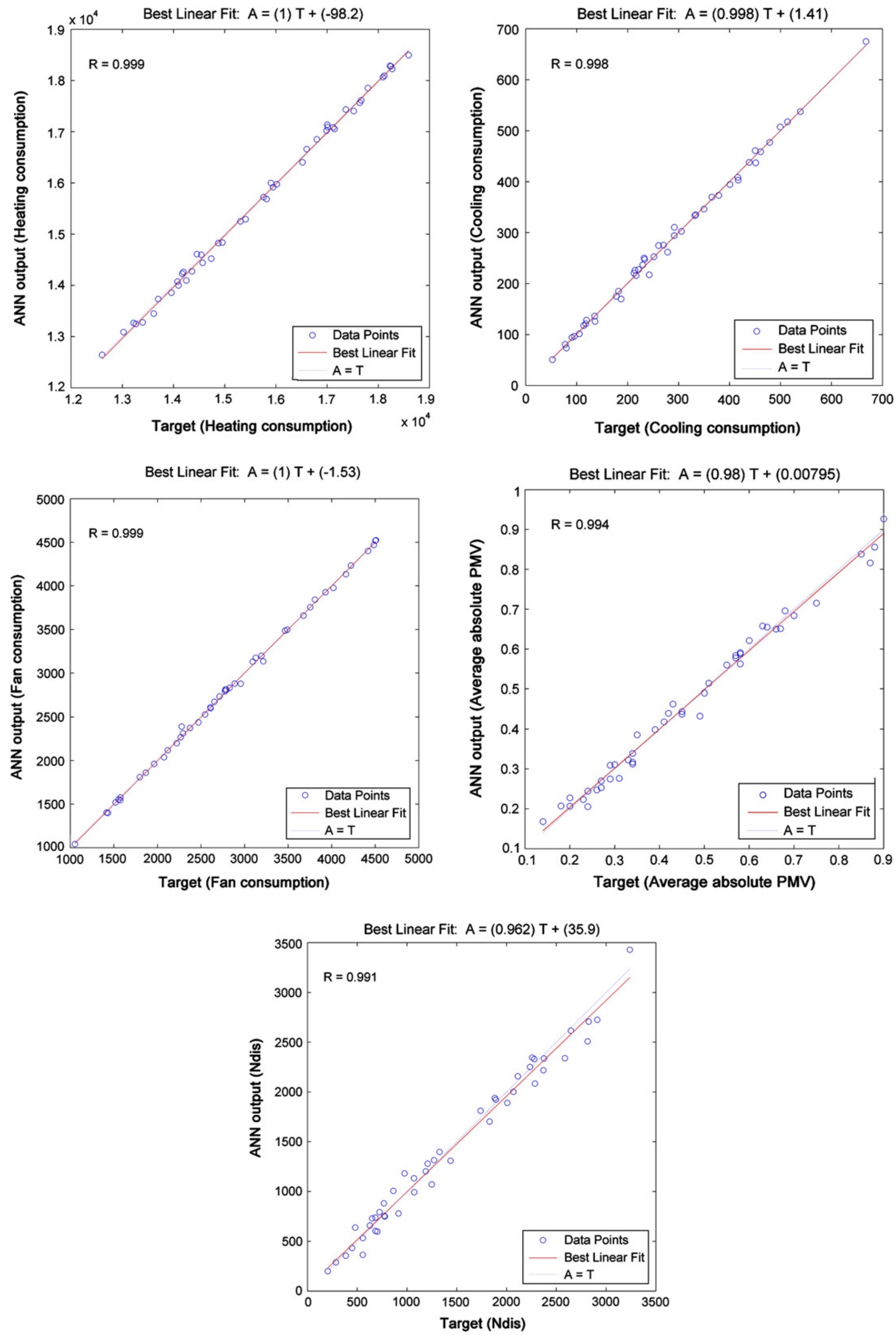

Fig. 2. Regression between ANN outputs and simulated targets.

the distribution of simulation parameters in the numerical experiment, Latin Hypercube Sampling Method was used [26]. This method is recognized to be able to generate a small yet representative sample of cases. According to McKay [26], a sample of than $2 \times N$ sampling data sets (where N is the number of variables) should be sufficient to accurately sample the search space. In the current study, this rule of thumb largely underestimated the number of cases required for ANN training, and as much as 450

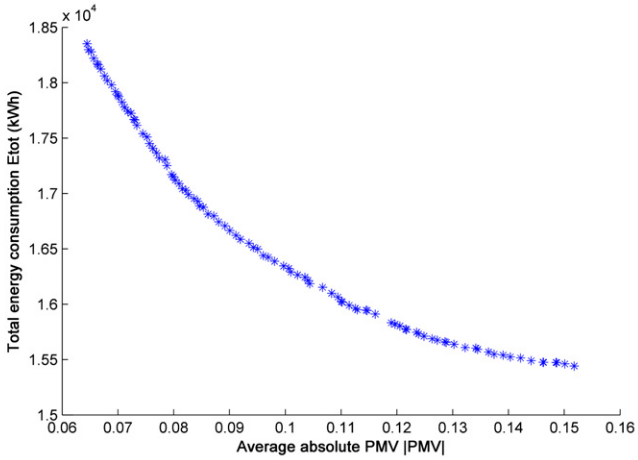

Fig. 3. Results of the first optimization.

cases had to be computed, which corresponds to 22.5 times the number of parameters. This additional need of data for ANN training is in agreement with Conraud [20].

All the simulation cases were run in TRNSYS using GenOpt automation engine [27], with a time-step of 2 min and a pre-simulation of one month. The simulation of the 450 cases took around three weeks on a Genuine Intel processor workstation at 1.66 GHz speed.

4.2. Training and validation

The ANN used in this study was composed of 20 neurons in the input layer (corresponding to the 20 variables), a hidden layer composed of 20 neurons, and an output layer composed of the five outputs previously described (i.e. |PMV|, N_{dis}, E_{heat}, E_{cool}, and E_{fan}). The ANN was trained using the Levenberg–Marquardt and Bayesian regularization algorithms. The training was considered to have reached convergence if both the sum of squared error (SSE) and the sum of squared weights stabilized over certain iterations. The ANN training reached this goal after 516 epochs, with a final SSE of 1.16.

Afterwards, a sample of 45 cases, different from the previous ones, was used to validate the ANN. For these cases, ANN outputs were compared with the corresponding simulations outputs. The distribution of the relative errors for the five outputs is summarized in Table 3. The average relative errors for energy consumptions were good, with respectively 0.4% for heating, 2.6% for cooling, and 0.95% for fan consumptions, leading to an average relative error around 0.5% for the total energy consumption. The average relative error regarding the average PMV was a bit higher (3.9%) but was still acceptable, since it resulted in very little variations in the PMV value, and therefore of very little change in terms of thermal sensation. The average relative error for the cumulative time with discomfort (5.2%) was significant, but can still be considered as acceptable since this output was only considered as a constraint. Inaccuracies while estimating this parameter would only lead to either a building being uncomfortable for few hours per year, or a building slightly more comfortable than expected. In both cases, the impact would hence be limited, and therefore the accuracy is acceptable. The regressions between the target simulated outputs and ANN predictions, illustrated in Fig. 2, also show a good agreement between the simulations and the predictions with regression coefficients very close to 1. The regressions between the target simulated outputs and ANN predictions, illustrated in Fig. 2, also show a good agreement between the simulations and the predictions with regression coefficients very close to 1.

5. Optimizations

5.1. First optimization

A first optimization was set-up, using the 20 variables described in Table 2. Results of optimization are illustrated in Fig. 3. In this study, all variables were treated as continuous variables. It should nonetheless be noted that both NSGA-II and the optimization methodology can easily be extended to discrete variables.

Optimal solutions range from an absolute average PMV of 0.064 for an annual energy consumption of 18,342 kWh, to an annual energy consumption of 15,441 kWh for an absolute average PMV of 0.152. A very good spreading of solutions is found between the two extrema. Also, in all cases, the constraint was properly handled, with a penalty term – and therefore a cumulative time with discomfort – equal to zero.

Optimization results were compared with the base case configuration, with four manually constructed designs expected to provide good results, and with five random designs. The variables used for the manually constructed cases can be found in Table 5 [23]. Results are illustrated in Fig. 4 (the penalty term was omitted for these evaluations). While three of the manually constructed designs enabled lower energy consumptions than NSGA-II's results, these cases had to be rejected because they gendered more than 1000 h per year with an average PMV higher than 0.5. Overall, we can see that NSGA-II's solutions are significantly better than the base and constructed cases, in terms of both thermal comfort and energy consumption.

The Table 4 summarizes the range of values taken by optimal solutions variables. The most salient fact of the optimization is the thickness of concrete in the interiors floors, set to the maximal values in all cases. This additional thermal mass enables to store more heat from sun radiation, and to smooth the temperature variations, especially in summer. Heating and cooling set points vary respectively between 22.3 °C and 23.5 °C, and between 24.6 °C and 24.9 °C, which is relevant with ASHRAE comfort range. Recirculation and heating supply airflow rates are always set to the minimal value, in order to reduce fan consumption. Finally, relative humidity set points are set to 60% in winter and summer to respectively improve the thermal comfort and decrease the dehumidification consumption. These relative humidity values are high, but are still in accordance with ASHRAE comfort zone. They may however cause humidity problems in winter. Generally, most variables takes a wide range a values, in order to find all optimal trade-offs between energy consumption and thermal comfort.

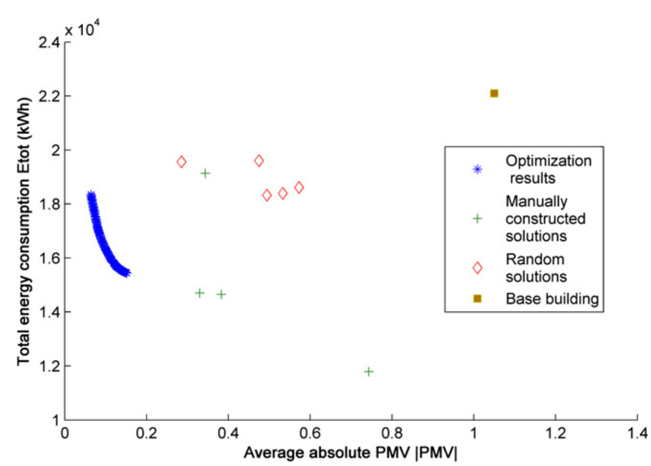

Fig. 4. Optimization results compared to base, random, and manually constructed cases.

Table 4
Variables ranges in optimal and base designs.

Variables		Boundaries	Base case	Optimal solutions in the first optimization		Optimal solutions in the second optimization	
				Min value	Max value	Min value	Max Value
Temperature set point (°C)	Heating	[20,25]	21	22.4	23.5	22.7	23.7
	Cooling	[23,27]	21	24.5	24.8	24.8	25.0
Starting delays (min)	Winter	[0,30]	Not applicable:	0	0	6.4	30
	Shoulder season	[0,30]	constant	30	30	28	30
	Summer	[0,30]	temperature	30	30	30	30
Stopping delays (min)	Shoulder season	[0,60]	set points all	52	60	55	60
	Summer	[0,60]	year long	24	60	60	60
	Winter	[0,60]		0	0	0	50
Supply airflow rates (m^3/s)	Recirculation	[0.118,0.708]	0.448	0.118	0.118	0.118	0.118
	Cooling	[0.118,0.708]	0.680	0.118	0.120	0.118	0.118
	Heating	[0.118,0.708]	0.618	0.469	0.708	0.529	0.708
Relative humidity set points	Winter	[30,60]	none	60	60	60	60
	Shoulder season	[30,60]	none	30	60	30.0	60.0
	Summer	[30,60]	none	60	60	60.0	60.0
Windows to wall ratio (%)	1st floor North	[20,60]	39	20	60	20	20
	1st floor South	[20,60]	48	23	45	26	50
	2nd floor North	[20,60]	18	20	20	20	60
	2nd floor SWest	[20,60]	56	20	20	20	20
	2nd floor SEast	[20,60]	39	60	60	20	28
Thermal mass (m)	Thickness	[0.05,0.25]	0.05	0.25	0.25	N.A.	N.A.

5.2. Second optimization

In the first optimization's results, the thermal mass of the building was in all cases set to the maximal value. Such a high thermal mass is rather unusual in residential building. Therefore, a second optimization study was performed, letting all the parameters except the thermal mass vary. In this optimization, only 19 variables were hence used, setting the thermal mass to a constant value (5 cm of concrete). Thanks to GAINN particular approach, this second optimization did not require any additional TRNSYS simulations. The ANN previously described was directly used, and only the optimization part had to be redone. Results of optimization are shown in Fig. 5, and variables ranges are summarized in Table 4.

Once again, the optimization was very efficient in terms of both convergence and spreading of the solutions, with the optimal front being an almost continuous curve. Optimal solutions range from an absolute average PMV of 0.073 for an annual energy consumption of 18,651 kWh, to an annual energy consumption of 15,705 kWh for an absolute average PMV of 0.166. Regarding the variable changes between the two optimizations, we can see in Table 4 that most variables remained similar in both optimization solutions. The most salient difference between the two optimizations results is the size of the north-west window, which was set in a significantly lower value in the second optimization. This can be explained by the fact that when the thermal mass of the house was smaller overheating was more likely to occur in summer.

Table 5
Variables used for manually constructed solutions.

Variables		Boundaries	Solution 1	Solution 2	Solution 3	Solution 4
Temperature set point (°C)	Heating	[20,25]	22	22	20.5	23
	Cooling	[23,27]	24.5	26	26.5	25
Starting delays (min)	Winter	[0,30]	30	30	5	30
	Shoulder season	[0,30]	30	30	5	30
	Summer	[0,30]	30	30	5	30
Stopping delays (min)	Shoulder season	[0,60]	60	60	60	0
	Summer	[0,60]	60	60	60	0
	Winter	[0,60]	60	60	60	0
Supply airflow rates (m^3/s)	Recirculation	[0.118,0.708]	0.118	0.118	0.118	0.708
	Cooling	[0.118,0.708]	0.472	0.472	0.118	0.708
	Heating	[0.118,0.708]	0.472	0.472	0.118	0.236
Relative humidity set points	Winter	[30,60]	50	50	60	60
	Shoulder season	[30,60]	50	50	60	40
	Summer	[30,60]	50	50	60	30
Windows to wall ratio (%)	1st floor North	[20,60]	4.7	4.7	4.7	4.7
	1st floor South	[20,60]	6.6	6.6	6.6	6.6
	2nd floor North	[20,60]	4.06	4.06	4.06	4.06
	2nd floor SWest	[20,60]	4.14	2	2	1.38
	2nd floor SEast	[20,60]	6.25	4	4	2.084
Thermal mass (m)	Thickness	[0.05,0.25]	0.1	0.1	0.05	0.25

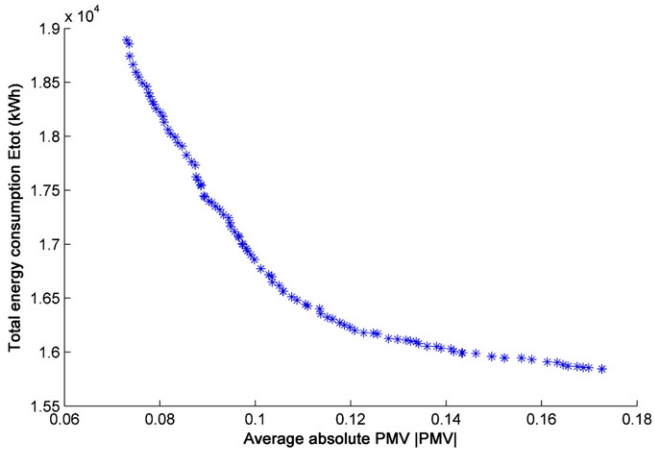

Fig. 5. Results of the second optimization with constant thermal mass.

What is interesting to note in Fig. 5 is the relation between the average PMV and the energy consumption. The curve seems to be composed of two lines, with two different slopes. In terms of design, we can note that in the first part of the curve (below $|PMV| = 0.11$), small decreases of thermal comfort can lead to relatively large reductions in energy consumption. In the second part of the curve, the inverse situation occurs, and small increases of energy consumption can lead to significant increases of thermal comfort. This case highlights the major advantage of a true multi-objective optimization, which is to provide a complete understanding of the situation, and to bring to light the potentiality of each investment. In the current case, the occupants of the house could be easily convinced to lower the average PMV from 0.8 to 0.11, in order to reduce energy consumption by up to 13%.

5.3. *Time considerations*

Each NSGA-II optimization took around 7 min on a Genuine Intel processor workstation at 1.66 GHz speed. Considering the whole methodology, the complete optimization time can therefore be considered as the simulation time required to create the database for ANN training: 3 weeks. If ANN was not used and if NSGA-II had been directly linked with TRNSYS, each optimization would have taken more than 10 years (based on the number of evaluations performed by NSGA-II). The time saving associated with GAINN is therefore colossal, and it is reasonable to say that the optimization would have just not been feasible without the methodology proposed in this study.

6. Conclusion and future work

This paper described an optimization methodology based on a combination of an Artificial Neural Network and a Multiobjective Evolutionary Algorithm. First, the ANN was trained and validated using simulation results. The database of cases was created using Latin Hypercube sampling, and GenOpt automation engine. The ANN proved to be able to provide acceptable approximations of the simulation results, with averages elatives errors below 1% for the total energy consumption, and below 4% for the average PMV. Reaching this accuracy however required the use of 450 training cases, corresponding to 22.5 times the number of variables. The ANN was then implemented inside NSGA-II to enable fast evaluations.

Regarding the optimization results, both of the two optimizations performed resulted in significantly improvements the energy performance and the thermal comfort of the house. The spreading of solutions revealed a large number of potential design. Finally, the methodology enabled to reveal and illustrate the impact of each investment in terms of energy consumption in terms of thermal comfort. In that sense, the current study could also be used as a convincing tool to make a building owner choose a greener solution, by showing him the energy impact of his thermal comfort choices.

It would be interesting as a future work to deeply study the accuracy of the ANN in the final solution sets. In this study, a small part of the final solution sets was simulated using TRNSYS. Results showed that the ANN performed very well in terms energy consumption (around 1% relative error), but generally underestimate the PMV. Further and more systematic studies are required in order to evaluate the accuracy of the ANN in the vicinity of optimal solutions, and study its impact on optimization.

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