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A BIM BASED APPROACH FOR CONFIGURING BUILDINGS' OUTER ENVELOPE ENERGY SAVING ELEMENTS

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SUMMARY: *This study introduces a novel approach to configuring buildings' outer envelopes with the objective of optimizing Life Cycle Cost. This approach is based on the assumption that not all building elements constituting the outer envelope are subjected to the same amount of thermal transmission losses or solar radiation. Therefore, an optimization approach based on segmenting external facades and roofs into independent objects in a building information model was developed. A Genetic Algorithm is coupled with Industry Foundation Classes, an Energy Simulation software tool and a Life Cycle Cost estimation model to achieve an optimal allocation of energy saving elements to buildings' external envelopes, the use of which allows for a positive return on additional investment in energy saving elements. The developed approach is applied to a case study of a desert building in Egypt. The paper also investigates the influence of Egyptian energy prices subsidization policy relevant to energy saving costs using the case study.*

KEYWORDS: *BIM, Life Cycle Cost, Energy, Optimization, Genetic Algorithm, Segmentation*

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1. INTRODUCTION

The early design phase of a building has a substantial influence on all of its subsequent phases and particularly to the overall Life Cycle Cost (LCC) of the project. Minor modifications to the early design can have significant impacts on LCC that can extend beyond the simple calculation of initial cost of the building. This applies when considering the increasing demand for energy consumption. This has led several researchers to investigate the use of energy efficient elements/systems in buildings to reduce their life cycle energy consumption (Rahmani et al, 2013), (Fischer et al, 2012). Sensitivity analysis and uncertainty analysis are becoming essential to provide designers with feedback on alternative systems available for use in their designs (MacDonald, 1999). This is based on the argument that at the early design stage, it is more appropriate for the decision making process to consider *"performance values against the probability of their occurrence"* rather than comparing a set of simulation results to a benchmark value (De Wit, 2004).

Traditionally, systems and building designs are evaluated on the basis of their initial investment cost, neglecting other costs such as operation, maintenance and repair (Sieglinde, 2007). Life Cycle costing is a rational and powerful approach to the proper evaluation of systems throughout their lives. In addition to initial construction costs, the lifecycle cost of a building covers the cost of repair, maintenance, utilities and those of the energy required to operate the building (i.e., heating, cooling and lighting costs). For additional detail, the reader is encouraged to refer to the National Institute of Standards and Technology (Sieglinde, 2007) for a description of and methodology for applying lifecycle cost analysis to buildings. Doubtless, lifecycle cost analysis is important and supports the optimization process during the building design phase. Additional details in this regard and the expected modeling challenges can be found in (Nielsen et al, 2002), (Winkler et al, 2002), and (Huberman et al, 2007). Moreover, the relationship among lifecycle analysis, sustainability and energy efficient solutions is addressed by (Nielsen et al, 2002), (Jung et al, 2007), (AbuBakr et al, 2008), (Lombard et al, 2008), and (Sartori et al, 2007).By reviewing and comparing energy saving materials to traditionally used materials in the Egyptian market, energy saving materials are relatively more expensive. Considering this fact along the large energy subsidization strategies that exist in developing countries which reach to 70% in Egypt , LCC analysis shows economically infeasible designs that go beyond the return on additional investment.

It is possible to assess the LCC of an existing design, whereas the inverse problem of realizing the optimum configuration (design) of a building given a set of performance criteria is much more challenging (Znouda et al, 2007). The primary challenge is optimizing multi-objective LCC elements (which often conflict) to achieve a feasible design that justifies investments in energy saving devices. Several factors often affect the feasibility of making investments in such devices. These factors include the following: the LCC of the devices themselves, Energy Prices, Energy subsidization rates, the building's location, weather conditions, the surrounding urban fabric, type of occupancy, etc.

This paper presents a novel approach to achieving an economically feasible building configuration (design) based on the selection and assignment of each building element (segment) or energy saving device to the building's outer envelope (facades and roof). This selection is made based on a set of potential building elements with different energy saving capacities and LCC. The building elements considered in this study are different types of windows, different types of walls with different insulating materials and different types of roof segments. The degree of granularity of wall and roof segments is determined using a BIM model to cover a single space. The further division of each segment into smaller segments is outside the scope of this study.

The paper investigates energy consumption in buildings from the perspective of LCC analysis and optimization. It emphasizes the strong relationship between LCC aspects (initial, operational and maintenance (IO&M) costs) and energy costs to explore potential trade-offs between energy consumption and IO&M costs throughout a building's lifecycle. This relationship is critical in determining whether additional investments in building elements with the potential for generating energy savings during its operational phase are justified. The paper also discusses the need for non-traditional optimization approaches (e.g., Genetic Algorithms (GAs)) to achieve a configuration of building elements that represents optimal LCC. The challenges pertaining to the interoperability of different domain applications within the context of a BIM based LCC analysis/optimization during the design stage of a building and a prototype for an interoperability platform for BIM, EnergyPlus, GA and LCC are described in a separate publication (Nour et al, 2012). The developed framework was applied to a desert building in Egypt as a case study with the aim of optimizing building configuration in terms of the types of elements (objects) that constitute the building's outer envelope. In a hot, arid desert climate, energy loads from cooling, heating and lighting must be considered. It has been demonstrated that these loads have to be optimized simultaneously to avoid conflicting effects resulting from optimizing one element at the expense of the others. This is evident from the use of energy saving windows and solar screens, which result in an increased need for energy for internal lighting. Furthermore, other lifecycle costs are also affected. Ultimately, therefore, it is necessary to conduct a multi-objective optimization study.

2. RESEARCH FOCUS

The main hypothesis in this study is that achieving the optimal energy performance of a building design by conducting an energy simulation does not ensure that the minimum LCC of a building is realized. Thus, initial, operation and maintenance costs must be considered in addition to the LCC energy component. The expectation is that if optimization techniques can manipulate the input data in the energy simulation according to changes made to the design of the building's outer envelope– on the level of individual objects –this will allow for the analysis of the trade-off between savings on energy consumption costs and the additional investment made in each object constituting the overall outer skin of the building. Furthermore, simulation results can contribute to achieving configurations of buildings' outer envelopes that can make additional investments in energy saving devices economically viable based on the assumptions that 1) not all segments (objects) of the building's outer envelope are subjected to the same thermal loads; and 2) energy consumption is not treated as more than a single element of the overall LCC spectrum.

3. METHODOLOGY

This study depends on open technologies and standards like BIM-IFC ISO 1030 STEP standard and EngergyPlus. Both of them are open technologies that are independent from any commercial proprietary technologies like (Bentley , AutoDESK, Graphisoft) or any other commercial software application. Revit is used as a BIM authoring tool only once at the initial design stage for a single export of a STEP ISO 10303 physical file, and then the evolution of the BIM model continues in the IFC format. The authors are not dependent on working under the umbrella of any particular proprietary software application or exchange format in this research study, it is important to be able to fully manipulate the tools used and not to be subject to any restriction due to functionality limitations of commercial software applications or black box technologies. This is particularly the case when dealing with the IFC-STEP models due to failure of software applications in conserving IFC data not belonging to the core of their applications. This is very famous among software applications, where data loss is inevitable with data exchange. Limitations of BIM tools and processes with relevance to energy simulation and optimization are detailed by (Maile et al, 2013) and the comparative analysis made by (Mapentzidis and Raslan, 2014) . Thus, the IFC Java toolbox developed by the authors (Nour et al, 2008) and used in this study guarantees a lossless data exchange between the used applications. This makes this study different from parallel research efforts made by researchers using available commercial software applications like (Bavastro, 2014), (Hyeun et al, 2013), (Rahmani et al, 2013), (Fischer et al, 2012), (Cahill et al, 2012), or researches trying to extend the IFC EXPRESS-ISO10303-11 schema like (Cemesova et al, 2013).

The following sections describe the methodology employed to achieve the objectives of this research. The methodology section begins with the mathematical formulation of the research problem and then describes the tools and techniques used in the study: the GA (Genetic Algorithm) as the optimization engine; applying the segmentation approach to the building's outer envelope; and the object-oriented IFC/BIM genetic optimization framework developed here that integrates all of the above aspects in addition to interfacing with the energy simulation software (EnergyPlus, 2014).

3.1 Mathematical Formulation

Building Life Cycle Cost (BLCC) elements consist of two sets of components; the first set represents the costs of fixed components that are not affected by selecting different design alternatives. This set of components is termed Fixed Life Cycle Cost elements (FLCC). This set is common to all possible designs that can be generated during the optimization process. The FLCC comprises the costs of building components for which no alternatives are available and that would not be affected by the development of new designs during the optimization process. The second set of components represents elements that posses predefined deign alternatives that are selected using the optimization process to formulate new designs. This set of elements is referred to as Variable Life Cycle Cost elements (VLCC). Equation 1 shows the Building Life Cycle Cost (BLCC) in terms of these two sets of life cycle costs. In this study, the VLCC represents the set of elements constituting the outer skin of the building, such as types of windows, wall segments and roof segments.

$$\mathrm{BLCC} = \mathrm{FLCC} + \mathrm{VLCC} \quad \text{(Eq. 1)}$$

In this paper, the objective function of the optimization process is to minimize the BLCC. This objective can be achieved by minimizing the VLCC component of the BLCC, where FLCC represents a constant value. All costs are in Egyptian Pounds (EGP).

The VLCC can be expressed as the sum of two major cost elements related to: (1) the life cycle cost of the selected building components involved in the design and (2) the effect of using such elements, represented by their influence on energy consumption costs throughout the building's lifecycle, as shown in Eq. 2.

$$\mathrm{VLCC} = \mathrm{LCC_C} + \mathrm{LCC_B} \quad \text{(Eq. 2)}$$

Where, $\mathrm{LCC_C}$ represents the lifecycle cost of the building components affecting the design (component level), and $\mathrm{LCC_B}$ primarily represents the cost of the energy required to operate the building (building level) according to thermal and visual preferences determined by architectural and energy designers. This cost element is affected by the materials used, the form of the building, the building's location and orientation, etc. The $\mathrm{LCC_C}$ is expressed as shown in equation Eq. 3, while the $\mathrm{LCC_B}$ will be addressed below.

$$\mathrm{LCC_C} = \sum_i \mathrm{lcc}_i^{(j)} \quad \text{(Eq. 3)}$$

Where $\mathrm{lcc}_i^{(j)}$ represents the lifecycle cost in EGP of component (i) using alternative (j). The sum of these lifecycle costs covers all variable building components involved in a specific design. The components involved, their lifecycle costs and their possible alternatives can be expressed in matrix and vector formats as follows (Eq. 4a, 4b & 4c):

The vector of the building components involved [C] is expressed in Eq. 4a as follows:

$$[\mathrm{C}] = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ \vdots \\ c_i \\ \vdots \\ c_C \end{bmatrix} \quad \text{(Eq. 4a)}$$

The vector of available possible alternatives of the building components involved [A] is shown in equation Eq. 4b as follows:

$$[\mathrm{A}] = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_i \\ \vdots \\ a_C \end{bmatrix} \quad \text{(Eq. 4b)}$$

Where a_i is the number of possible alternatives for component (i).

The lifecycle costs of the components involved in possible alternatives are expressed in a matrix format, denoted $[\mathrm{lcc}_{ij}]$, of size $\mathrm{C}\times\mathrm{J}$ (C components by J alternatives), where J represents the maximum number of alternatives in the vector [A] of components involved, as follows (Eq.4c).

$$\mathrm{J} = \max[\mathrm{A}] = \max_i(a_i) \quad \text{(Eq.4c)}$$

The $\left[\mathrm{lcc_{ij}}\right]$ matrix is depicted in equation Eq.4d as follows:

$$\left[\mathrm{lcc_{ij}}\right] = \begin{bmatrix} \mathrm{lcc_{11}} & \mathrm{lcc_{12}} & \cdots & \mathrm{lcc_{1j}} & \cdots & \mathrm{lcc_{1J}} \\ \mathrm{lcc_{21}} & \mathrm{lcc_{22}} & \cdots & \mathrm{lcc_{2j}} & \cdots & \mathrm{lcc_{2J}} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ \mathrm{lcc_{i1}} & \mathrm{lcc_{i2}} & \cdots & \mathrm{lcc_{ij}} & \cdots & \mathrm{lcc_{iJ}} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ \mathrm{lcc_{C1}} & \mathrm{lcc_{C2}} & \cdots & \mathrm{lcc_{Cj}} & \cdots & \mathrm{lcc_{CJ}} \end{bmatrix} \qquad \text{(Eq.4d)}$$

The $\mathrm{lcc_{ij}}$ in EGP is calculated using equation Eq.5, which aggregates the various lifecycle cost components, as follows:

$$\mathrm{lcc_{ij}} = \begin{cases} \left(\mathrm{IC_{ij}} + \mathrm{RC_{ij}} + \mathrm{RRC_{ij}} + \mathrm{MC_{ij}}\right), & \text{considering the time value of money} \\ \infty, & \text{for } \mathrm{j} > \mathrm{a_i}, \quad \forall\, \mathrm{i} \end{cases} \qquad \text{(Eq.5)}$$

Where, IC, RC, RRC and MC represent initial, replacement, repair and maintenance costs in EGPs, respectively. The infinity value in the $\mathrm{lcc_{ij}}$ calculation represents a penalty to ensure that Eq.4c is satisfied for any $\left[\mathrm{lcc_{ij}}\right]$ that has a (j) value greater than its corresponding available number of alternatives (a). The $\mathrm{lcc_{ij}}$ is primarily a design-dependant value that varies from one building to another based on component quantity. Accordingly, the $\mathrm{lcc_{ij}}$ can be expressed in terms of quantity ($\mathrm{q_{ij}}$) in metric quantity units (i.e., linear meter m', m2, m3, etc.) and equivalent unit lifecycle cost in EGP/unit ($\mathrm{ulcc_{ij}}$), as shown in Eq.6a.

$$\mathrm{lcc_{ij}} = \mathrm{q_{ij}} \times \mathrm{ulcc_{ij}} \qquad \text{(Eq.6a)}$$

Elements' quantities are not changed in different design variants during the optimization process and are thus held constant (Eq.6b and 6c).

$$\mathrm{q_{ij}} = \mathrm{q_i} \qquad \text{(Eq.6b)}$$

$$\mathrm{lcc_{ij}} = \mathrm{q_i} \times \mathrm{ulcc_{ij}} \qquad \text{(Eq.6c)}$$

According to equation Eq. 6c, the initial, replacement, repair and maintenance costs in equation Eq.5 are modified to be unit costs in EGPs, as shown in equation Eq.7.

$$\mathrm{lcc_{ij}} = \mathrm{q_i} \times \begin{cases} \left(\mathrm{uIC_{ij}} + \mathrm{uRC_{ij}} + \mathrm{uRRC_{ij}} + \mathrm{uMC_{ij}}\right), & \text{considering the time value of money} \\ \infty, & \text{for } \mathrm{j} > \mathrm{a_i}, \quad \forall\, \mathrm{i} \end{cases} \qquad \text{(Eq.7)}$$

The quantities can be expressed in a quantity vector [Q] as follows (Eq.8):

$$[\mathrm{Q}] = \begin{bmatrix} \mathrm{q_1} \\ \mathrm{q_2} \\ \mathrm{q_3} \\ \vdots \\ \mathrm{q_i} \\ \vdots \\ \mathrm{q_C} \end{bmatrix} \qquad \text{(Eq.8)}$$

The quantity vector can be determined for any initial building design using manual quantity takeoff for the set of components considered or can automatically be extracted from the BIM model. The bases of and assumptions for various calculations for the unit initial, replacement, repair and maintenance costs are discussed in the following section.

3.2 Cost assessment:

In lifecycle costing (at the component level), it is important to determine: (1) the value of a cost (a monetary value in EGP) and (2) its timing (when the cost should appear on the life span). Table 1 highlights the known/unknown information regarding various costs and the required models and assumptions proposed in this study.

TABLE. 1: Lifecycle costs and required models

Cost Component	Cost Value	Timing
Initial Cost	**Unknown** (cost model is needed). A detailed cost assessment approach is appropriate.	**Known** (at time 0).
Replacement Cost	**Unknown** (can be assumed to be 100% of Initial Cost).	**Unknown** (service life prediction model is needed)
Repair Cost	**Unknown**	**Unknown**
Maintenance Cost	**Unknown** (can be assumed to be a percentage of the Initial Cost).	**Known** (yearly).

Repair costs are a major component of lifecycle costs. However, despite their importance, there is no standard method for calculating them. The authors elected to decompose the components to the subcomponent level (i.e., moving to a more detailed level in the building hierarchy, e.g., from the wall level to the layers constituting the wall). In so doing, it is appropriate to assume that performing any “Replacement Act” for one or more of the subcomponents would be equivalent to a “Repair Act” at the component level. According to the previous act, repair costs can be eliminated from the calculation subject to the condition of using the subcomponent level as the basis for cost calculations. A positive result of this decomposition is that it makes it possible to imitate the construction process, and accordingly, employ a detailed cost estimation approach in making the initial cost estimate. The subcomponent level determines the set of trades or activities required to construct the component (e.g., a wall component). The initial cost (construction cost) of each subcomponent is calculated based on its unit quantity. Then, summing the costs would yield the component’s initial cost (Eq. 9). The cost model will be discussed in a separate section.

$$\mathrm{uIC_{ij}} = \sum_{s} \mathrm{uIC_{sij}} \quad \forall\ \text{subcomponent s} \ \in \text{component } \mathrm{C_{ij}} \tag{Eq.9}$$

The initial cost $\mathrm{IC_{ij}}$ in EGP represents the key cost element in the lifecycle cost, as other cost elements (replacement and maintenance) are functions of the initial cost. Mathematically, the initial cost of any subcomponent is calculated using a detailed cost estimation approach that considers basic resources and building technology practices. When considering any subcomponent (s), it can be regarded as an activity with unit quantity in estimations using a pre-specified work crew suited to work on that activity or subcomponent (e.g., wall cladding). This crew is denoted $\mathrm{cr_{ijs}}$ and has a known composition (laborers and equipment) in addition to a daily production rate ($\mathrm{p_{ijs}}$). The combination of crew’s production rate and the unit quantity yields the time required to complete one unit, denoted $\mathrm{t_{ijs}}$, in days. Knowing the daily rates (costs in EGP) of the basic resources (laborers and equipment) and the crew composition makes it possible to calculate the daily crew cost ($\mathrm{dcCr_{ijs}}$). The final cost of producing a unit quantity can then be calculated by summing the costs of all materials used. The labor, equipment and material costs per unit are stored in simple database fashion. The following set of equations depicts the calculation of the unit initial cost of a subcomponent (s) related to component (i) of alternative (j).

$$\mathrm{dcCr_{ijs}} = \sum_{l} \mathrm{dcL_l} + \sum_{e} \mathrm{dcE_e} \quad , \forall l \in \mathrm{Cr_{ijs}} \text{ and } \forall\, e \in \mathrm{Cr_{ijs}} \tag{Eq.10a}$$

$$\mathrm{t_{ijs}} = \frac{1}{\mathrm{p_{ijs}}} \tag{Eq.10b}$$

$$\mathrm{uIC_{ijs}} = \mathrm{t_{ijs}} \times \mathrm{dcCr_{ijs}} + \mathrm{q_s} \times \sum_{m} \mathrm{ucm_{ijms}}, \qquad \forall\, m \in \text{subcomponent (s)} \tag{Eq.10c}$$

Where, dcL and dcE represent the daily cost of Labor and daily cost of Equipment, respectively, and $\mathrm{ucm_{ijms}}$ represents the unit cost of material (m) involved in the construction of subcomponent (s).

Returning to Table 1, two unknowns remain, the percentage of maintenance costs with respect to the calculated initial cost and the service life. Construction practitioners and facility managers in Egypt were consulted regarding maintenance costs, and they recommended using a value of approximately 0.5% of the initial cost, which can increase linearly with the same amount until a replacement is necessary. Although these figures were used in the cost model, they remained data inputs under user control according to the standards, building location and surrounding environment of each component alternative. Furthermore, a deterioration model developed by (Hosny et al, 2011) was adapted to estimate the service life, which is a function of subcomponent deterioration and user satisfaction. The service life (l) is illustrated in Figure 1, located at the intersection of a preferred satisfaction level (input) and a custom deterioration curve generated by the deterioration model (Hosny et al, 2011). Knowing the subcomponents involved in a component, their initial costs and service lives, total cash flow can be predicted and used to calculate the lifecycle cost at the component level ($\mathrm{LCC_C}$) in Eq. 2.

The mathematical part related to the building level (quantified at the building level-$\mathrm{LCC_B}$) is as follows. At the building level, the design of the building using a set of materials and components types substantially affects its energy consumption. However, quantifying the amount of energy required by a given design is a challenging task requiring energy simulation using reputable software such as EnergyPlus (EnergyPlus, 2014) from the Department Of Energy (DOE). The annual energy in kWh/year required for heating, cooling and lighting are assessed using EnergyPlus as a function of numerous inputs to the program, some of which represent variables in the design optimization problem. These inputs include the design itself (the form and design ratios), the building's location to capture the effects of weather, the building's orientation, the surrounding environment and material used for the building's skin (envelope), as illustrated (the variable part of the lifecycle cost - VLCC). The expected energy consumption is as follows and is estimated using EnergyPlus:

$$Annual\ Energy\ Consumption\ (AEC) = Annual\ Energy\ for\ Heating\ + Annual\ Energy\ for\ Cooling\ + Annual\ Energy\ for\ Lighting \tag{Eq. 11a}$$

Where AEC is in kWh/year

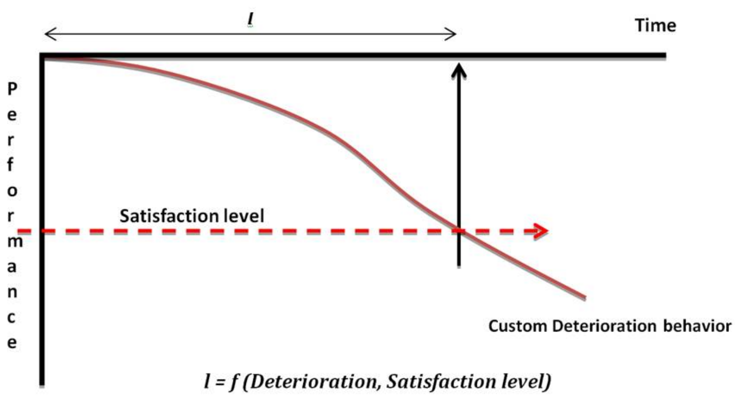

FIG. 1: Service life in relation to deterioration and satisfaction

To calculate the energy cost (LCC_B), the annual energy consumption (in kWh/year) based on equation Eq. 11 a (the simulated consumption) is multiplied by the electricity price (EP) in EGP (Eq.11b).

$$LCC_B = AEC \times EP \qquad \text{(Eq. 11b)}$$

As it is not possible to develop a reasonable formula for the energy consumption as a function of all of the aforementioned factors and variables, the optimization process becomes very complex. In this case, optimization cannot be performed using mathematical programming and needs to involve micro-level energy simulation within the optimization process. Genetic Algorithms (GAs) are not only used for this reason but also due to the combinatorial nature of the optimization problem. The number of variables in the design optimization problem is expected to exceed 100, resulting in billions of possible designs. Additional details on GAs and their implementation are presented in the next section.

3.3 GAs optimization

Genetic Algorithms (GAs) have been used to solve a wide range of engineering problems (Goldberg, 1989) for the following reasons: 1- They represent a heuristic search and optimization approach inspired by natural evolution in addition to being successfully applied to a wide range of real-world problems of significant complexity with minor modifications (McCall, 2005). 2- They can be coupled with complex energy simulation software (such as EnergyPlus) via the development of a software interface (Caldas et al, 2003). 3- They have proven effective in solving complex problems that cannot be readily solved using other optimization techniques. (Monks et al, 2000), (Turin et al, 2011), (Zemella et al, 2011), (Coley, 1997), (Park et al, 2003) and (Yoon et al, 2011).

In this study, GA is used to automate the search for an optimal combination of individual objects that constitute a building's outer envelope. As the set of potential solutions / combinations (points) is quite large, as depicted in Figure 2 that shows a very simple example of how the number of alternatives can grow up very quickly, the total number of possible solutions related to this study is 2.9E+45 design options and proves to be very difficult to be completely explored using an exhaustive search, especially given the time required for each energy simulation session for the building. The GA process begins searching using random sampling within an optimization solution space (population) and then employs stochastic operators to direct a process based on the pre-defined, multi-criteria objective functions to control the evolution of successive populations (generations) (Goldberg, 1989). The primary evolution operators are cross-over and mutation. Each combination of objects (genes) representing a certain solution is called a chromosome. This chromosome encodes all of the parameters of its objects in the form of the genes' values. The probability of each chromosome being selected for reproduction (cross-over or mutation) is proportional to the relative fitness of its solution. This fitness is determined by the value resulting from the objective function(s).

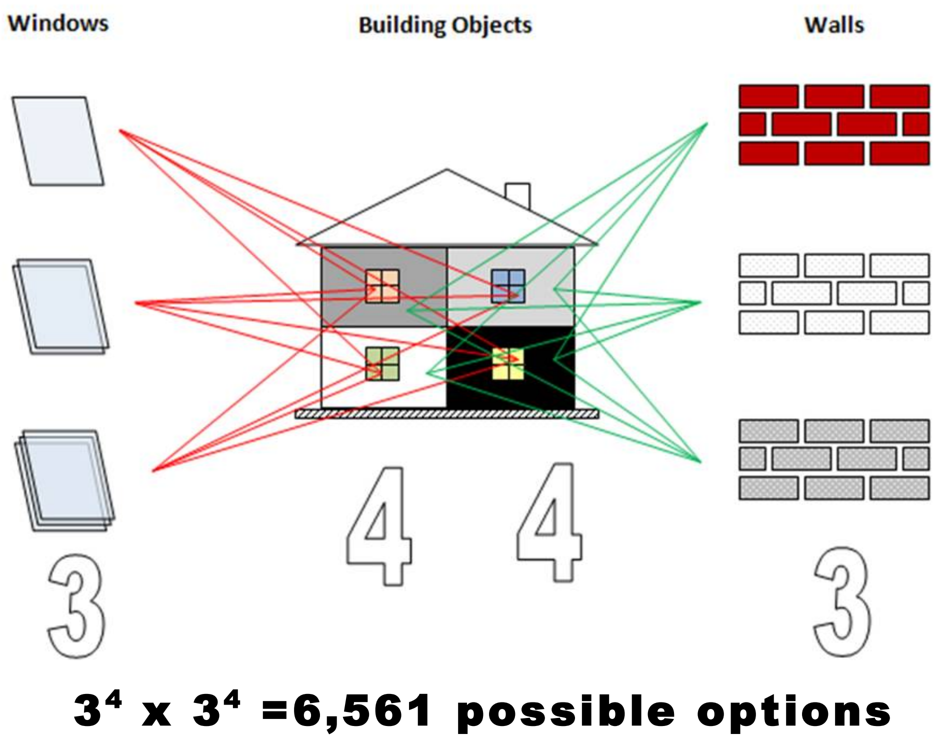

FIG. 2: The combinatorial nature of the optimization problem

By reviewing the literature on integrating energy simulation software with GA, the following software tools were found to be the most common: 1- DAKOTA (Eldred, 2003), 2- OPTIONS (Keane, 2003), and 3- GenOpt (Wetter, 2004).

According to (Wang et al, 2005), DAKOTA is a user interface that can be employed to combine user-developed simulations with a set of optimization methods, which is not the case with EnergyPlus. Additionally, OPTIONS is an optimization package that emphasizes the comprehensiveness of optimization methods to a greater extent than their re-use or customization. GenOpt is a generic optimization tool that can be coupled with energy simulation software. It is easy to customize. However, it is not capable of manipulating IFC objects in the BIM model.

Additionally, there are several commercial software applications such as MATLAB (Matlab, 2004), GEATbx (Pohlheim, 2014), AmOPt (AMOpt, 2004), and iSight (Koch et al, 2005). The primary common disadvantages of such software packages are the following: 1- They focus on optimization and lack the ability to conduct simulation analysis. 2- They do not provide APIs (Application Protocol Interface) sufficient for customization and code reuse at the class level. For further details and a comprehensive comparative analysis of available simulation optimization software, it can be referred to (Nguyen et al, 2014).

This study developed a GA java genetic optimization engine (Nour et al, 2012) in the form of abstract classes that are sub-classed by inheritance to be customized to specific optimization problems. This engine is responsible for manipulating EnergyPlus Input Data Files (IDF) at both the initial population and evolution stages, where each chromosome is represented as an IDF file, as shown in Nassi–Shneiderman diagram in Figure 3.

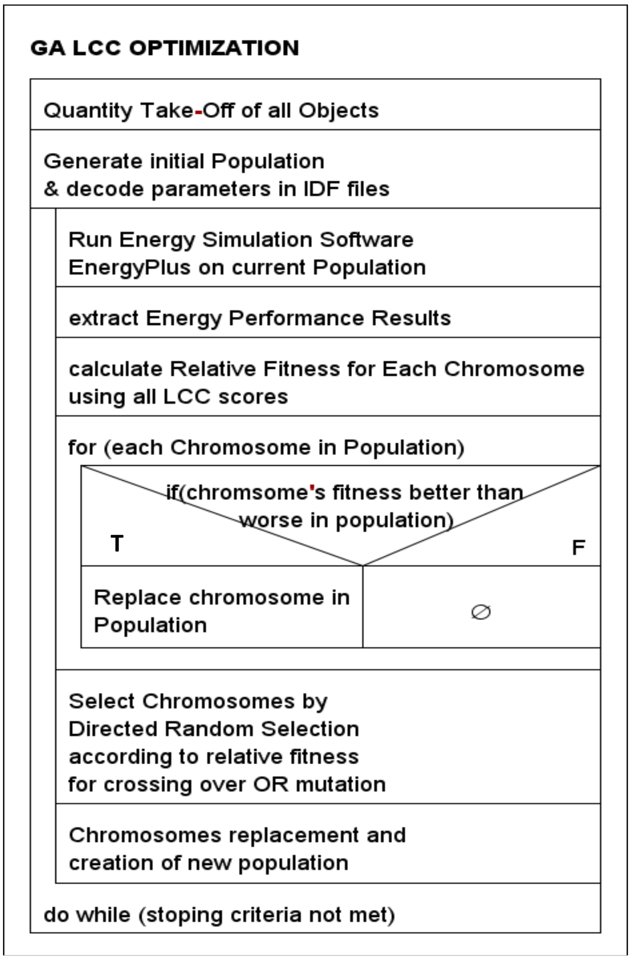

FIG. 3: Nassi-Shneiderman Diagram showing Energy/GA optimization

The process begins with a quantity take-off of all elements constituting the building's outer envelope. This is only performed once, as none of the objects' dimensions are altered during the simulation/optimization process. As a second step, a completely random initial population of chromosomes (building envelope designs) is created. Each chromosome's simulation parameters are decoded in the form of an EnergyPlus IDF file (Nour et al, 2012). Then, a "do while ()" loop begins running EnergyPlus simulation software on each chromosome (IDF file) in the current population. After each energy simulation session, individual chromosomes in the entire current population are evaluated through the aggregation of the entire spectrum of LCC array scores, including the building's average annual energy consumption in monetary units. Furthermore, all monetary figures are aggregated in their NPVs (Equivalent annual Net Present Values). Each chromosome is ranked according to its relative fitness score and the entire population is (further) refined via the LCC minimization objective functions, where better chromosomes (designs) replace worse ones. The "do while" loop continues to run and can be only broken once no significant improvement is achieved over a certain number of iterations, i.e., stopping criteria**.**

3.4 BIM

The BIM technology is object oriented. Objects are very practical for storing single pieces of structured information, such as those required to describe a window or a wall, and all of its characteristics stored in the object's attributes. Objects allow information to be structured in a manner that better represents the real-life perception of "real things" due to its semantic, geometrical and topological significance. Moreover, specialized software tools can be used to simulate, check and assess the overall performance of the combination of objects.

The prior literature on BIM has focused on two main challenges: the first is multidisciplinary BIM collaboration, including data communication between design and analysis models. The second is the aggregation of simulation results to achieve transparency in the design evaluation and decision making processes (Eastman et al, 2008). To address both challenges, it is crucial to have a centralized data model that is accessible to various domain applications (Eastman, 1999). Researchers such as (Van Treeck et al, 2003) have attempted to integrate a BIM model, a thermal multi-zone model and a CFD (Computational Fluid Dynamics) mesh model. In their work, a building model is imported from a CAD tool to an energy simulation domain, where a CFD mesh is automatically generated. This is achieved by mapping the BIM model into a boundary representation using a graph structure to decompose the BIM into a set of required building objects. Other research efforts such as (Augenbroe et al 2003); (Augenbroe, 2004) proposed an interoperability approach based on the "Project Windows" concept. These windows represent subsets of data used by clusters of related domains. An application of this concept is presented in (Augenbroe et al, 2003).

In this study, BIM technology is not only employed to resolve for software interoperability issues, but also (and more importantly) to improve control over the inputs to the GA controlled simulation/optimization process at the object level of granularity. This enables the independent manipulation of each object with respect to or regardless of any design constraints, as demonstrated in the segmentation section below.

3.5 Segmentation

The innovation in this study lies in its attempt to realize a multi-objective LCC optimization, where energy consumption is considered as a single component within the LCC spectrum. This is achieved through the use of BIM, not only to resolve interoperability issues, but more importantly, because BIM is an object-oriented building product model that facilitates the configuration of the outer envelopes of buildings using their individual components considered at the object level. Traditionally, architects - as a common practice - select the same type of window for all of the windows on a given façade, and the same applies for all wall and roof segments. In contrast to this traditional approach, the work presented in this study emphasizes the ability to individually determine the type of each element (object) based on the LCC analysis, simulation and optimization studies to realize a more feasible investment in energy saving elements and devices, i.e., the LCC optimization analysis influences the design rather than merely being an evaluation tool. In this work, objects' dimensions are not considered. The primary focus is on the ability to interchange all objects constituting the entire building's outer envelope using a set of predetermined (allocated) potential object types with the aim of reaching an optimal LCC design configuration.

3.6 An Object-Oriented IFC/BIM genetic optimization framework

It was necessary to develop a Java IFC/BIM based, object-oriented genetic optimization framework (Nour et al, 2012) that is capable of simultaneously interfacing with energy simulation software such as EnergyPlus, IFC/BIM models and LCC databases. This framework consists of five main modules: a- LCC databases, b- the IFC/BIM model, c- the Java Genetic Algorithm simulation Engine, d- EnergyPlus energy simulation software and e- software that interfaces with and integrates all of the above modules. The entire framework and all processes involved are depicted in Figure 4. The first step begins with the creation of a 3D BIM Model using a CAD BIM authoring tool and a quantity take-off for elements constituting the outer envelope of the building. The results are incorporated into the cost model for further calculations. In the second step, an EnergyPlus IDF (Input Data File) is extracted from the BIM model and relevant HVAC data are instantiated. The IDF file is the primary input in both the energy simulation software (EnergyPlus) and the LCC calculation. In the third step of the process, the GA optimization engine performs a complete optimization trial and checks the stopping criteria. In step four, the optimization engine provides new building designs for further improvement. At the fifth step, if there is no further improvement and the stopping criteria are met, the optimization session concludes and the final design is converted back into an IFC/BIM model.

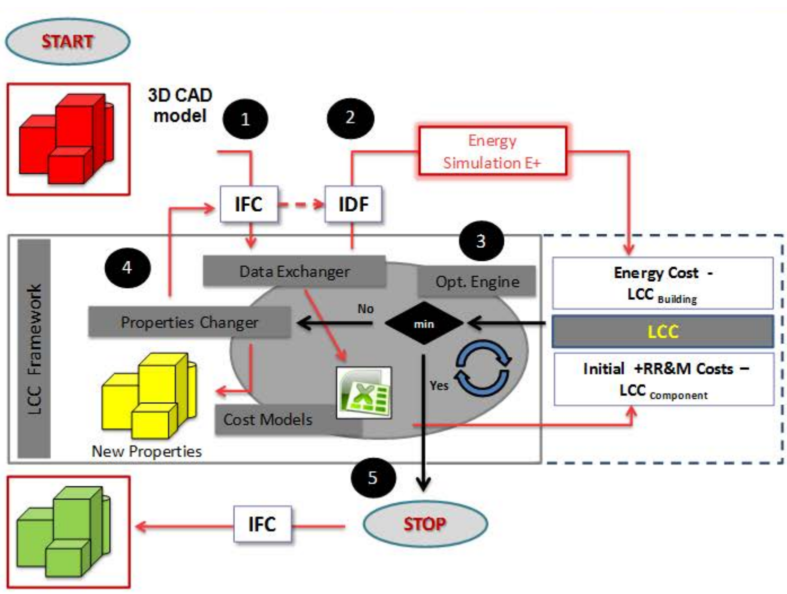

FIG. 4: Framework and Process

The LCC optimization framework is implemented and applied to a prototype building design in Egypt provided in the form of an Architectural IFC/BIM model. The prototype is a two-story building (500 m^2 in area) with several alternatives available for walls, windows and roofing; an overview of the building is depicted in Figure 5. The building consists of 24 windows, 94 wall segments and 19 roof slabs (color coded in Figure 5). The IDF files corresponding to the different IFC/BIM design versions are created using gbXML (gbXML, 2014) transformations. After adding the HVAC data to the IDF file, it becomes a representation of the building's design in a format suited to energy assessment and simulation using EnergyPlus. Cooling and heating is provided through a system of AC split units which are set to 20^o C and 25^o C for heating and cooling, respectively. Before conducting the LCC assessment, the orientation of the building was optimized on a pure energy consumption basis using energy simulation software without the need for GA in a separate pre-processing step, as shown in Figure 5.

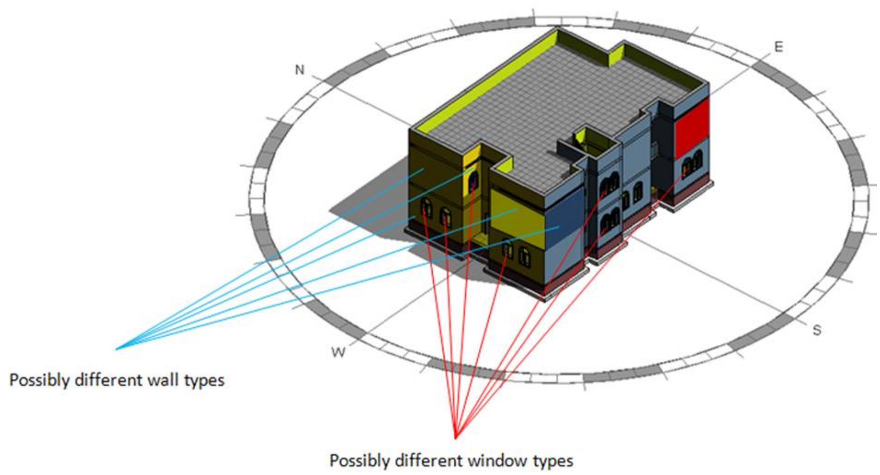

FIG. 5: A perspective of the case study showing the orientation selection and building outer envelope configuration options

4. CASE STUDY RESULTS AND ANALYSIS

The initial cost is calculated using a cost model developed based on the principles discussed above. The lifecycle cost is converted into an equivalent annual value per unit quantity. Once a design represented by an EnergyPlus IDF file is adapted during the optimization process, the energy simulation software becomes responsible for providing the annual energy demand in kWh/year, which can be converted into monetary units and incorporated into building operating costs.

With the unique feature of accumulating all data from previous energy simulation sessions, several analyses were conducted to understand the relationship among energy price, optimum design (envelope configuration) and building lifecycle cost with relevance to current Egyptian subsidization strategies. Three main analyses are provided in this study to demonstrate the effect of changing energy prices in Egypt on design optimality with respect to LCC. Energy simulation runs (building designs) performed during optimization, in addition to the two extreme design cases of (1)- minimum initial cost with maximum energy consumption and (2)- maximum initial cost with minimum energy consumption, are used in the analyses under different subsidization strategies (from 70% subsidization to no subsidization – a total of eight energy price levels).

The eight energy price levels begin with the current energy price of 0.45 EGP (45 piasters), which corresponds to the 70% subsidization strategy currently in place in Egypt, and the remaining energy prices correspond to reduced subsidization levels (i.e., 60%, 50%,…0%). The reduction in subsidization levels is considered because the Egyptian government intends to gradually reduce or eliminate the subsidies in the near future.

The two extreme cases, however, represent the bounds for the analysis from the perspective of both energy savings and initial cost. The first extreme case represents the minimum initial cost case in which no investments are made in energy saving building components, resulting in a minimal impact on energy saving. The second case however, focuses on the use of a number of energy saving components with a higher initial cost. Figure 6 depicts the relationship between the annual value of lifecycle costs on the vertical axis and annual energy costs on the horizontal axis at various energy prices.

The figure is a combined figure for the eight energy price levels. Each sub figure represents the building designs in the last GA population set (the last 200 designs (chromosomes) during the optimization rounds) in addition to the two extreme designs of minimum and maximum energy consumptions, mentioned earlier where it gives the annual equivalent energy cost for the design and its annual equivalent LCC. The optimum design within this last round of optimization (last 200 designs) is also shown and linked to the two extreme designs. The vertical and horizontal axes represent the total lifecycle cost (including energy cost) in annual worth equivalent and the annual energy consumption for the design, respectively. The figure is presented to show the performance of the optimization and how the optimum design moves between the two extreme cases with respect to energy prices which are highlighted as big numbers in each sub figure. The optimum design configuration however is not shown but can be retrieved as the optimum point in each figure represents a chromosome and the values of its genes represent the optimum type of each window, wall and roof segment.

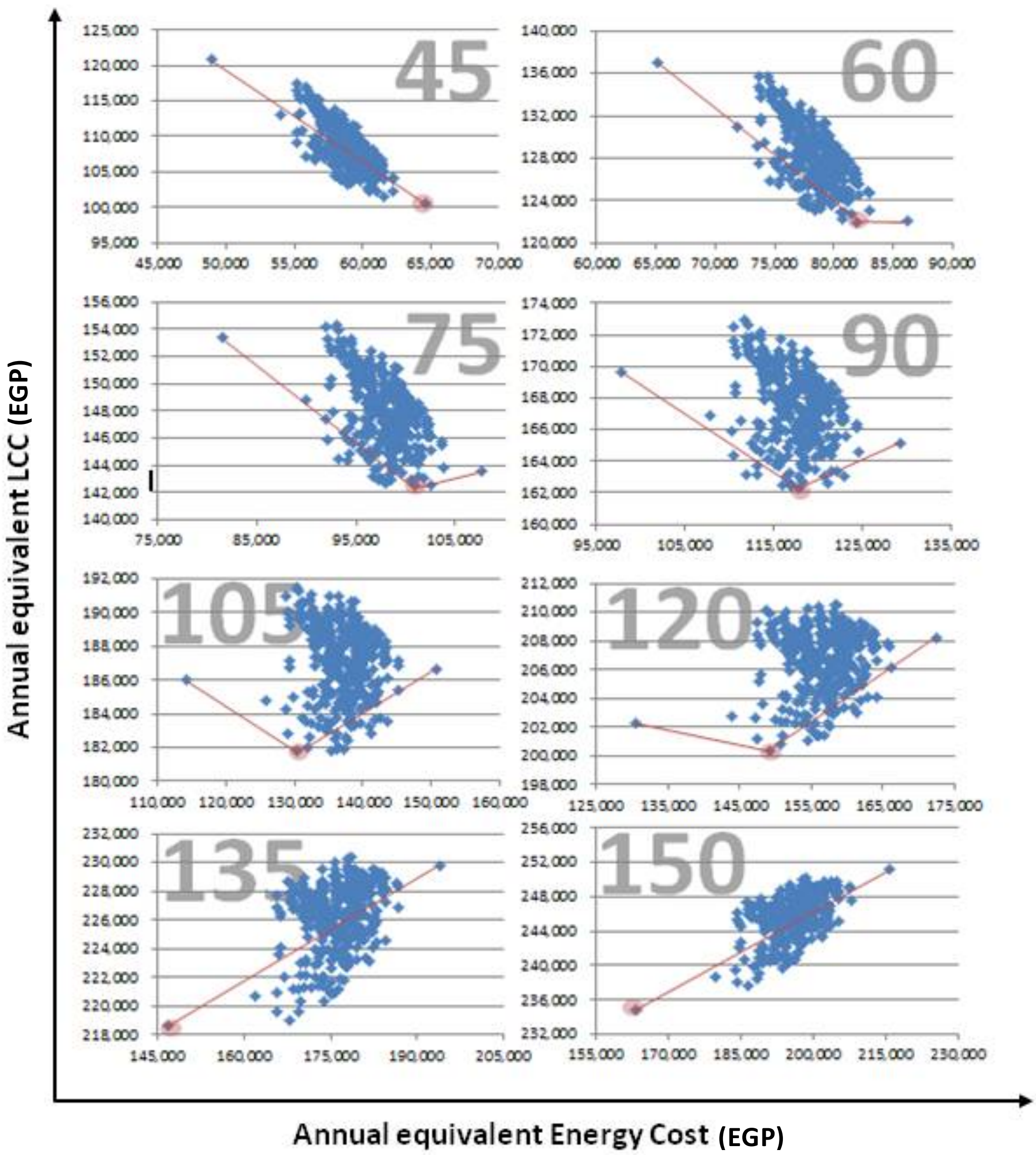

FIG. 6: Optimization Results under different energy prices

The optimum, highlighted design in each chart in Figure 6 corresponds to the minimum lifecycle cost. A broken line is drawn to link the two extreme designs to the optimum point (clearly identifiable in charts with energy prices between 0.6 EGP to 1.20). For energy prices of 0.45, 1.35 and 1.50 EGP, the optimum design coincides with one of the extreme cases. At the current energy price of 0.45 EGP per kWh (70% subsidization level), the optimum design is located at the extreme point and characterized by maximum energy consumption or less initial cost. This implies that it is not worth investing in well-insulated walls, roofs or windows. Beginning at 0.60 EGP per kWh (60% subsidization), it is possible to obtain other design configurations that provide the same lifecycle cost at a lower energy cost. As energy prices increase (subsidies are reduced), the optimum design approaches the other extreme point characterized by the use of better and more expensive energy saving building components. At 1.35 EGP and above, the extreme point of maximum initial cost and minimum energy consumption becomes the optimal LCC design. Figure 7 tracks the optimum design relative to the two extreme points at each energy price.

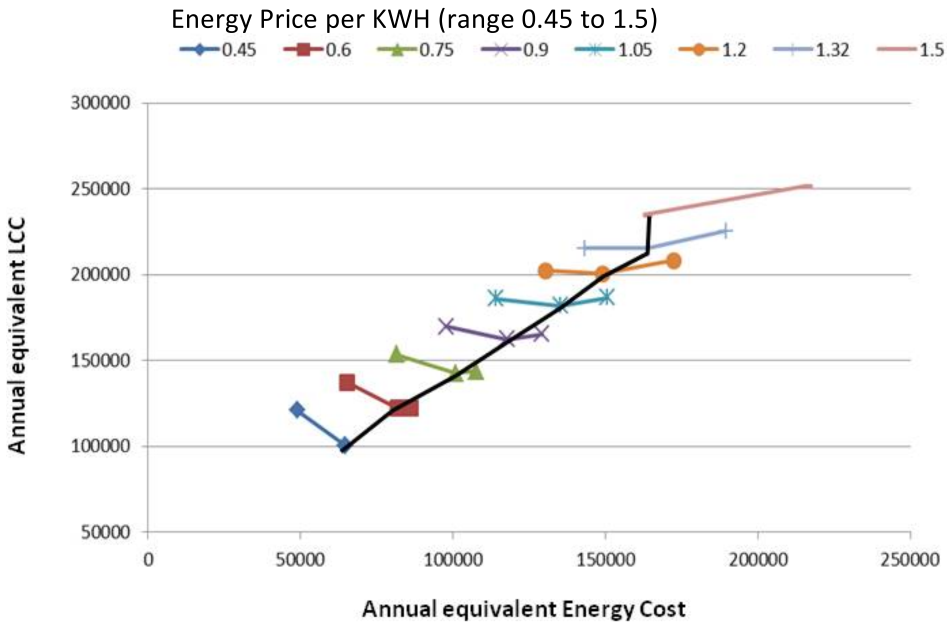

FIG. 7: Optimum LCC Design Contour at various Egyptian Energy prices range from (0.45 to 1.5 LE/KWH)

The optimum contour is also depicted in the figure that links the optimal LCC design points. When energy prices are below 0.6 EGP, the optimum design is that with the lowest initial cost, and when energy prices are above 1.32 EGP, the optimum design is that with the greatest energy saving capacity (corresponding to the maximum initial cost). Lastly, the payback period with respect to energy prices and the subsidization level is depicted in Figure 8. As shown in the figure when the energy price reaches 0.9 LE/KWH then the discounted payback period will be 14 years.

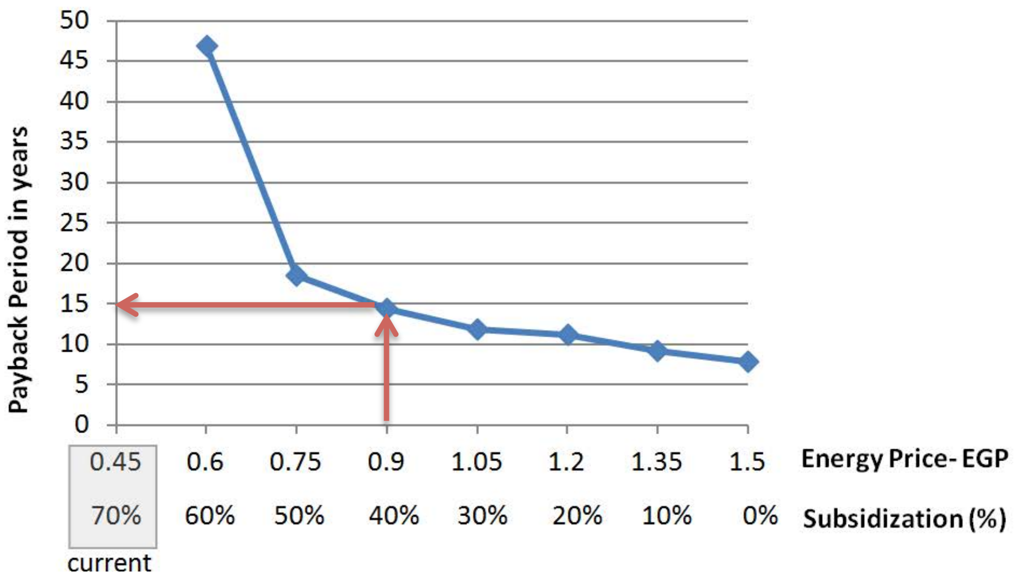

FIG. 8: *Energy Price/Subsidization-Payback Period Tradeoff*

It is evident that as energy subsidies decline, the optimal LCC design can be achieved with reduced payback periods for the additional investments made in energy saving components. The selective, genetic-based optimization approach makes it possible to generate a new configuration of buildings' outer envelopes with an optimum LCC design that goes beyond the decision of whether to make additional investments in energy saving components, i.e., beyond the range of extreme points depicted in Figure 6. This approach provides a new margin for genetic-controlled simulation to achieve reduced LCC. This approach is able to alter the decision making process, which would have previously, resulting in energy saving components not being used due to their excessive cost, by providing a reasonable (optimum) design configuration that remains economically feasible.

5. CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

This study outlined the development of a novel approach to selecting and allocating energy saving systems (elements and materials) and then assigning them certain locations on a building's outer envelope with the objective of optimizing the building's Life Cycle Cost (LCC). The allocation and assignment are based on the fact that a building's elements or segments constituting the outer envelope (skin) are not all subject to identical thermal loads. Therefore, this study introduces an optimization approach based on segmenting a building's external facades and roofs into independent objects (segments) of a Building Information Model (BIM). Genetic Algorithm (GA) analysis is coupled with 1) an IFC (Industry Foundation Classes)/BIM model, 2) an energy simulation tool (EnergyPlus) and 3) a Life Cycle Cost Estimate Model. The aim of the paper is to achieve an optimal configuration of a building's energy saving elements (BIM - Objects) that allows for a positive return on additional investments for their use. This is achieved by eliminating the use of any unnecessary energy saving element that does not generate a demonstrably significant reduction of LCC through the GA controlled simulations. The approach developed in this study was applied to an actual case study of a desert building in Egypt, as a proof of concept, with the aim of optimizing buildings' designs in terms of types of elements (objects) that constitute the building's outer envelope. The paper also investigated other influential factors such as energy prices and policies relevant to energy saving costs using a case study.

This study is based on the optimization of individual BIM objects / segments formulating the outer facades of a building with no restriction on using a single type of windows or wall segments on the same facade. Most of the research efforts up to date try to carry out the optimization using the same type of elements at least on the same façade.

This study confirmed the effect of buildings' energy performance on their overall lifecycle costs and the need for optimization. The strong relationship between energy consumption, as a major component of a building's LCC, and the remaining components determines the feasibility of additional investments in energy saving systems relative to their repayment periods. Thus, a comprehensive LCC optimization study including energy efficient building systems is necessary at the design stage to support decision makers' efforts to achieve optimum building design. This study introduced a GA/BIM based solution model that has the ability to select suitable building components –on the individual object level- from the available alternatives to formulate an entire building design configuration with minimum lifecycle costs.

The paper also confirms the sensitivity of LCC to energy costs, where future forecasts of energy prices are crucial and must be considered in optimization and payback analysis studies to achieve an appropriate decision making process regarding future investments in energy saving building elements.

Both the approach to optimization developed in this study and its application using the software prototype have generated novel opportunities for assessing the tradeoffs between a building's energy performance and the remaining LCC components. This is achieved by avoiding the use of expensive energy saving elements at irrelevant locations on the building's outer skin.

Despite interoperability being considered one of the main advantages of using BIM technology, in this work, the main advantage lies in the BIM/IFC model's object-oriented degree of granularity that facilitates the segmentation of the building's outer envelope into individual segments (objects) that correspond to independent G.A. genes on a chromosome constituting a unique design configuration.

This study has emphasized that using GA to solve optimization problems in a sequential, multi-stage manner reduces the need for processing power and generates better optimization results. This is particularly the case when independent variables are involved. An example is first optimizing a building's orientation with respect to the cardinal directions, and then optimizing the configuration of the elements constituting the outer envelope of the building with respect to LCC.

Further research extending the work presented in this study should address the subject of employing splitting techniques to further sub-divide existing objects (building segments) to finer degrees of granularity that can also be optimized using nontraditional approaches to investigate the effect of the degree of granularity selected to model segments. An example of this would be to redefine the dimensions of wall segments, roof segments and, lastly, windows. A further application would also make it possible to define the window to wall ratio individually for each segment of the building's outer envelope.

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