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Efficient Genetic Algorithm sets for optimizing constrained building design problem

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Abstract

The main aim of this paper is to find the appropriate set of Genetic Algorithm (GA), control parameters that attain the optimum, or near optimum solutions, in a reasonable computational time for constrained building optimization problem. Eight different combinations of control parameters of binary coded GA were tested in a hypothetical building problem by changing 80 variables.

The results showed that GA performance was insensitive to some GA control parameter values such as crossover probability and mutation rate. However, population size was the most influential control parameter on the GA performance. In particular, the population sizes (15 individuals) require less computational time to reach the optimum solution. In particular, a binary encoded GA with relatively small population sizes can be used to solve constrained building optimization problems within 750 building simulation calls.

Keywords: Constrained building optimization problem; Genetic Algorithm (GA); GA control parameters; Simulation calls; Thermal comfort

1. Introduction

Energy used in buildings has the highest potential and lowest cost for carbon reductions. There are many regulations and policies were established to encourage construction of sustainable buildings. In addition, there are many building simulation tools made available freely to assist designers and practitioners to attain a sustainable design. However, the design of sustainable buildings is not straight forward. There are many physical processes that lead to conflicting objectives such as making the buildings energy efficient by well tightening and insulation of the envelope without compromising the occupants' comfort. This requires trying large possible solutions which need heuristic optimization algorithms.

A comparison between several heuristic optimization algorithms showed that Genetic Algorithm (GA) is robust on getting the optimum(s) simulation (Wetter and Wright, 2004; Brownlee et al., 2011; Bichiou and Krarti, 2011; Sahu et al., 2012) while the building simulation program "EnergyPlus" is very operative (Crawley et al., 2001). In addition, many researchers have developed platforms to utilize different simulation engines and optimization algorithms to optimize building design problems (Wetter, 2001; Mourshed et al., 2003; Wang et al., 2005; Bleiberg

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and Shaviv, 2007; Geyer, 2009). Other works have evaluated the building variables significance on the optimum solutions (Wang et al., 2005; Bleiberg and Shaviv, 2007; Geyer, 2009).

Wright and Loosemore (1993) developed a new method of constraint by combining many constraints into a single objective of a multi-objective optimization problem. Wright and Zhang (2005) developed an 'aging operator' that penalized highly dominant solutions to aid in solving highly constrained problems. Evins et al. (2012) optimized the solar gain to a building by evaluating the population size, number of generations, crossover and mutation probabilities, selection method and seeding method to investigate the configuration of a Genetic Algorithm, while, Hamdy et al. (2009) used a single-objective preparation step and a post-optimization refining step to improve the performance of a Genetic Algorithm.

The authors of the present paper have examined the robustness of Genetic Algorithms in solving unconstrained building optimization problem with limited number of variables (Alajmi and Wright, 2014). The authors also proved that small population sizes (5 and 15 variables) showed better performance than the largest population size (30) in respect of reaching the optimum solutions with less number of building simulation program calls.

The sensitivity of the optimization algorithm and its components such as population size, number of generations, crossover and mutation probabilities, selection method and seeding method is a real concern in solving a whole building optimization design problem.

Therefore, the main aim of this paper is to find the most appropriate GA set that can find the optimum (energy efficient building), or near optimum solutions, in a reasonable computational time (less numbers of simulation calls to the building simulation program "EnergyPlus" as it is required to calculate the building consumption and occupants' comfort index) for constrained building optimization problem. This will be conducted by manipulating two different population sizes 5 and 15 which are considered to be relatively small. Also, two different probabilities (70% and 100%) of the reproduction parameters (crossover and mutation rate) will be encountered. This approach will be tested for eight different control parameter sets for 750 number of generations to find the most efficient set that can achieve efficient energy building without compromising the occupants' comfort.

2. GA parameters sets

The Genetic Algorithms (GA's) iterate on a set of solutions "population". First, an initial solution for the population is assigned (each variable being randomly assigned a value within its bounds). Then, the process of generating a new better solution goes through five main subordinate operations in an iterative manner. Although the GAs showed effectiveness in handling building optimization problems, the GA's main operators such as population size, crossover probability, and mutation rate need to be tuned in order to find the best performance for the constrained building optimization problem. Selection of appropriate GA operators is a trade-off between fast convergence, and maintaining the exploratory power of the algorithm (to prevent false convergence).

A detailed configuration of the simulation-based building optimization problem and the most effective parameters of GA on solving unconstrained building optimization problem are explained by the authors in a previous study (Alajmi and Wright, 2014). Therefore, in this study, the control parameter sets are only composed of two population sizes 5 and 15 with two crossover probabilities 0.7 and 1.0 and mutation rates of 1 and 2 based on the outcomes of the previous study. In addition, the number of simulation calls is restricted to 750. Therefore parameter sets that will be implemented in this numerical experiment (constrained building optimization problem) are listed in Table 1.

The number of building simulation runs performed during this experiment can be found by multiplying the number of parameter sets (8) by the number of initial population runs (10 in this work) times the number of simulations (750 calls). This ends up with 60,000 building simulation runs.

3. The building design variables

The building is a typical mid-floor layout of an office building (located at Chicago, Illinois, 42° latitude, −88° longitude) that was chosen to test the GA performance. As shown in Fig. 1, the floor consists of five zones (North, South, East, West, and Interior) each of which has an exterior wall along its perimeter and a single window with overhang shading. The internal zone "I" is bounded by partition walls of perimeter zones. The total floor area is ($46\ \mathrm{m} \times 24\ \mathrm{m} = 1104\ \mathrm{m}^2$) with a floor height of 2.7 m. The finding that comes out as a result of this floor can be later multiplied by the number of identical floors in the building.

The considered variables can be classified into the building envelop (indices 1–23) which are self-explanatory and the HVAC system control (indices 24–80) which includes pre-cooling or pre-heating starting time, AHU setpoint temperatures, and zone heating and deadband setpoints. The variables with their lower, upper limits, and their initial start, are listed in Table 2.

The design variables in Table 2 (indices 24–26) are representing the time that the HVAC system will start on. These are three options of starting the system on before the occupants arrived (pre-heating/cooling concept). The design variable in the table (indices 27–38) gives each month an option to select from the three defined system availability schedules (A, B, and C).

The indices 39–44 define the air supply setpoint temperature via the AHU equipment design variables. Three schedules of air supply set points are formulated for

Table 1
Parameter sets of constrained building optimization problem.

Population size	Crossover rate (%)	Mutation rate	Number of simulation
5	70	1	750
	70	2	
	100	1	
	100	2	
15	70	1	750
	70	2	
	100	1	
	100	2	

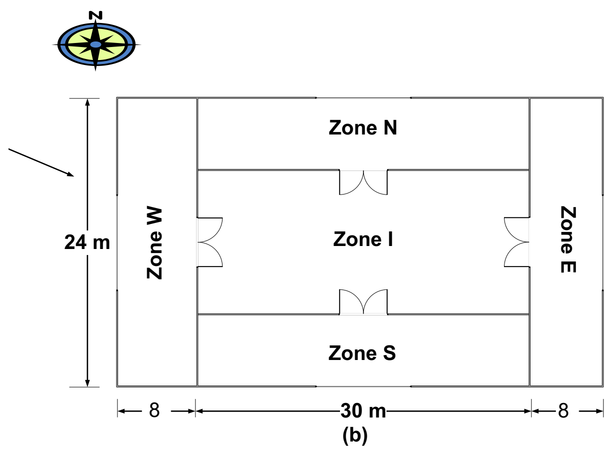

Figure 1. Plan view of the five-zone studied floor in the considered building.

occupied/unoccupied periods. This gives the opportunity of each month to select from these schedule options what is the most appropriate air supply temperature for each month (indices 45–56).

Similarly, the remaining design variables in the table are formulating the heating and deadband of the zone temperature control (indices 57–68). This heating setting with the deadband will automatically formulate the cooling setpoints to form three options of schedules. This again gives the opportunity for each month to select from the three options of schedules of forming the zone heating and cooling setpoints (indices 69–80).

A basic way to control the HVAC system is by scheduling its operation, i.e. when the HVAC system should be turned on or off. As shown in Table 3, the HVAC system is scheduled to be off after the occupants working hours, at the weekends, and on holidays. In this paper, the problem formulated to give three different scenarios for the starting time of the system (pre-cooling or pre-heating) after it's presumably switched off for an unoccupied period. These different scenarios are an option for every month of the year with the particular scenario used in any month identified by a discrete problem variable, see Table 2, indices 24–38.

The basic control of the air handling unit (AHU) is implemented by a schedule which usually linked with HVAC system availability operation, i.e. the AHU available to work when the HVAC system is available. Also, AHU can be put on the on/off mode during its availability based on the zone thermostat setting. Generally, the air supply sets to a certain temperature for winter and another sets for summer. These settings satisfy the occupant comfort requirement during these seasons, however, uncomfortable environment or excessive operation of the AHU might occurs in the mild seasons. For this reason,

Table 2
Envelop and HVAC system design variables.

Index	Variable	Lower limit	Upper limit	Initial	Increment
1–2	North & South window width (m)	0.5	29	0.1	0.1
3–4	East & West window width (m)	0.5	23	7.2	0.1
5–8	North, South, East, & West window height (m)	0.5	2.1	0.9	0.1
9–12	North, South, East, & West window overhang (m)	0.0	1.5	0.3	0.05
13–14	Window's internal and external pane specification (–)	0	3	0	1
15	Window gas types; air, argon, etc. (-)	0	5	1	1
16	Light, medium, and heavy weight external wall construction (–)	0	2	0	1
17	Light, medium, and heavy weight internal wall construction (–)	0	2	0	1
18	Light, medium, and heavy weight ceiling construction (–)	0	2	0	1
19	Light, medium, and heavy weight floor construction (–)	0	2	0	1
20–22	Light, medium, and heavy wall insulation thickness (m)	0.05	0.2	0.05	0.05
23	Building azimuth (°)	0	90	0	5
24–26	Schedule A, B, & C of system availability (on/off) for the unoccupied period (19–7 h)	0	13	3	1
27–38	System availability (on/off profile) of the 12 months (January to December) choosing from the three options.	1	3	0	1
39–44	Schedule A, B, and C of AHU supply setpoints temp. for occupied/unoccupied periods (winter months °C)	12	18	18	0.25
45–56	AHU supply setpoints temperature options (January to December)	1	3	0	1
57–62	Zone heating setpoint schedule A, B, and C occupied/unoccupied periods (°C)	18	22	20	0.25
63–68	Zone deadband setpoint schedule A, B, and C occupied/ unoccupied period (°C)	20	24	22	0.25
69–80	Heating setpoints temperatures and deadband options for 12 months (January to December)	0	23	0	1

Table 3
System availability time schedule.

Schedule Type A, B, & C	Schedules (Hours)		
	1-7	8-18	19-24
System Availability	on/off ← vary starting pre-heat/cool time	ON	on/off → switch the HVAC system off

the setpoint temperature of supply air to the zone is important in terms of being able to provide sufficient cooling to any zone and/or heating if necessary by using the reheat element if it is integrated within the zone equipment.

In this paper three different schedules profiles (A, B, & C) of supply air temperature are set to find the most appropriate profile of each month. In each schedule profile two different initial setpoints are assigned, for unoccupied and occupied working hours, see Table 4.

For this reason the design variables forming 18 problem variables, since each month (from January to December which equates 12 design variables) has three options of supply air temperature setpoint schedule for unoccupied and occupied working hours (6 design variables), as shown in Table 2, indices 39–56.

The mechanical systems (HVAC) act to satisfy the zone demand. If this demand is determined accurately, only the demand load will be maintained; no excessive or waste of energy will occur. Therefore, the zone thermostat is interpreting the temperature that is desired by the occupants in a particular season. For this reason, in this building example, the zone thermostat setpoints were allowed to vary to find which uses the least energy within the satisfactory level of the occupants (comfort zone temperature), see Table 5. The control type that is used to implement this concept in this example is known as a Dual Setpoint (heating and cooling) with deadband. This control is applicable to control the zones over the whole year. During the hot season, the cooling set-point temperature will trigger the HVAC cooling system to put it on operation mode (if the zone temperature is beyond the cooling thermostat temperature setting). Similarly, during the cold season the heating set-point temperature will trigger the heating system to put it on (if it is below the heating thermostat temperature setting). Whereas, during the mild season neither the cooling nor the heating turn on, the system will be in a situation called deadband. As this deadband interval increases the opportunity of keeping the system off increases, which will contribute to save more building energy consumption.

Similar to the supply air temperature, three schedule options of the zone thermostat temperature are set. The design variables of heating setpoint and deadband are manipulated for each month before EnergyPlus starts to simulate the building. While the cooling setpoint is calculated from the heating setpoint and deadband, i.e. the cooling setpoint is automatically calculated by EnergyPlus from the following formula (cooling setpoint = heating setpoint + deadband).

Also, heating setpoint and deadband are defined for both the occupied and unoccupied periods. For every month there will be three zone temperature set points options. This way of formulating the zone temperature setpoints form a 24 design variables, see Table 2, indices 57–80.

4. Design constraints

In building optimization problems, there is a limitation on the range of possible solutions. For instance, in this paper not only the lowest building energy consumption needs to be achieved, but also the optimum solutions have to satisfy the occupants' comfort. As such inthis situation the comfort requirements are constraining the search space.

At some point during the annual run operation of a HVAC system, the zone loads may not be met due to the under-size of the HVAC system. This is likely due to the fact that HVAC systems are sized for design day conditions, which represents a percentage of number of occurrences of outside conditions. Subsequently, the thermal comfort may not be satisfied the whole year around. Also, multi-zone systems contribute to increasing the probability of discomfort due to this system having a high degree of diversity among the zone loads. Since, in this research, the HVAC system is sized using design days conditions, and the building is conditioned using a multi-zone HVAC system, the comfort constraint has been formulated to count the number of hours that occupants are going to experience thermal discomforts. However, the amount of discomfort should be limited to the smallest fraction as

Table 4
AHUs supply temperature setpoint options.

Operation profile in each month	Schedule options	Working hours (hrs)	Setpoint temp. (°C)	Initial values (°C)
January–December	Option A, options B & C	Unoccupied (19–7), occupied (8–18)	12–18	18 (winter months)
		Unoccupied (19–7), occupied (8–18)	12–18	16.5 (summer months)

Table 5
Setpoint air temperature options.

Operation profile in each month	Schedule options	Mode	Working hours (hrs)	Setpoint temperature (°C)	Initial values (°C)
January–December	Options A, B, & C	Heating	Unoccupied (19–7), occupied (8–18)	18–22	20
		Deadband	Unoccupied (19–7), occupied (8–18)	2–4	2

possible. For this reason, the thermal comfort constraints in this optimization problem have been formulated in such a way that there is a compromise in annual occupant discomfort.

In this research, two comfort sets are evaluated: the thermal comfort constraint based on the average violation in predicted percentage of dissatisfaction (PPD), and the established Dutch "weighted hours of violation" approach.

5. Thermal comfort constrained

5.1. Predicted percentage of dissatisfaction (PPD)

The average thermal comfort violation in PPD can be expressed as follows,

$$c(X) = \frac{\sum_{i=1}^{n} z_i}{n} \tag{1}$$

$$z_i = \begin{cases} PPD_i - PPD^{ub}, & \text{if}(PPD_i > PPD^{ub}) \\ 0.0, & \text{else} \end{cases}$$

where *PPD* is the predicted percentage of dissatisfied (ASHRAE Standard 55, 2010; ISO Standard 7790, 2005), PPD_i = PPD at load condition i, PPD^{ub} = PPD upper limit (set to 10% in this paper), and n = number of load conditions. The constraints are formulated such that:

$$c(X) \leqslant b \tag{2}$$

are feasible, where b is the constraint bound (set to 0.5 in this research). Therefore, in this research, a solution is feasible, if the average *PPD* above 10% is no greater than 10.5% PPD (averaged for annual operation).

The thermal comfort of the occupants is calculated directly by EnergyPlus as a function of the zone environmental conditions. The occupants are assumed to be having an insulation clothing value equivalent to 0.57 clo in summer and 1.0 in winter. The room air velocity is assumed to be 0.137 m/s.

This comfort constraint was applied to each zone (North, South, East, West, and Interior) giving a total of 5 constraints. Note this thermal constraint is created similar to other comfort constraint concepts but with better design to overcome the steepness that occurred within other thermal comfort.

5.2. Dutch thermal comfort code

This comfort constraint is similar to the existing Dutch code for thermal comfort which is based on a weighted number of hours of operation above a specified PPD limit. It can be expressed as follows,

$$c(X) = \sum_{i=1}^{n} z_i \tag{3}$$

$$z_i = \begin{cases} \frac{PPD_i}{10}, & \text{if}(PPD_i > PPD^{ub}) \\ 0.0, & \text{else} \end{cases}$$

where the PPD limit (PPD^{ub}), is taken as 10%. The 10% limit is based on Annex D of ISO7730 which is equating approximately to ±0.5 predicted mean vote (PMV). The equation for z_i assumes that the comfort indices are the averages over an hour period, so that dividing the PPD by 10, is a "conversion" to a weighted number of hours. For example, in a given hour, an average PPD of slightly higher than 10% would result in a z_i of 1 weighted hour, and for a PPD slightly higher than 20%, 2 weighted hours.

The Dutch recommendation is that the sum of weighted hours is <150 (in both winter and summer); the limit broadly equates to a recommendation that comfort limits should not be exceeded for more than 5% of the time (~100 h) in either winter or summer (5% in each season).

5.3. Comparison of average comfort violation and Dutch code

The new average thermal comfort violation constraint, which is implemented in this research, is gradually started proportionally with constrained values. In contrast, the Dutch metric is a step function where it is started gives value to the constrained when it's only above 10%, as any lower value assigned to be 0 even if it is slightly below the starting value (10%). In general, such discontinuities are not going to fail the GA search but might make the search harder.

However, the disadvantage of the new constraint function is that, at present, the specification of the constraint bound is left to the designer, whereas in the Dutch approach, the constraint bounds have been specified. In this research, the new and more continuous constraint formulation is used with a constraint bound of 0.5% (which is equivalent to an average annual PPD value of less than 10.5%).

6. Results and discussion

Optimization for each parameter set shown in Table 1 has been run 10 times, each time with different initial starting search points. The minimum, maximum, mean, and standard deviation of the objective function (building energy consumption) for each parameter set is summarized in Table 6. The second column in this table indicated the parameter sets on the following order: population size, crossover probability, and mutation rate. The underlined values indicate the minimum value in that column. Note that all final (optimum) solutions were feasible.

From Table 6 it can be noticed that there are some relatively high percentage differences between the parameter sets. Thus, the choice of the best parameter set is not clear. For this reason, a further statistical analysis is required to test these differences which will be discussed in the following sections.

6.1. Statistical hypothesis and t-test

A hypothesis that compared sample means is used in this optimization problem (null hypothesis or the alternative hypothesis). The null hypothesis (H_o) assumes there is no significant difference between the compared means, where the alternative hypothesis (H_1) assumes that there is a significant difference. The *t*-test is used to verify these hypotheses for the two compared samples. Note, that the solutions are paired by the optimization problem and initial populations. The number of paired samples to be compared can be calculated out by a factorial combination formula:

$$\binom{n}{k} = \frac{n!}{k!(n-k)} \tag{4}$$

where n is number of variables which need to be combined and k is the number of combination sets or pairs. For 8 variables ($n = 8$) with two paired combinations ($k = 2$), the total number of combinations will be found as follows:

$$\frac{8!}{2!(8-2)!} = 28 \tag{5}$$

These comparisons can be implemented using the *t*-test technique for every two samples in turn, which can be done by any statistical package. A total of 28 comparisons that were performed between the different parameter sets are shown in Table 7. In this table, the value shown in the intersect cell between the two compared parameters is representing the *t*-test value that is derived from the set of equations that is described by Alajmi and Wright (2014).

These values are compared with the *t*-critical value ($t_{critical} = 2.26$ for 95% confidence) as shown in Table 7. Any value that exceeds the t value is shaded to indicate that the compared samples are statistically different.

6.2. Analysis of paired differences

Most of the paired comparisons in Table 7 show a value that is less than $t_{critical} = 2.26$. This is an evidence not to reject the null hypothesis, i.e. there are no real differences between most of the parameter sets. In other words, the parameters that are used to design the GA (population sizes, crossover probability and mutation probability) are not significantly different in achieving the optimum value of the objective function in this problem. However, the shaded cells of *t*-test value indicate significant differences between the compared pairs.

Another way of distinguishing the good parameter set from the worse is to find how many times the control parameter set shows a lesser performance than the other eight parameter sets. For example, the parameter set [5, 0.7, 2] (in index 4 in Table 8), which give a 14.3% probability of this parameter set giving a worse result than the other parameter sets (each set has been compared with 7 others so that $1/7 \times 100 \approx 14.3\%$). Similar values for all parameter sets are given in Table 8.

From Tables 7 and 8 a statistically and numerically significant difference was presented. It seems from Table 8 that parameter sets with a high mutation rate are showing the worse solutions. However, a further analysis to verify this observation will be discussed in the following section.

6.3. Effect of crossover and mutation probability

A further examination of the control parameters has been conducted through three separate comparisons. First, a study of the impact of population size on the performance was investigated while the other parameters (crossover probability and mutation rate) were equated. Four different parameter sets were compared to study the population size effect. None of the comparisons in Table 9 are statistically significant, however, it can be observed that the larger population sizes result in slightly better solutions

Table 6
Final best objective function values.

Index	Parameter Sets	Minimum	Maximum	Mean	Standard deviation
Building energy consumption (MWh/annum)					
1	[5, 1.0, 1]	85.2	109.1	91.6	7.2
2	[5, 1.0, 2]	81.0	95.0	89.7	4.7
3	[5, 0.7, 1]	82.3	100.6	91.2	5.3
4	[5, 0.7, 2]	83.3	104.4	92.2	5.7
5	[15, 1.0, 1]	**<u>77.2</u>**	94.0	87.2	5.5
6	[15, 1.0, 2]	85.8	93.1	90.7	**<u>2.6</u>**
7	[15, 0.7, 1]	82.6	**<u>91.3</u>**	**<u>87.0</u>**	2.6
8	[15, 0.7, 2]	85.6	106.0	93.2	6.2

Table 7
Paired *t*-test values.

Parameter sets*	[5, 1.0, 2]	[5, 0.7, 1]	[5, 0.7, 2]	[15, 1.0, 1]	[15, 1.0, 2]	[15, 0.7, 1]	[15, 0.7, 2]
[5, 1.0, 1]	0.81	0.16	0.16	2.18	0.47	1.98	0.66
[5, 1.0, 2]		0.80	1.45	0.97	0.51	1.56	1.47
[5, 0.7, 1]			0.43	1.54	0.26	1.94	0.76
[5, 0.7, 2]				1.57	0.63	**2.99**	0.408
[15, 1.0, 1]					1.97	0.09	**2.48**
[15, 1.0, 2]						**3.47**	1.10
[15, 0.7, 1]							**3.22**

*Population size, crossover rate, mutation rate.

Table 8
Probability of the worse solution.

Index	Parameter sets	Probability (%)
1	[5, 1.0, 1]	0
2	[5, 1.0, 2]	0
3	[5, 0.7, 1]	0
4	[5, 0.7, 2]	14.3
5	[15, 1.0, 1]	0
6	[15, 1.0, 2]	14.3
7	[15, 0.7, 1]	0
8	[15, 0.7, 2]	28.6

for comparisons having low mutation rates (indices 1 and 3), as the difference is positive.

In the second comparison, the crossover probability was investigated. This control parameter (crossover probability) shows no statistically significant percentage difference in the GA's effectiveness, in particular for the low mutation rate (1) (indices 1, and 3 in Table 10). However, the higher crossover probability shows a noticeably poorer performance with the higher mutation rate (see indices 2 and 4).

As shown in Table 11, there is a significant difference in the solutions for the comparison as shown in index 4. More generally, it appears that the higher the mutation rate, the more likely that the solutions will be poor (as indicated by the negative differences).

From the above statistical analysis of the constrained building optimization problem, a conclusion can be drawn that the parameter sets that contain the larger population size (15) has the best performance, in particular with a lower mutation rate. In addition, to find which population sizes perform better than the others with respect to the number of simulation calls that are required to reach convergence (convergence velocity) a further analysis is required.

Table 9
Population sizes percentage difference.

Index	Parameter sets	Percentage difference (%)
1	[5, 1.0, 1]–[15, 1.0, 1]	5.71
2	[5, 1.0, 2]–[15, 1.0, 2]	−1.24
3	[5, 0.7, 1]–[15, 0.7, 1]	5.07
4	[5, 0.7, 2]–[15, 0.7, 2]	−1.17

Table 10
Impact of crossover probability.

Index	Compared parameter sets	Percentage differences (%)
1	[5, 1.0, 1]–[5, 0.7, 1]	0.52
2	[5, 1.0, 2]–[5, 0.7, 2]	−3.06
3	[15,1.0, 1]–[15, 0.7, 1]	0.25
4	[15, 1.0, 2]–[15, 0.7, 2]	−2.87

Table 11
Impact of mutation rate.

Index	Compared parameter sets	Percentage differences (%)
1	[5, 1.0, 1]–[5, 1.0, 2]	2.40
2	[5, 0.7, 1]–[5, 0.7, 2]	−1.17
3	[15, 1.0, 1]–[15, 1.0, 2]	−4.49
4	[15, 0.7, 1]–[15, 0.7, 2]	−7.41

6.4. Convergence velocity

The stopping criterion for the search in this experiment is at 750 simulation calls. The performance of the search to this point is investigated using the reduction ratio (Alajmi and Wright, 2014). This gives the reduction in objective function values averaged over 5 results. Note that this analysis is done only on the new objective function values rather than on all evaluations. Note also that basing the reduction ratio on the mean of 5 solutions has the effect of "smoothing the results".

The effectiveness of the parameter sets influence on the GA convergence velocity and the reduction rate of the best solutions will be examined.

The results were for the best solutions found after a given number of simulation calls. This illustrates the convergence behavior of the search. Another way of looking to the GA performance is to analyze how it is exploring the search space.

These results show that the smallest population size (5) generally has a poorer performance, especially with a high mutation rate, but also showed that small population sizes

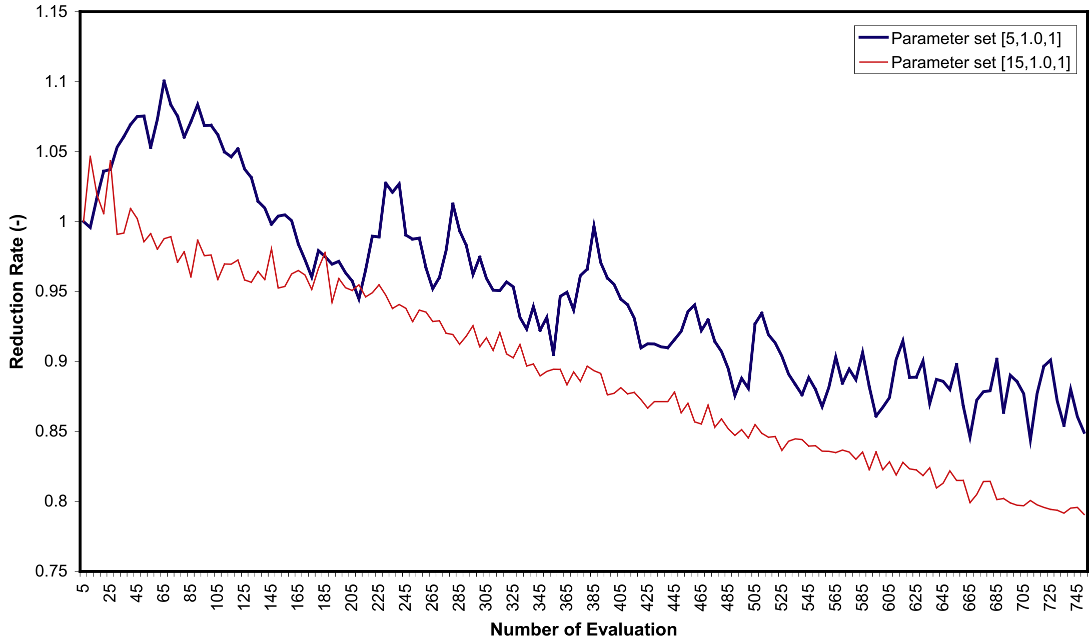

Figure 2. Effectiveness of population size on GA performance of crossover probability 1.0 and mutation rate 1 for every five unique solutions.

Table 12
Number of function calls until it reaches the feasibility region.

Index	Parameter sets	No. of fun. calls to feasibility solutions
1	[5, 1.0,1]	290
2	[5, 1.0,2]	195
3	[5, 0.7, 1]	180
4	[5, 0.7, 2]	135
Average		200
5	[15, 1.0, 1]	170
6	[15, 1.0, 2]	175
7	[15, 0.7, 1]	145
8	[15, 0.7, 2]	155
Average		161

are less directed in their search path to the optimum solutions in comparison to the 15 population sizes. This is due to the nature of a small population which has a high chance to be prematurely collapsed into identical solutions. When this happens in this research, the population is re-seeded with randomly initialized solutions before the search continues while the best solution is retained. The re-seeding causes some disruption to the search direction but increase the exploratory power of the search, see Fig. 2.

The analysis described so far has been concerned with the objective function values. The speed with which the search finds a feasible solution is discussed in the following section.

6.5. Parameter sets trend toward the feasibility region

In this constrained building optimization problem, a comparison of which experiment sets reach the feasibility region quicker is conducted. Fast convergence to the feasible region is considered to be an indication of good performance. This is because it will have more chance to search for the optimum solution within the feasible search space before the process is terminated (after 750 simulation calls). A comparison between the control parameter sets in this respect is shown Table 12.

In this table the average number of simulations is 200 for the parameter sets that compromise a population size of 5, while it is 161 for those parameters sets of population size 15. This suggests that the population size of 15 results in better performance. Given that the search is able to find a feasible solution in less than 200 simulation calls suggests that the optimization problem is weakly constrained.

7. Closing discussion

In general, optimization of the building design problem while considering the occupants comfort is an essential process toward energy efficient building. For this reason, preparing the necessary engine to handle this problem efficiently and economically is of great importance on national and international bases. This paper provides the technical information required to make the optimization of constrained building design problem as reliable as possible by linking EnergyPlus simulation program to an efficient Genetic Algorithm (GA). Thus, EnergyPlus linked to GA with a population size of 15, crossover probability of 1 and mutation rate of 1 provides competent methodology capable of optimizing complicated constrained building optimization problems. This GA parameter set produces optimized solutions with high conversion speed in less number of simulation calls of EnergyPlus program.

Eighty building variables have been optimized so that the building consumed minimum energy while occupants of the building are feeling comfortable. Thus, using the current developed results would contribute in optimizing every aspect in building envelop, HVAC systems and HVAC operation strategies under different climate conditions. This will reduce the building energy consumption and produce more energy efficient buildings that can help in producing green building and net zero energy building.

8. Conclusion

The performance of eight different control parameter sets of GA for optimum solutions of a constrained building optimization problem, with fixed number (750) of trial simulations was investigated. Based on the reported results a general conclusion can be stated that mid-size population (15) with high crossover probability (1.0), and low mutation rate (1) is the most appropriate control parameter set of GA applied in a constrained building optimization problem. In this problem an energy efficient building design was achieved without compromising the occupants comfort. This was accomplished with the small number of simulation calls of the building simulation program (EnergyPlus) which means less time needed to get the optimum solutions.

The number of design variables in this study was too large because many aspects of the building envelop and HVAC system operation controls were considered. This makes the evaluation of the individual design variables influence on the objective function too difficult. Therefore, reducing the number of design variables of the problem will reduce the search space which subsequently simplifies the problem and gives an opportunity to collate each design variable with the objective. Such an approach could be considered in any further research of constrained building optimization problems.

References

Alajmi, A., Wright, J., 2014. Selecting the most efficient genetic algorithm sets in solving unconstrained building optimization problem. Int. J. Sustainable Built Environ. 3, 18–26.

ASHRAE Standard 55, 2010. Thermal Environment Conditions for Human Occupancy. American Society of Heating Ventilating and Air-conditioning Engineers, Atlanta, USA.

Bichiou, Y., Krarti, M., 2011. Optimization of envelope and HVAC systems selection for residential buildings. Energy Build. 43 (12), 3373–3382.

Bleiberg, T., Shaviv, E., 2007. Optimization for enhancing collaborative design. In: Proceedings of the Building Simulation.

Brownlee, A.E., Wright, J.A., Mourshed, M.M., 2011. A multi-objective window optimisation problem. In: Proceedings of the 13th Annual Conference Companion on Genetic and Evolutionary Computation, GECCO'11. ACM, New York, NY, USA, pp. 89–90.

Crawley, Drury B., Lawrie, Linda K., Winkelmann, Frederick C., Buhl, W.F., Joe Huang, Y., Pedersen, Curtis O., Strand, Richard K., Liesen, Richard J., Fisher, Daniel E., Witte, Michael J., Glazer, Jason, 2001. EnergyPlus: creating a new-generation building energy simulation program. Energy Build. 33 (4), 319–331, ISSN 0378-7788.

Evins, R., Pointer, P., Vaidyanathan, R., Burgess, S., 2012. A case study exploring regulated energy use in domestic buildings using design-of-experiments and multi-objective optimisation. Build. Environ. 54, 126–136.

Geyer, P., 2009. Component-oriented decomposition for multidisciplinary design optimization in building design. Adv. Eng. Inf. 23.

Hamdy, M., Hasan, A., Siren, K., 2009. Combination of optimisation algorithms for a multi-objective building design problem. In: Proceedings of the Building Simulation.

ISO Standard 7790, 2005. Moderate Thermal Environments – Determination of the PMV and PPD Indices and Specification of the Conditions for Thermal Comfort. International Organisation for Standardisation, Geneva.

Mourshed, M.M., Kelliher, D., Keane, M., 2003. Ardot: a tool to optimise environmental design of buildings. In: Proceedings of the Building Simulation.

Sahu, M., Bhattacharjee, B., Kaushik, S., 2012. Thermal design of air-conditioned building for tropical climate using admittance method and genetic algorithm. Energy Build. 53, 1–6.

Wang, W., Rivard, H., Zmeureanu, R., 2005. An object-oriented framework for simulation-based green building design optimization with genetic algorithms. Adv. Eng. Inf. 19.

Wetter, M., 2001. GenOpt a generic optimization program. In: Proceedings of the Building Simulation.

Wetter, M., Wright, J., 2004. A comparison of deterministic and probabilistic optimization algorithms for nonsmooth simulation-based optimization. Build. Environ. 39 (8), 989–999.

Wright, J., Loosemore, H., 1993. An infeasibility objective for use in constrained Pareto optimization. Evolutionary Multi-Criterion Optimization. Lecture Notes in Computer Science, 1993/2001. Springer.

Wright, J., Zhang, Y., 2005. An ageing operator and its use in the highly constrained topological optimization of HVAC system design. In: Proceedings of the Building Simulation.