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# Using the Big Bang – Big Crunch Algorithm for Rational Design of an Energy-Plus Building

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**Abstract**

Reduction of the energy consumption without compromising living standard has become very important issue in architecture, civil engineering and building industry. This problem includes numerous independent and often contradictory aspects. That indicates that a compromise between construction cost and energy efficiency should be found.
The study presented in this paper has shown that choice of structural system and its elements can significantly influence the total price of a building as well its environmental impact. Since these two aspects are usually directly confronted, the decision-maker should be aware of all their advantages and disadvantages. Therefore, numerical analysis for exploring different possibilities should not be exclusive, i.e. not to provide only one solution, but to offer at least several solutions in order to enable decision-maker to get a good insight and to make the most appropriate choice considering given situation. The methodology presented in this paper, based on multi-objective Big Bang – Big Crunch algorithm, has proven to be successful in solving this kind of problem.


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## 1. Introduction

The continuous rising of energy consumption is a current global concern, primarily because energy is still mainly coming from limited non-renewable sources. Besides that, the more energy is consumed, the more carbon emissions are released into the atmosphere. According to a report from the World Business Council for Sustainable Development [1], the construction sector is responsible for the highest energy consumption rate, estimated at approximately 40% of the total energy used worldwide and the resulting carbon emissions are estimated to be even higher than those of all transportation sector combined. Therefore, reduction of energy consumption without compromising the quality of living is a matter of extreme importance towards a global sustainability.

In terms of sustainable development, the main objective for the building optimization is the reduction of energy use while possibly generating some energy, such as solar or wind energy. But the more energy-efficient is the building, the more expensive tends to be its construction. Consequently, it is hard to find a compromise between energy efficiency and construction costs.

Besides that, reduction of energy consumption without compromising living standard has become very important issue in civil engineering and building industry. On the other hand, this problem includes numerous independent and often contradictory aspects because the design of an energy-efficient building usually includes more expensive insulation materials and better heating, ventilating and air-conditioning (HVAC) systems, which all can have significant impact on the total price of the construction. That indicates that a compromise between construction cost and energy efficiency should be found.

Further inconvenience in solving this problem is the fact that considering energy efficiency and using renewable energy sources a building cannot be observed independently of its natural environment. This demands inclusion of additional software for providing energy consumption data for different types and kinds of buildings and different lighting and HVAC systems according to the local meteorological data of a given region. Pitman and King [2] proposed methodology for the building shape optimization in order to establish balance between received solar energy via façade and energy consumption by lighting and HVAC systems using the EnergyPlus software. Other authors have also researched methods for maximizing energy efficiency and minimizing the cost and at the same time by optimizing type and of quality of windows and insulation materials [3], room shape and orientation, as well as the windows size and positioning [4] or architectural and constructional aspects of the building and performances of the HVAC systems [5,6].

In past two decades, numerous random search optimization methods, such as simulated annealing, evolutionary programming, genetic algorithms, tabu search and particle swarm optimization, which are all probabilistic heuristic algorithms, have been successfully used for solving different optmization problems. In 2006, Erol and Erskin introduced a new optimization method inspired by one of the theories of the evolution of the universe, namely the Big Bang and Big Crunch theory [7]. During the past few years, this method has been proven to have a low computational time and high convergence speed. The Big Bang–Big Crunch (BB–BC) optimization method similarly generates random points in the Big Bang phase and shrinks these points to a single representative point via a center of mass in the Big Crunch phase. After a number of sequential Big Bangs and Big Crunches where the distribution of randomness within the search space during the Big Bang becomes smaller and smaller about the average point computed during the Big Crunch, the algorithm converges to a solution. The BB–BC method has been shown to outperform the enhanced classical Genetic Algorithm for many benchmark test functions.

Motivation for the study presented in this paper was to find the efficient way to fulfil the both demands using multi-objective optimization. Therefore, two objective functions were developed: one for minimizing total expenses, and another one for minimizing environmental impact. The nature of given problem and the combination of continuous and discrete variables indicated that the best tool for solving this task would be a multi-objective Big Bang–Big Crunch algorithm. Developed algorithm was successfully tested on numerous examples, one of which is presented in the paper. Obtained results indicate that the proposed methodology can be successfully used for optimal green building design which would satisfy both the energy efficiency demands on one side and economy aspects on the other.

## 2. Mathematical Formulation of the Problem

Multi-disciplinary design optimization is a field of science that uses optimization methods for solving design problems that incorporate a number of disciplines and allows designers to incorporate all relevant disciplines simultaneously. The optimum of the simultaneous problem is superior to the design found by optimizing each discipline sequentially, since it can exploit the interactions between the disciplines. However, including all disciplines simultaneously significantly increases the complexity of the problem and demands the whole teams or different experts.

Besides that, optimization problems are often multi-modal; i.e. they possess multiple good solutions. They could all be globally good or there could be a mix of globally good and locally good solutions and the goal is to obtaining all or at least some of them. Due to their iterative approach, classical optimization techniques do not perform satisfactorily when they are used to obtain multiple solutions, since it is not guaranteed that different solutions will be obtained with different starting points in multiple runs of the algorithm.

Standard optimization problem can be described as the minimization of a given objective function:

$$y = f_{(x_1, x_2, \ldots, x_n)} \tag{1}$$

to inequality constraints:

$$g_{j(x_1, x_2, \ldots, x_n)} \leq 0, j = 1,2, \ldots, p \tag{2}$$

as well as equality constraints:

$$h_{k(x_1, x_2, \ldots, x_n)} \leq 0, k = 1,2, \ldots, q \tag{3}$$

However, single-objective optimization may unnecessarily constrain a designer. For example, operating costs for lights and for space conditioning can both be expressed in the same units, but a designer may have reason to favor day-lighting from north-facing windows over increased conduction losses and attendant increases in heating and cooling costs. Capital costs for equipment and the building envelope can in principle be included in a life-cycle-cost objective function but may better be considered separately, if capital and operating budgets are separate. Multi-criteria optimization methods move away from a sum of individual objectives and provide the designer with explicit information about the tradeoffs between different criteria.

In general, optimal design of an energy efficient building has to meet two confronted demands: to minimize total cost of construction, and to minimize environmental impact and energy consumption, which is usually obtained by the implementation of expensive insulation materials and equipment. Consequently, there is no unique, i.e. the best solution, but a number of more or less acceptable ones among which designer choses a satisfying one considering given demands and limitations. Therefore, optimization task cannot be formulated by a single objective function, but requires at least two functions and belongs to the area of multi-objective optimization.

It has to be emphasized that there is an important distinction between building performance simulation and building energy analysis. Building energy analysis was acceptable before personal computers became available and affordable. On the other hand, realistic building simulation tools could not be widely practically applied without computers because the attempt to imitate physical conditions with including time as the independent variable results in extremely complex series of calculations, which can be accomplished only by consequential forming and solving sets of equations in discrete time-steps. True simulation methods require significant computational resources because hundreds or even thousands of equations have to be formed and solved to model even a very simple house.

Current design methods mainly depend on trial-and-error optimization using dynamic energy simulation tools coupled with the knowledge of the designers. Simulations are usually used in a scenario-by-scenario basis, where

designer generates one solution and subsequently use the computer to evaluate it. This can be a slow and tedious process and typically only a few scenarios are evaluated from a large range of possible choices.

For a nontrivial multi-objective optimization problem, there is no single solution that simultaneously optimizes each objective. In that case, the objective functions are said to be conflicting, and there exists a (possibly infinite number of) Pareto optimal solutions. A solution is called non-dominated (or non-inferior, Pareto optimal, Pareto efficient), if none of the objective functions can be improved in value without impairment in some of the other objective values. Without additional preference information, all Pareto optimal solutions can be considered mathematically equally good (as vectors cannot be ordered completely). When decision making is emphasized, the objective of solving a multi-objective optimization problem is referred to supporting a decision maker in finding the most preferred Pareto optimal solution according to his/her preferences. In this case, a human decision maker plays an important role and therefore is expected to be an expert in the problem domain.

Because of the complexity of the problem, the two objective functions to be minimized in this research were the life-cycle cost (C) and the life-cycle environmental impact (EI):

$$MIN: C_{(X)} = IC_{(X)} + OC_{(X)} \tag{4}$$

$$MIN: EI_{(X)} = EC_{(X)} + EO_{(X)} \tag{5}$$

where IC is the initial construction cost (€); OC is the present worth of life-cycle operating costs (€); EC is the environmental impact (MJ) due to building construction, and EO is the environmental impact (MJ) due to the building operation for heating, cooling, lighting and other similar processes.

The environmental impact of a building is evaluated by the cumulative exergy consumption [8], where exergy is defined as "the amount of work obtainable when some matter is brought to a state of thermodynamic equilibrium with the common components of the natural surroundings by means of reversible processes, involving interaction only with the common components of nature" [9]. EC is represented by the embodied energy of all fuels consumed in pre-operation phase, while EO is expected total energy consumption during the life of a given building.

The variables considered in presented study are categorized into four groups: shape, structure, envelope configuration and overhang. Building shape is defined by the edge lengths and the angles between each edge and the true north axis. This representation is more useful than the traditional one (edge lengths and angles between edges) because it defines both the shape of the building and its orientation in the global coordinates. Therefore, shape-related variables are edge length (m) from a1 to an-2 (values an-1 and an will be calculated according to the obtained angle values) and the edge bearing (angle between the true north axis and the corresponding edge) from α1 to αn-1.

The building structural system has an impact on the envelope design by determining the applicable wall types. The structure-related variable defines different available alternatives for the building structural system (e.g., steel frame vs. concrete frame). Its purpose is to ensure the compatibility between walls, roofs, floors and overhangs. The building envelope system can be divided into opaque walls, floors, roofs, and windows. A wall can be decomposed into a number of successive layers such as cladding, insulation, and sheathing. The sequence and material types of wall layers depend on the wall type. In order to consider alternative wall constructions simultaneously, both wall type and wall layer are represented as related discrete variables. The same principle applies to roof type and roof layers, floor type and floor layers. In addition, this study considers window type and window ratio for each façade as variables.

The overhang design is closely related to the window below it. In this study, the overhang width is the same as the window width, which is set equal to the length of the corresponding wall. The overhang-related variables are: overhang type (a discrete variable that indicates the possible overhang types for each façade, including the option of no overhang); overhang depth for each façade and overhang height for each façade.

## 3. Big Bang – Big Crunch (BB-BC) Optimization Algorithm

The BB–BC method developed by $E_{rol}$ and $E_{ksin}$ [7] consists of two phases: a Big Bang phase, and a Big Crunch phase. In the Big Bang phase, candidate solutions are randomly distributed over the search space. Randomness of

solutions of any given optimization problem can be seen as equivalent to the energy dissipation in nature while convergence to a local or global optimum point can be viewed as gravitational attraction. Since energy dissipation creates disorder from ordered particles, BB-BC algorithm uses randomness as a transformation from a converged solution (order) to the birth of totally new solution candidates (disorder or chaos).

Similar to other evolutionary algorithms, initial solutions are spread all over the search space in a uniform manner in the first Big Bang. Erol and Eksin associated the random nature of the Big Bang to energy dissipation or the transformation from an ordered state (a convergent solution) to a disorder or chaos state (new set of solution candidates). Their method is basically similar to the Genetic Algorithms in respect to creating an initial population randomly. The creation of the initial population randomly is called the Big Bang phase. In this phase, the candidate solutions are spread all over the search space in a uniform manner.

The Big Bang phase is followed by the Big Crunch phase. The Big Crunch is a convergence operator that has many inputs but only one output, named as the center of mass, since the only output has been derived by calculating the center of mass, where the term mass refers to the inverse of the merit function value [10]. The point representing the center of mass that is denoted by xc and can be calculated according to:

$$\vec{x}^{c} = \frac{\sum_{i=1}^{N} \frac{1}{f^{i}} \vec{x}^{i}}{\sum_{i=1}^{N} \frac{1}{f^{i}}} \tag{6}$$

where $x_i$ is a point within an n-dimensional search space generated, $f_i$ is a fitness function value of this point, and N is the population size in Big Bang phase.

The convergence operator in the Big Crunch phase is different from ‘exaggerated’ selection since the output term may contain additional information (new candidate or member having different parameters than others) than the participating ones, hence differing from the population members. This one step convergence is superior compared to selecting two members and finding their centre of gravity. This method takes the population members as a whole in the Big-Crunch phase that acts as a squeezing or contraction operator; and it, therefore, eliminates the necessity for two-by-two combination calculations [6].

After the Big Crunch phase, the algorithm must create new members to be used as the Big Bang of the next iteration step. This can be done in various ways, the simplest one being jumping to the first step and creating an initial population. The algorithm will have no difference than random search method by so doing since latter iterations will not use the knowledge gained from the previous ones; hence, the convergence of such an algorithm will most probably be very low. An optimization algorithm must converge to an optimal point; but, at the same time, in order to be classified as a global algorithm, it must contain certain different points within its search population with a decreasing probability. To be more precise, we mean that, large amount of solutions generated by the algorithm must be around the 'so-called' optimal point but the remaining few points in the population bed must be spread across the search space after certain number of steps. This ratio of solution points around the optimum value to points away from optimum value must decrease as the number of iterations increases; but, in no case, it could be equal to zero, which means the end of the search.

The convergence, i.e. the use of the previous knowledge (centre of mass), can be accomplished by spreading new off-springs around this centre of mass using a normal distribution operation in every direction where the standard deviation of this normal distribution function decreases as the number of iterations of the algorithm increases.

After the second explosion, the new centre of mass is calculated. These successive explosion-contraction steps are carried repeatedly until a stopping criterion has been met. The parameters to be supplied to normal random point generator are the centre of mass of the previous step and the standard deviation. The deviation term can be fixed, but decreasing its value along with the elapsed iterations produces better results.

After the Big Crunch phase, the algorithm creates the new solutions to be used as the Big Bang of the next iteration step, by using the previous result (centre of mass). This can be accomplished by spreading new off-springs

around the centre of mass using a normal distribution operation in every direction, where the standard deviation of this normal distribution function decreases as the number of iterations of the algorithm increases [6]:

$$x^{new} = x^{c} + \frac{lr}{k} \tag{7}$$

where $x^c$ stands for centre of mass, $l$ is the upper limit of the parameter, $r$ is a normal random number and $k$ is the iteration step. Then new point $x^{new}$ is upper and lower bounded.

The BB–BC approach takes the following steps [6]:

*Step 1:* Form an initial generation of N candidates in a random manner.
*Step 2:* Calculate the fitness function values of all the candidate solutions.
*Step 3:* Find the centre of mass. Best fitness individual can be chosen as the centre of mass.
*Step 4:* Calculate new candidates around the centre of mass.
*Step 5:* Return to Step 2 until stopping criteria has been met.

## 4. Case Study

The case study consists in the design of a single-story building located in Belgrade, Serbia. The building footprint takes the rectangular shape with floor area of 1000 m2 and floor-to-floor height of 2.7 m. In the building energy simulation program (EnergyPlus), the heating season is from October 15th to March 15th, while the cooling season is from June 15th to August 31st. The indoor design temperatures are set to 22°C for both the heating and cooling, without night setback or setup. A period of 25 years is used in the life-cycle analysis for building performance.

The interval of each edge length is set between 5 and 200 m. Shape-related variables are defined here as continuous variables. Six window types are available for each façade, as follows: double clear glazing; reflective double glazing; low-e double glazing with a coating with emissivity = 0.2 or 0.1 on the exterior of the inside pane and low-e double glazing with a coating with emissivity = 0.2 or 0.1 on the interior of the outside pane.

Two considered alternative structural systems are steel frame and concrete frame. Both of them have the same two possible exterior wall types: concrete block wall and steel-stud wall. However, they have different floor types: the steel deck on open web steel joist floor type is used for the steel frame while a cast-in-place concrete floor type is used for the concrete frame.

Two wall types have been considered. The concrete block wall consists of cladding, rigid insulation, vapor barrier, concrete block, and finish, while the steel-stud wall consists of cladding, rigid insulation, air barrier, sheathing, steel-stud with cavity insulation, vapor barrier, and finish. Only the insulation layers are optimized because all other layers have minor impact on the two considered performance criteria. The rigid insulation layers can either be expanded poly-styrene (EPS) or extruded polystyrene (XPS) with different thicknesses. For the concrete block wall, the rigid insulation has the following eight alternatives: 76, 102, 127 and 152 mm for the both EPS and XPS. For the steel-stud wall, the rigid insulation has the following six alternatives: 25, 51 and 76 mm for the both EPS and XPS. Two possible values are defined for the overhang type: no overhang and aluminum overhang. The overhang depth varies between 0.1 and 1.2 m, while the overhang height is fixed to be 0.2 m.

## 5. Results

Obtained solutions are visibly grouped into two isolated regions – one with lower costs and larger environmental impacts (the best solution: 4.18·105€ and 2.470·107 MJ), and the other one, with lower environmental impacts but larger costs (the best solution: 4.790·105€ and 2.485·107 MJ). These two Pareto zones are directly connected with the allowed structural systems. The steel frame system has a lower cost but higher environmental impacts than the concrete frame system. The steel-stud wall is the optimal wall type for all solutions. For the steel-stud wall, the stud insulation has converged to 127 mm fiberglass in the stud cavity. The rigid insulation converged to 102 mm XPS for the first Pareto zone and 76 mm EPS for the second one.

As it was expected and logically assumed, the longer wall in all solutions (length ranging from 35 to 45 m) is south-oriented in order to take advantage of the passive solar heating. Since the building in this case study has a fixed floor area and height, the perimeter can be employed as a valuable indicator to measure the compactness of a building. It is found that the perimeter ranges between 120 m to 130 m and roughly 75 % of the solutions have a perimeter around 125 m. The general trend is that the perimeter increases with the life-cycle cost and that the LCC increases and the LCEI decreases as the perimeter of the pentagon and the length of its south edge increase.

All solutions have the optimal window type as the double glazing with coating (emissivity = 0.2). Differences between two proposed types of glazing were negligible. The window ratio on the south façade varies while it has converged to the lower bound 0.2 for all other façades.

If overhang is used, its depth takes the lower bound 0.1 m for most solutions. The largest overhang depth is 0.25 m for the solutions with the longest south wall and the largest window ratio. There should be no overhang on non-south façades because there is no direct sun on the north façade and the solar angle is low for the east and west façades.

Proposed methodology significantly outperformed the ones examined in the previous researches [11,12].

## 6. Summary

Buildings created as sustainable environments achieve this label through the efficient operation and maintenance of the building systems, but it is the but it is the smart and creative initial layout of the spaces and the structural design that ultimately take full advantage of achieving the goal of zero or nearly zero energy performance. Therefore, the first and best place to consider the energy efficiency of any building is during the design stage, not when the building has been completed and in use. Reduction of the energy consumption without compromising living standard has become very important issue in architecture, civil engineering and building industry. This problem includes numerous independent and often contradictory aspects because the design of an energy-efficient building usually demands more expensive insulation materials and better heating, ventilating and air-conditioning systems, which can all have significant impact on the total price of the construction. That indicates that a compromise between construction cost and energy efficiency should be found.

The study presented in this paper has shown that choice of structural system and its elements can significantly influence the total price of a building as well its environmental impact. Since these two aspects are usually directly confronted, the decision-maker should be aware of all their advantages and disadvantages. Therefore, numerical analysis for exploring different possibilities should not be exclusive, i.e. not to provide only one solution, but to offer at least several solutions in order to enable decision-maker to get a good insight and to make the most appropriate choice considering given situation. The methodology presented in this paper, based on multi-objective Big Bang – Big Crunch algorithm, has proven to be successful in solving this kind of problem.

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