Life-Cycle Energy/Cost Optimization of Retrofit Combinations for Existing Buildings

By

Sokratis Papadopoulos

A Thesis Presented to the

Masdar Institute of Science and Technology

in Partial Fulfillment of the Requirements for the Degree of

Master of Science

In

Engineering Systems and Management

Life-Cycle Energy/Cost Optimization of Retrofit Combinations for Existing Buildings

By Sokratis Papadopoulos

A Thesis Presented to the Masdar Institute of Science and Technology in Partial Fulfillment of the Requirements for the Degree of

Master of Science in Engineering Systems and Management

May 2015

AUTHOR'S DECLARATION

I understand that copyright in my thesis is transferred to Masdar Institute of Science and Technology.

Author ______________________________

RESEARCH SUPERVISORY COMMITTEE MEMBERS

Dr. Afshin Afshari, Chair, ______________________________
Masdar Institute of Science and Technology

Dr. Peter Armstrong, ______________________________
Masdar Institute of Science and Technology

Dr. Elie Azar, ______________________________
Masdar Institute of Science and Technology

Dr. Sgouris Sgouridis, ______________________________
Masdar Institute of Science and Technology

Abstract

The increasing emphasis placed on sustainable practices, in light of environmental and socio-economic considerations, has highly prioritized the enhancement of energy performance in existing building infrastructure. The building sector contributes a large proportion of the world's total energy consumption and at this stage, building retrofitting is the most common approach implemented for the improvement of energy efficiency in buildings. The present thesis investigates a plethora of potential retrofit actions, while a Life Cycle Analysis (LCA), based on Net Present Value (NPV) optimization, is conducted for four typical Abu Dhabi buildings. In addition, the building retrofit problem is formulated as a multi-objective optimization problem, where conflicting objectives are optimized simultaneously and their trade-offs are assessed. A coupling scheme between MATLAB and EnergyPlus is introduced in order to perform a Genetic Algorithm-based single and multi-objective optimization. The computational intensity of this approach is being addressed with a novel Ensemble Learning-based building representation that can significantly reduce the evaluation time of both the simulation and the objective function(s). The results of the study are reported and they illustrate the effectiveness of ensemble learning models in building simulation-based optimization, with important implications for the field of building efficiency.

This research was supported by the Government of Abu Dhabi to help fulfill the vision of the late President Sheikh Zayed Bin Sultan Al Nahyan for sustainable development and empowerment of the UAE and humankind.

Acknowledgments

I would like to express my gratitude to my research advisor Dr. Afshin Afshari for the exposure to such high-level research. Without his constant guidance the present work would have never been completed. Additionally, I would like to thank my friends, who were always supporting my efforts and encouraging me in every difficulty I faced during the last two years.

Sokratis Papadopoulos,

Masdar City, March 26, 2015.

Contents

List of Tables

List of Figures

CHAPTER 1

Introduction

1.1 Background & Motivation

The building sector is one of the major in terms of energy consumption and CO_2 emissions nowadays. Especially in countries with tropic climates, buildings' energy consumption is intense and continuous due to high temperatures and humidity. According to the International Energy Agency (IEA)[30], buildings hold the responsibility for almost 40% of the total energy consumption in the European Union and 32% in the rest of the world. Additionally, the projections of the U.S. Energy Information Agency (EIA) to the year 2040 indicate significant increase in the energy demand of the building sector, ranging from 15-20% regarding the building type [48].

Back in 2013, climate change experts formed the Intergovernmental Panel on Climate Change, under the supervision of United Nations, aiming to set an upper limit on the greenhouse gases (GHG) allowed to be emitted, so no irreversible changes in the environment could occur. The threshold was set at one trillion metric tons of CO_2 [51], number that is possible to be exceeded in only few decades if no immediate measures are taken towards the decrease of GHG emissions.

It is evident that the building sector should implement Demand Side Management (DSM) measures, as a tool to reduce the amount of GHGs emitted worldwide. Reducing buildings' energy consumption and improving their efficiency is a major challenge of our era and significant effort has been made. Research and development on energy-efficient building technologies includes among others systems such as, building envelope, heating ventilation and air conditioning (HVAC) system, lighting system and equipment. In parallel, on the policy-making side, governments launch frameworks such as building codes and building certification as well as tax incentives in order to promote the adoption of the aforementioned technologies by the market [33], [39].

Upon the design of new buildings, relatively limited interventions and investments can achieve high energy performance. In contrast, retrofitting existing buildings is a more costly process. The decision maker (DM) needs to identify the measures, taking into consideration technical, technological, social, economic and ecologic aspects [29]. However, both in designing new buildings and in retrofitting existing ones, it is crucial that the identified solution is accurate. Selecting and applying the optimal retrofit strategy (based on the DM's objectives) is very important, since there might become necessary to re-retrofit the building in the future at a much higher cost [5].

Deciding on a retrofit plan only based on one objective (energy efficiency, upfront cost, occupants' thermal comfort) can be misleading and yield undesired results. The DM should either aggregate the objectives under a unified objective function, such as the evaluation of the Net Present Value (NPV) of the investment [52], or quantify the tradeoff between contradicting objectives via multi-objective optimization [17], [4].

1.2 Relevance to Masdar Institute, Abu Dhabi and the United Arab Emirates (UAE)

Since the foundation of the country in 1971, UAE has been on ongoing economic growth. The backbone of UAE's economy are the oil exports, accounting for almost 80% of the government's revenues [49]. This growth lured large numbers of foreigners, rapidly increasing the population of the Emirates. Along with the demographic growth, the electricity consumption increased. The total electricity consumption in the UAE in 2010 was estimated at 85.2 billion kilowatt hours (kWh), whereas in 2009 it was significantly lower ($\sim 8.5\%$) [49]. The unconstrained use of energy and the continuous growth of the UAE has ranked the country among the ones with the higher GHGs emissions per capita worldwide [27]. Moreover, the subsidization of electricity price until recently in Abu Dhabi resulted in boosting the extensive energy usage within the Emirate.

The last few years Abu Dhabi is implementing policies towards effective DSM. Starting from January 2015, Abu Dhabi introduced progressive rate charges in water and electricity, following Dubai's Electricity and Water Authority example. Furthermore, regulatory frameworks has been introduced in the construction of new buildings. Building codes like the Estidama Pearl rating system [12] lead to more sustainable construction and operation of buildings.

Despite the efforts of Abu Dhabi government, there is still plenty of room for improvement in the field of building energy efficiency. Smeetsa and Bayar [49] tried to estimate the annual CO_2 emissions of Abu Dhabi with a dynamic econometric model. Their findings are rather disappointing, estimating emissions of 82 Mtons of CO_2 and projecting a growth of 85% within the next 10 years.

Therefore, it is clear that more measures need to be taken by the Emirate of Abu Dhabi and the UAE in general, to minimize the energy consumption in the building sector. By identifying the optimal retrofit plan for typical Abu Dhabi buildings, the opportunity is given to policymakers to establish realistic and effective frameworks towards this path.

1.3 Thesis Research Objectives

As mentioned earlier, there is need for transition towards high performance buildings in order to decrease their environmental footprint. Existing buildings are more sensitive to this aspect, as planning potential interventions in existing structures could be more complex than in building design phase.

The aim of the current research is to propose and evaluate the performance of a novel building retrofit optimization approach that reduces the computation time significantly. The method is applied in four typical case study buildings in Abu Dhabi, namely villa, residential, office and commercial and the optimal retrofit action from a wide range of retrofits is identified. The actions to be consider under the scope of this thesis correspond to interventions in the building envelope and HVAC system. More specifically, the objectives of the present thesis are summarized below:

- Identify the optimal retrofit solution for four typical Abu Dhabi building types in terms of NPV optimization, examining a wide range of retrofit actions. In order to achieve this, representative building models are developed, as well as a coupling scheme between MATLAB and EnergyPlus that enables the automation of the different retrofit scenarios simulation.

- Propose a novel approach in the aforementioned NPV optimization problem, integrating ensemble learning models, which mimic the energy behavior of the studied building, in a genetic algorithm-based optimization framework. Successful implementation of the proposed approach, reduces significantly the simulation time, while maintaining convergence in the real optimal solution.

- Using the novel optimization framework, perform multi-objective optimization between the conflicting objectives of retrofit investment cost and building's annual energy consumption, giving the decision-maker insights related to the trade-offs between competing objectives.

1.4 Thesis Overview

In this section the main framework of the present thesis is discussed [Figure 1.1]. Initially, the building energy performance models are developed using regional weather data and building specifications. Then, different retrofit actions are simulated in an automated way under a coupling scheme between MATLAB and the simulation engine. After simulating all possible scenarios, the NPV of each one of them is calculated and tabulated. The real optimal obtained from the extensive simulation is later on compared with the output of a less complex model described below. Following, a representative sample is obtained, based on which a surrogate model is trained to substitute the original building model in the optimization routine. Such action enables the DM to bypass the simulation evaluation in the chosen objective function, reducing the computation time significantly. Finally, an optimization algorithm evaluates the surrogate model's output to identify the set of retrofits that optimize the NPV of the investment and the non-dominated retrofit solutions based on the trade-off between retrofit's investment cost and annual energy consumption of the building.

1.5 Thesis Organization

The present thesis is organized as follows. Chapter 2, presents the state of the art literature review in existing building retrofit optimization. This chapter discusses the evolution in the retrofit optimization field, from multi-criteria analysis to multi-objective optimization and more recent

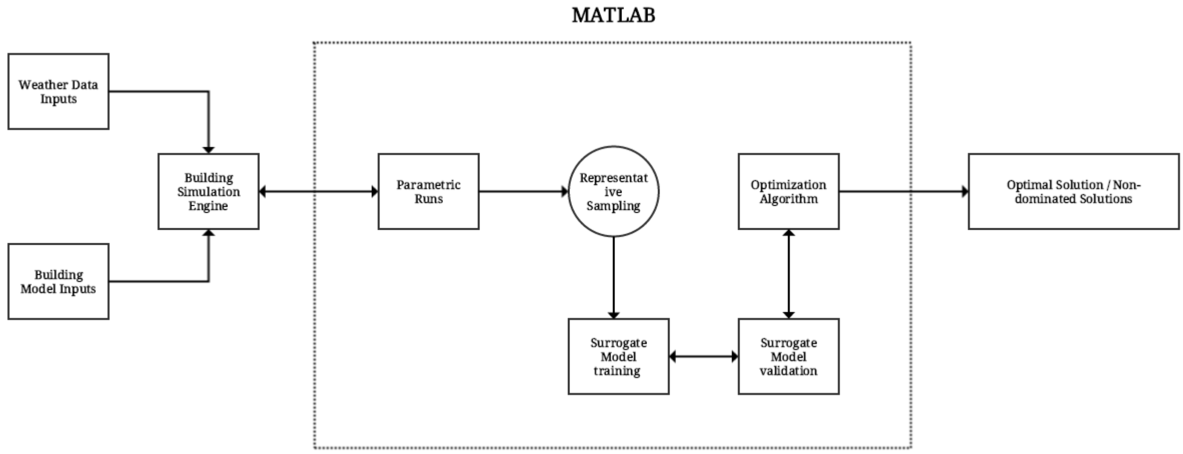

Figure 1.1: Description of the Optimization Approach

modeling techniques, such as surrogate models. Chapter 3 includes the design and schedule specifications for the different business-as-usual buildings, as well as information regarding the various costs incorporated in the study. Chapters 4 and 5, include discussion over the techniques used for this work and describe the components of the developed optimization framework. The main principles behind genetic algorithms (GA) and ensemble learning (EL) are meticulously described. Furthermore, the problem formulation is presented. Chapter 6, discusses the results of both single and multi-objective optimization problem for each building type and the performance of the proposed approach is evaluated. In Chapter 7, a sensitivity analysis is performed on the previously identified optimal solutions and Chapter 8 provides insights regarding additional retrofits that could be included in future studies and continuous space interpolation, based on the findings of this work's. Finally, in Chapter 9, the conclusions of this thesis are summarized and future work topics are proposed.

CHAPTER 2

Literature Review

2.1 Building Performance Simulation

During the past few decades there is an increasing trend in applications of computer simulation in order to model complex engineering systems. In building performance simulation (BPS), dynamic energy simulation tools are often used to analyze the thermal performance of a given building or achieve targets, such as reduction of energy consumption, improvement of indoor thermal comfort or minimization of the building's environmental impact.

Based on the increase in simulation applications, researchers and designers developed different methods to evaluate actions and support decisions regarding building retrofit. There are two main categories in these methods: models in which the potential retrofit solutions are known a priori [21, 28, 19, 46, 1] and models in which the alternative retrofit solutions are part of an optimization problem [5, 4, 16, 3, 24, 42, 6, 2, 54].

In the first approach, the DM carries out an energy analysis and the predefined scenarios are evaluated. It is usual practice for DM to identify criteria under which the retrofits are evaluated. Then, by assigning weights to them they form a single design criterion and solve the problem. Multi-criteria analysis (MCA) was introduced by Gero et al. [21], when they developed a model to assess the trade-offs between building thermal performance, investment cost and useable area during the building design phase. More recently, Kaklauskas et al. [29] proposed a multivariate design approach for the refurbishment of existing buildings and revealed the strongest and weakest retrofit measures. Jaggs and Palmar [28], Flourentzou and Roulet [19] and Rey [46] proposed MCA-based models for the evaluation of retrofitting scenarios, targeting energy efficiency and indoor environment quality. Afshari et al. [1], assessed several retrofit options in a typical office building of Abu Dhabi using novel Marginal Abatement Cost Curves, estimating the CO_2 abatement and life-cycle cost of each intervention.

2.2 Building Retrofit Optimization

Despite the fact that the lines of such research helped addressing several problems in the building retrofit domain, most of them consider a predefined set of solutions. When the number of these solutions is small, there can be no guarantee that solution reached is optimal. On the other hand, when the number of defined solutions is large, the problem becomes difficult to handle. Furthermore, MCA models constraint the DM from information regarding the sensitivity of each parameter with respect to other criteria [5].

The second approach incorporates mathematical programming techniques, based on single-objective (SOO) and multi-objective optimization (MOO). Optimization techniques allow the DM to consider larger sets of retrofit options, implicitly bounded by the constraints and the search space. Optimization methods are iterative processes that produce progressively solutions, until they reach the optimal (or near optimal) included in the search space. Diakaki et al. [16], applied several MOO techniques, trying to improve existing buildings' efficiency, considering a simplified building model. The results of their study urged building efficiency research to focus more on MOO retrofit problems. Asadi et al. [4] proposed a MOO model trying to maximize the energy savings from a retrofit plan, while keeping the investment cost low. Extending their work, they developed an optimization framework coupling three different software. Initially, they simulated a residential building in TRNSYS and optimized three single objectives (energy savings, retrofit cost and thermal comfort) in GenOpt. Finally, they developed a Tchebycheff optimization method in MATLAB to perform MOO [3].

2.3 Building Retrofit Optimization using Genetic Algorithms

Taking into consideration the plethora of variables the DM can consider in a retrofit plan (e.g. envelope interventions, HVAC system, lighting controls, renewable energy installations), as well as the several objective functions that need evaluation (e.g. energy consumption, social factors, life-cycle cost), the decision making problem becomes more complex. The combinatorial blast, along with the increased computation time, make the solving procedure an extremely difficult task. In such cases, heuristic optimization techniques (most commonly GA based) are essential to yield reliable solutions. Hamdy et al. [24] applied a multi-objective GA to identify the trade-offs between cost-effective and low CO_2 emission residential buildings. More recently, Penna et al. [42] investigated the optimal retrofit solution in terms of maximum economic performance, minimum energy consumption and acceptable thermal comfort using a GA. Their study revealed that it is possible to approach nearly net zero energy buildings, maintaining acceptable costs but aggravating indoor thermal comfort. Ascione et al. [6] proposes a new methodology for cost-optimal building energy performance. Specifically, they implement a GA in a MATLAB-EnergyPlus coupling scheme, aiming to determine cost-optimal energy efficiency measures, by means of energy performance and indoor thermal comfort MOO.

Regarding the settings of the GA when applied to simulation-based building optimization problems, recent work from Alajmi and Wright [2] have performed sensitivity analysis in several control parameters of the GA. Their results show that population size as well as crossover probability and mutation rates are important factors in GAs performance. In particular, small populations of about five individuals can help reach the optimal solution faster without significantly affecting the accuracy.

The main disadvantage of the GA is the high burden when there is a need for many evaluation function calls. In building energy modeling applications, the evaluation function includes the external call of a simulation software. These simulations may range from few seconds to hours based on the complexity of the building model and the user's desired accuracy. It is obvious that the computation process can takes days, weeks or even months under such circumstances.

2.4 Building Retrofit Optimization using Surrogate Models and Genetic Algorithms

Trying to address the above mentioned issue, researchers mainly resort to two methods. The first is to use extremely simplified building models. Although this method often reduces the computation time in acceptable levels, eventually might lead in oversimplification risking inaccurate building models [41]. The second commonly used method is to adjust the setting of the GA to achieve faster convergence. Selecting very small number of population sizes and/or generations, though, might affect the convergence of the algorithm in the optimal solution [53, 9].

An interesting field, where not much attention has been paid yet, is to reduce the computation time while maintaining simulation accuracy by the use of surrogate building models. Such meta-models, include Artificial Neural Networks (ANN), Response Surfaces Approximation models and Support Vector Machines [23]. The meta-models are trained based on simulation data and then mimic the behavior of the initial building model in the GA runs. Magnier and Haghighat [35] were the first to apply meta-models in building retrofit optimization. They used a simulation-based trained ANN in combination with GA to optimize energy consumption and indoor thermal comfort in a residential dwelling. The idea behind integrating the ANN in the GA is to benefit from the rapid evaluation of the cost functions provided by the ANN and the optimization strength of the GA. Recently, Asadi et al. [5] proposed a MOO framework, based on the combination of ANN with GA. They identify a wide search space including alternative wall and roof insulation, window types, HVAC systems and solar collectors, targeting to optimize consumption, investment cost and thermal discomfort. Yu et al. [54], used a GA to optimize the accuracy of a back propagation ANN. Then, they simulated a typical Chinese building to feed the ANN and coupled it with a MOO GA to assess the energy consumption-thermal comfort trade-off.

2.5 Research Contribution

The research conducted in this work aims to propose a novel approach in surrogate-heuristic coupled building retrofit optimization, based on ensemble learning algorithms. The identification of new surrogate approaches in the field of BPS is of high importance, as it mitigated problems related to the computation time of the optimization, while maintaining the initial model's accuracy. Furthermore, a transition from discrete to continuous search space will be attempted and the accuracy of the models will be assessed. As far as the objective functions concerned, the optimal life-cycle retrofit plan will be identified through the evaluation of its NPV. Extending the work of Afshari et al. [1], more retrofit actions and their combinatory effect will be assessed for typical Abu Dhabi buildings. Finally, the problem of conflicting objectives in building retrofitting will be tackled by solving a MOO problem. The building's energy consumption and the investment cost will be simultaneously optimized by the use of a multi-objective GA.

CHAPTER 3

Modeling the Business-As-Usual Buildings

The first step of the present thesis is the definition of the Business-As-Usual (BAU) models for the four different building types of the Abu Dhabi Emirate. It is worth mentioning that each building type represents an *average* building of this type in Abu Dhabi. It is obvious that individual buildings of each type may vary in specifications. The BAU models for each building type can be further disaggregated regarding their energy efficiency or age, but such modeling is beyond the scope of this thesis.

The data required to model the BAU buildings were obtained from a combination of two reports from different entities. The first is the PDS Energy and Water Benchmarking Study, a report prepared by ARUP at the request of UPC. The aim of the report was to develop the Estidama sustainability rating system for the building sector of Abu Dhabi. ARUP undertook several site inspections and also used databases obtained from UPC and the Abu Dhabi Distribution Company. The second report is the Abu Dhabi Municipality Demand Side Energy Efficiency Program for Sector E3 and was prepared as a collaborative project between Schneider Electric, Masdar and Abu Dhabi Municipality, targeting among others to acquire knowledge regarding buildings' operation and energy use, as well as to propose efficient energy conservation measures.

At this point, it is important to mention that both documents are not publicly available. Based on the reports mentioned above, the BAU models were developed for each building type and their specifications are presented in the following sections.

3.1 Design Specifications

The geometry characteristics for each building contain information regarding the orientation from North, length (m), width (m), total Gross Floor Area (GFA) (m^2) and Window to Wall Ratio (WWR) (%). The thermal performance of each building's envelope was expressed in terms of wall and roof u-values (W/m^2-K). U-value is a measure of heat loss in a building element. Low u-values indicate high thermal performance and high levels of insulation. Information regarding the absorptivity (%) of buildings' roof were also obtained. Similarly to walls and roof, the windows' u-value is modelled. Additionally, windows' thermal performance is also impacted by another parameter, the solar heat gain coefficient (SHGC). SHGC is defined as the fraction of incident solar radiation that actually enters a building through windows as heat gain. As far as the HVAC system is concerned, as no thermal loads are assumed is such climate zones, information regarding the efficiency of the cooling system are gathered. Regarding the air-tightness of the buildings, the infiltration rate in air changes per hour (ACH) is obtained for each building type. The specifications of the BAU for all four building types are summarized in Table 3.1.

	Villa	*Residential*	*Office*	*Commercial*
Orientation from North	50	50	50	50
Length(m) x Width (m)	10x15	25x25	40x40	100x195
Total GFA (m^2)	300	22500	24000	78000
Number of Floors	2	15	15	4 (3+basement)
Floor Height (m)	3.5	3.5	3.5	3.5
WWR (%)	25	50	70	12.5 & 5*
Roof u-value (W/m^2-K)	1.29	1.29	1.29	1.29
Wall u-value (W/m^2-K)	2.25	2.25	2.25	2.25
Window u-value (W/m^2-K)	3.88	3.88	3.88	3.88
SHGC	0.63	0.63	0.63	0.63
Roof Absorptivity	0.8	0.8	0.8	0.8
Air Infiltration (ACH)	0.75	0.75	0.5	0.5
Chiller COP	2	2.5	2.5	2.5
People Density ($m^2/person$)	50	25	10	10
Thermostat Setpoint	22	22	22	22
Lighting Intensity (W/m^2)	12	12	10	25
*Ratio of skylight to roof				

Table 3.1: Design specifications of all BAU buildings

3.2 Schedules Specifications

Based on the two aforementioned reports realistic schedules regarding occupancy, lighting and equipment were designed. In terms of the HVAC system, constant operation is assumed when the room temperature is below the defined thermostat set point. Tables 3.2 , 3.3 and 3.4 illustrate the schedules applied in the present work expressed in fractions, where 1 represents fully occupied building and 0 no occupancy of the building.

Office		
Occupancy		
Weekdays	24:00-07:00	0.3
	07:00-19:00	1
	19:00-24:00	0.3
Weekend/Holiday	Always	0.3
Lighting		
Weekdays	24:00-07:00	0.15
	07:00-19:00	1
	19:00-24:00	0.15
Weekends/Holidays	Always	0.15
Equipment		
Weekdays	24:00-07:00	0.3
	07:00-19:00	1
	19:00-24:00	0.3
Weekends/Holidays	Always	0.3

Table 3.2: Office Schedules

Commercial		
Occupancy		
All Days	24:00-07:00	0
	07:00-08:00	0.4
	08:00-22:00	0.8
	22:00-23:00	0.4
	23:00-24:00	0
Lighting		
All Days	24:00-08:00	0.3
	08:00-22:00	1
	22:00-24:00	0.3
Equipment		
All Days	24:00-08:00	0.3
	08:00-22:00	1
	22:00-24:00	0.3

Table 3.3: Commercial Schedules

Villa/Residential		
Occupancy		
Weekdays	24:00-07:00	0.9
	07:00-09:00	0.5
	09:00-17:00	0.3
	17:00-18:00	0.5
	18:00-24:00	0.9
Weekend/Holiday	24:00-08:00	0.9
	08:00-18:00	0.5
	18:00-24:00	0.9
Lighting		
All Days	24:00-06:00	0.
	06:00-07:00	0.2
	07:00-09:00	0.5
	09:00-19:00	0
	19:00-22:00	0.9
	22:00-23:00	0.7
	23:00-24:00	0.3
Equipment		
All Days	24:00-06:00	0.
	06:00-07:00	0.2
	07:00-09:00	0.5
	09:00-19:00	0
	19:00-22:00	0.9
	22:00-23:00	0.7
	23:00-24:00	0.3
	19:00-24:00	0.3

Table 3.4: Villa/Residential Schedules

3.3 Retrofit Cost

In this section the information regarding the investment cost of each retrofit action and the revised electricity tariff for each building type is discussed. The values of the aforementioned costs are the core of the NPV optimization. The majority of capital costs related to each intervention were calculated based on data obtained from the National Renewable Energy Laboratory (NREL) [32]. To obtain costs related to cool roof and window overhang retrofits, we resorted to the studies of Levinson et al. [34] and Nielsen [40] respectively.

For the LCA a 25 year NPV optimization framework is proposed. It is important to additionally consider the lifetime of each retrofit in the analysis and the replacement cost, as the study period might exceed the lifetime of some retrofits. After identifying a set of scenarios for each different retrofit, an attempt will be made to transit in the continuous space by applying curve fitting in the data.

For the sake of coherence, all units were converted to the International System of Units and all costs were converted to Arab Emirates Dirham (AED), using exchange rate of 3.67 $AED/\$$.

3.3.1 Chiller

In the case of chiller retrofitting there is a fixed cost related to the equipment replacement and a normalized cost defined by the chiller's capacity, expressed in $^{AED}/_{kW}$. The normalized cost varies based on the chiller's Coefficient of Performance (COP). The lifetime of the chiller is 19 years and in this case a replacement cost need to be considered in the analysis, discounted in the 19th year of the cash flow. In table 3.5 three different chiller retrofit scenarios and their respective costs are presented.

COP	*Fixed Cost (AED)*	*Normalized Cost* ($^{AED}/_{kW}$)
3	3156	618
4	3156	1057
5	3156	1505

Table 3.5: Chiller Costs

3.3.2 Air Leakage

The cost of reducing the air infiltration in a building depends on the total floor area. As the baseline infiltration rate differs among different building types, the cost of retrofitting for every building type varies. As discussed previously, Villa and Residential buildings have infiltration rate of 0.75 ACH, whereas for Office and Retail buildings the baseline rate drops to 0.5 ACH. In Tables 3.6 and 3.7, the capital cost of limiting air leakage per floor square meter is depicted.

Air Tightness	*Cost (AED/m^2)*
0.45 ACH	55.4
0.15 ACH	102.8

Table 3.6: Villa and Residential Air Tightness Costs

Air Tightness	*Cost (AED/m^2)*
0.3 ACH	37.2
0.1 ACH	79.1

Table 3.7: Office and Retail Air Tightness Costs

3.3.3 Wall Insulation

The addition of insulation in existing walls is priced in AED/m^2 of opaque wall. Depending on the thickness or the type of the insulation material the capital cost may vary significantly. For this work, Extruded Polystyrene (XPS) foam is studied as a wall insulation material. XPS is a rigid insulation formed by polystyrene polymer, manufactured following an extrusion process. The study identifies three potential thickness values from the NREL database and their respective cost is presented in Table 3.8.

Wall Insulation	*Thickness*	*Cost (AED/m^2)*
R-5 XPS	1in	51.4
R-10 XPS	2in	67.2
R-15 XPS	3in	87

Table 3.8: Wall Insulation Costs

3.3.4 Roof Insulation

Similarly to wall insulation, in this study XPS is applied as potential retrofit action for the improvement of buildings' roof insulation, with the addition of a fiberglass component. The costs related to roof insulation measures can be found in Table 3.9.

Roof Insulation	*Thickness*	*Cost* (AED/m^2)
R-38 Fiberglass, R-15 XPS	3in	142
R-38 Fiberglass, R-20 XPS	4in	161.8
R-38 Fiberglass, R-25 XPS	5in	181.7

Table 3.9: Roof Insulation Costs

3.3.5 Glazing

Three different window types are tested as replacement to the existing ones. A representative sample has been chosen from the commercially available options, ranging from double-pane to triple-pane, low-e high performance windows (Table 3.10).

Glazing	*U-value* (W/m^2-K)	*SHGC*	*Cost* (AED/m^2)
Double-pane, Clear, Non-metal frame, Air fill	2.8	0.56	355
Double-pane, Low-e, Non-metal frame, Air fill	2.1	0.3	366
Triple-pane, Low-e, Insulated frame, Air fill	1.1	0.27	840

Table 3.10: Window Replacement Costs

3.3.6 Window Overhangs

Window overhangs can act as a mean to reduce the solar heat gain, especially in regions with high temperatures like the UAE. There was no direct database to obtain the values regarding overhang costs, so values used in Nielsen's PhD thesis [40] were implemented to estimate the value of installing overhangs above an existing building's windows. The installation cost for aluminum overhangs is assumed 1100 AED/m^2. For the purpose of this study three different lengths of overhang were considered, accounting for roughly for 25, 50 and 100% of the window height.

3.3.7 Cool Roof

Applying a layer of light-color paint in the roof is common practice among designers to reduce roof's absorptivity, especially in low-rise buildings (such as villas). The corresponding costs to reduce the roof's absorptivity to 0.6 and 0.4 are 23.7 AED/m^2 and 31.6 AED/m^2 of roof respectively [34].

3.4 Electricity Cost

The electricity unit cost is extremely important in order to evaluate any potential retrofit plan. The return of investment most commonly comes from the energy savings through the life-cycle of the project multiplied by the electricity unit price. The new increased electricity tariffs for the Emirate of Abu Dhabi, retrieved from Regulatory and Supervision Bureau [45] and effective from January 1st 2015, are as follows:

- For villas, up to 200 $^{kWh}/_{day}$ the pricing is 0.21 $^{AED}/_{kWh}$. Above 200 $^{kWh}/_{day}$ the rate increases to 0.318 $^{AED}/_{kWh}$.

- For residential buildings, the HVAC system consumption follows the fixed commercial electricity rate in 0.16 $^{AED}/_{kWh}$, whereas the tariff for individual apartment lighting and equipment loads is set to 0.21 $^{AED}/_{kWh}$ up to 20 $^{kWh}/_{day}$ and 0.318 $^{AED}/_{kWh}$ when the load exceeds the threshold.

- For commercial and buildings, the electricity tariff is fixed to 0.16 $^{AED}/_{kWh}$.

- For office buildings, as the building can be posed under both governmental (0.293 $^{AED}/_{kWh}$) and commercial (0.16 $^{AED}/_{kWh}$) electricity tariff based on the ownership, both cases will be studied.

CHAPTER 4

Genetic Algorithms

GAs have been extensively used in cases of building retrofit optimization, as discussed in Chapter 2. The ability of the GA to efficiently handle non-linear problems with multiple local-minima and frequent discontinuities gives a fundamental advantage in problems where the objective function(s) is evaluated through an external simulation software. Introduced by Holland [26] in 1975, GA mimics the natural biological evolution of living organisms. As such, GAs exploit the search space in an intelligent manner to solve optimization problems. Following the principles of Charles Darwin's "survival of the fittest" theory, each generation of the algorithm produces fittest individuals, dominating over the weaker ones and eventually reaching the individual that represents the optimal solution.

The following sections aim to introduce the reader to the major components governing the GA execution. These include the representation of individuals (potential solutions) within the population, the fitness function evaluation and the genetic operators that are used for the implementation of the algorithm.

4.1 Chromosome representation

In GA, the individuals of the population are encoded as strings (chromosomes), analogous to the structure encountered in organisms' DNA, corresponding to a unique position in the search space and a candidate solution. Depending on the nature of the problem, the representation of a chromosome can include real, integer or binary values for every single variable (gene).

Structuring the initial population is another important aspect of the GA. The set of individuals should belong in the feasible region of the problem, otherwise computationally expensive repair techniques must be applied [11]. In the building retrofit optimization problem this is not a concern, as there are no complex constraint equalities or inequalities. The feasible range for each variable is defined by its upper and lower bound in the search space.

Regarding the generation of initial population, it is common approach to follow an almost random process, in order to enhance the diversity among the individuals and cover wider range of the solution space [44].

4.2 Fitness Scaling

Different approaches have been developed to assess the fitness scores of each individual. The raw fitness score is usually converted in a form suitable for evaluation from the selection function.

Several scaling options are available in MATLAB. Proportional scaling creates a scaled value of an individual's fitness score proportional to its raw fitness score. Top scaling equally scales the top individuals, completely diversifying them from the weaker ones. Shift linear scaling scales the raw scores in a way that the expectation of the fittest individual equals to the average fitness score of the population multiplied by a constant number.

The range of the scaled values has an important role in the performance of a GA. If the range is wide, the high-ranked individuals reproduce very fast preventing the GA from exploring a large area of the search space. On the other hand, when the variation between scaled values is small almost all individuals have the same chance to reproduce and the search for the optimal solution is decelerated.

For the purpose of the current research, rank scaling was applied. Rank scaling scales the raw fitness scores not based on the score itself but based on the rank of the individual. An individual with rank n corresponds to scale score of $1/\sqrt{n}$. The square root in the denominator makes low-ranked individuals nearly equal to qualify for reproduction. Rank scaling is the most suitable approach in order to remove effect of the spread of the raw scores [37]. The following example is an illustration of the aforementioned statements, retrieved from Mathworks website [36].

In Figures 4.1 and 4.2 the results of a GA using rank and top scaling are shown. As default settings, top scaling has assigned 40 percent of the fittest solutions to the same value and for the rest of the individuals the value is set to zero.

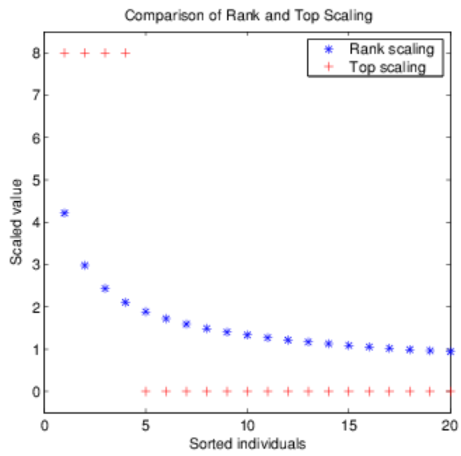

Figure 4.1: Comparison of Rank and Top Scaling

As top scaling limits the parenting population only to the fittest individuals, the variance of the populations is lower than in rank scaling.

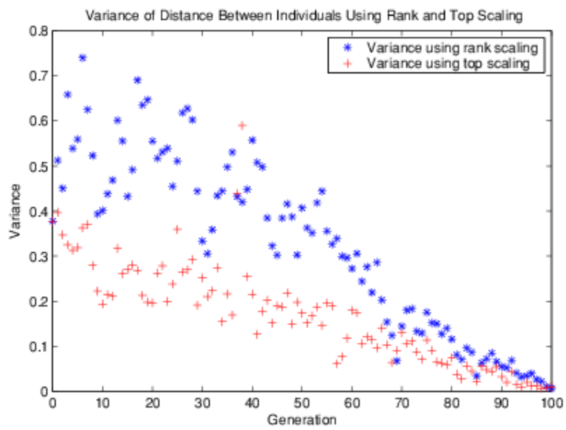

Figure 4.2: Variance of Distance Between Individuals using Rank and Top Scaling

4.3 Genetic Operators

4.3.1 Selection

During the selection process, the number of times each individual progresses for reproduction is determined. Parent selection strategy often regulates the bias in the reproduction process.

There are both stochastic and deterministic selection options that can be applied in GAs.

Roulette wheel selection assigns space from the wheel to the fittest individuals proportionally to their scale values. Then random ”spins” choose the individuals that will produce the next generation. Tournament selection randomly clusters individuals in size-specified tournaments. The winning individuals of each tournament are set to be parents.

The selection routine chosen for this study is stochastic uniform sampling. During stochastic uniform sampling all candidate parents lay out a line where the length of each individual is proportional to its scaled value. The algorithm progresses across the line in equal-size steps and depending on the area it steps, the algorithm allocates a parent [37].

4.3.2 Crossover & Mutation

In natural genetics, crossover and mutation are major components of the evolution theory. Crossover occurs when the new chromosome has attributes from both parents. Several crossover techniques can be applied in GAs.

Single point crossover chooses a random integer between 1 and the number of genes comprising the chromosome and then selects the number of entries before this point as the first parent's attributes and the number of entries after the point as the second parent's attributes that will be transferred to the child. Concatenation of these entries form the child vector.

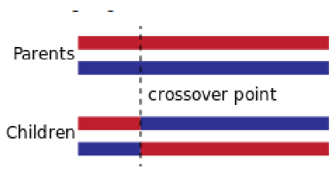

Figure 4.3: Single-point Crossover

Two point crossover, similarly to single point crossover, selects two random integers m, n between 1 and the number of genes in the chromosome. Entries numbered less or equal to m are selected from the first parent, entries from $m+1$ to n from the second parent and entries greater than n from the first parent. The entries are concatenated to form the next generation's child.

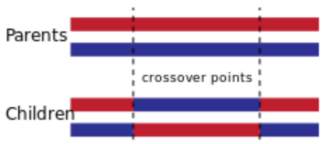

Figure 4.4: Two-point Crossover

Scattered crossover is a stochastic approach were initially a random binary vector of equal length to the chromosome is created [38]. Then the values of the vector that equal to 1 correspond to the genes that will progress from the first parent and the values that equal to zero will progress from the second parent. For the present work scattered crossover has been applied.

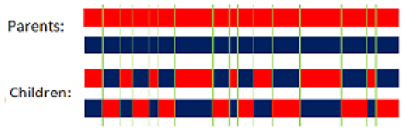

Figure 4.5: Scattered Crossover

Mutation refers to a random process where a gene is replaced by another so that the genetic structure is modified. Mutation in GAs is implemented with low probability, similar to natural evolution, ranging from 0.001 to 0.01 [11]. The role of mutation in GAs is to restore any genetic material that may have been misplaced during the phases of selection and crossover. The mutation probability used in this research is set to 0.01 in order to improve the exploration of the search space. If the entry of the parent vector is chosen for mutation, its corresponding replacement value is chosen from a Gaussian distribution with μ equal to the current value of the entry.

In every generation the individuals with the best fitness values automatically progress to the next generation without crossover or mutation. The default MATLAB value of $EliteCount = 2$ is used for this study.

4.4 Genetic Algorithm applied to Building Retrofit Optimization problem

Relating the general GA properties to the retrofit optimization problem, one can represent a chromosome by assigning each one of the decision variables to a gene:

x_{COP}	x_{INF}	x_{WALL}	x_{ROOF}	x_{WIN}	x_{OVER}	x_{COOL}
4	2	3	1	2	2	3

Table 4.1: Chromosome of a Retrofit Plan

Assuming the initial population is comprised of 5 individuals, the parent selection will be based on the individuals fitness scores.

In Table 4.2, Individual 3 has the higher objective value, which corresponds to the highest fitness value. Therefore, Individual 3 is ranked first and based on the scaling holds the larger

								Objective Function Value	*Rank*	*Rank Scaling*
Individual 1	5	2	2	4	2	4	2	9.1	4	0.50
Individual 2	3	1	3	1	4	1	1	8.4	5	0.45
Individual 3	2	1	1	2	2	3	3	11.2	1	1.00
Individual 4	4	3	4	1	1	3	3	10	2	0.71
Individual 5	5	2	4	4	1	1	3	9.5	3	0.58

Table 4.2: Parent Selection

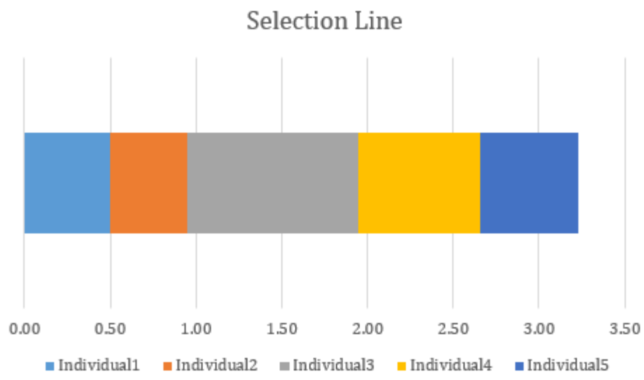

Figure 4.6: Selection Line

part in the selection line. The values used in the aforementioned example are fictitious and are used for the reader to better understand the GA's selection process.

Based on Figure 4.6, the fittest individuals will compose the majority on next generation's population. After crossover and mutation of the current population, a new population will be generated and the same procedure will be followed until the GA meets a stopping criterion.

4.5 Genetic Algorithm pseudo code

Algorithm 1 summarizes the steps discussed in Chapter 4. After the initial population is defined, the fitness of each chromosome is evaluated. Then, the fittest individuals are being selected from the existing population and recombined via crossover/mutation to form the new generation. The fitness of the chromosomes comprising the new population is evaluated. Finally, this procedure is followed recursively until one of the GAs stopping criteria is met.

4.6 Multi-objective GA

A major benefit that makes GAs popular for building retrofit optimization is its ability to handle MOO problems. As most of the objectives needed to be optimized in a building retrofit study are conflicting (investment VS energy savings, energy savings VS thermal comfort etc.), MOO

Algorithm 1 GA pseudo code

initialize population P_t
evaluate fitness of P_t
while not stopping criterion is met **do**
  $t \leftarrow t+1$
  select P_t from P_{t-1}
  recombine P_t by crossover and mutation
  evaluate P_t
end while

GAs are able to handle more than one objective functions in a very efficient way.

There are two general approaches in engineering MOO problems. The first is to combine each objective function into a single objective function with specific weight in each objective. Methods like weighted sum method, goal attain or compromise programming have been developed, but the main problem lies in the correct assignment of weights to express the DM's preferences. Minor changes in the weights can alter the solutions significantly, and this is the reason why DMs often prefer a set of non-dominated instead of a single solution [31].

The second approach is to identify a set of non-dominated solutions (Pareto optimal solutions). A solution is called Pareto optimal if it is not dominated by any other solution in the search space. A Pareto optimal solution cannot be improved without impairing at least one of the other problem objectives [13]. Identifying the Pareto optimal solutions in a MOO problem by means of evolutionary programming is the approach where recent research focuses [54, 35, 5] and the one applied in this thesis work.

The first ever MOO GA, namely Vector Evaluated Genetic Algorithm (VEGA), was proposed by Scaffer in 1985 [47]. Several multi-objective evolutionary algorithms were proposed in the following years such as Multi-Objective Genetic Algorithm (MOGA) [20], Strength Pareto Evolutionary Algorithm (SPEA) [56], Non-Dominated Sorting Genetic Algorithm (NSGA) [50] and Fast Non-Dominated Sorting Genetic Algorithm (NSGA II) [14].

NSGA-II is the MOO algorithm used for the present work. NSGA-II is an improved version of NSGA, proposed by Deb et al. [14]. NSGA is a popular non-domination based algorithm, but its complexity as well as its lack of elitism have been criticized. Its modified version (NSGA-II) uses a better sorting algorithm incorporating sorting. A controlled elitist variant of NSGA-II is the one implemented in MATLABs Global Optimization Toolbox to solve MOO problems [37].

4.6.1 Description of NSGA-II

In the beginning, a random initial population P_o is created and the population is sorted based on non-domination. The rank of each solution occurs through its nondomination level. Then, another population Q_o is created through tournament selection, crossover and mutation form the initial one. After this initial generation, the two abovementioned populations are aggregated to form a combined population $R_t = P_t \cup Q_t$. Population R_t is then sorted based on nondomination and ensures elitism since both members of the previous and the current population are included. Now that all non-dominated solution sets F_i have been identified and ranked, the high ranked solution sets progress to the next generation. In the last solution front to progress in the next generation, the solutions are sorted using a crowd-comparison operator in order to fill all the remaining slots of population P_{t+1}. The new population P_{t+1} now uses selection, crossover and mutation to produce the population Q_{t+1} and the iterative process continues. The crowd distance sorting enhances the diversity of NSGA-II among non-dominated solutions [14]. Figure 4.7 illustrates the previously described NSGA-II steps.

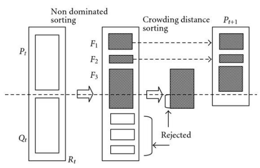

Figure 4.7: NSGA-II Procedure

4.6.2 Implementation of NSGA-II Integer Variables

The current MATLAB Global Optimization Toolbox has a limitation in handling integer variables. Although the majority of decision variables could be represented as continuous functions, the variable related to window type can only be represented as integer due to the fact that different properties define each window (u-value and SHGC).

To perform mixed-integer MOO in MATLAB, customized creation, crossover and mutation functions were used. By these means it was ensured that every generation's children included only integer values for the selected variables.

4.7 Building Retrofit Optimization problem formulation

The problem formulation for the present study is presented below.

$$\underset{X}{\text{maximize}} \qquad \text{NPV}(X) = \sum_{t=0}^{T} \frac{ES(X)_t}{(1+DR)^t} - InvestmentCost(X)$$

where

$$Cost_1 = \sum_{i=1}^{4} x_{chiller,i} * cost_{chiller,i}$$

$$Cost_2 = \sum_{j=1}^{3} x_{airtigh,j} * cost_{airtigh,j} * GFA$$

$$Cost_3 = \sum_{k=1}^{4} x_{wall,k} * cost_{wall,k} * A_{wall}$$

$$Cost4 = \sum_{l=1}^{4} x_{roof,l} * cost_{roof,l} * A_{roof}$$

$$Cost_5 = \sum_{m=1}^{4} x_{win,m} * cost_{win,m} * A_{win}$$

$$Cost_6 = \sum_{n=1}^{4} x_{over,n} * cost_{over,n} * TotalWindowLength$$

$$Cost_7 = \sum_{p=1}^{3} x_{coolroof,p} * cost_{coolroof,p} * A_{roof}$$

$$InvestmentCost = \sum_{y=1}^{7} Cost_y$$

subject to

$$\sum_{i=1}^{4} x_{chiller,i} = 1$$

$$\sum_{j=1}^{3} x_{airtigh,j} = 1$$

$$\sum_{k=1}^{4} x_{wall,k} = 1$$

$$\sum_{l=1}^{4} x_{roof,l} = 1$$

$$\sum_{m=1}^{4} x_{win,m} = 1$$

$$\sum_{n=1}^{4} x_{over,n} = 1$$

$$\sum_{p=1}^{3} x_{coolroof,p} = 1$$

$$X = \{x_{chiller}, x_{airtigh}, x_{wall}, x_{roof}, x_{win}, x_{over}, x_{coolroof}\}$$

$$i,k,l,m,n \in I\{1,...,4\}$$

$$j,p \in I\{1,...,3\}$$

where ES(X) stands for the energy savings occurred from the retrofit set X, DR is the discount rate considered for the study and T represents the length of the study period.

When the problem is targeting a single objective, the objective function is formulated under the NPV of the investment. For MOO, the objective functions are formulated as follows and the problem is solved under the same constraints.

$$\begin{aligned} \underset{X}{\text{minimize}} \quad & \text{EnergyConsumption}(X) \\ \underset{X}{\text{minimize}} \quad & \text{InvestmentCost}(X) \end{aligned}$$

CHAPTER 5

Ensemble Learning

5.1 Application in Building Retrofit Optimization

Recent trends in building retrofit optimization show that research tends to incorporate surrogate building models in the optimization process [35, 5, 54]. By using such models, the evaluation of the objective function(s) is not based on time-consuming simulations but in a rapid run of the surrogate model.

Existing literature focuses mainly to the training of ANN to substitute the building simulation models. Yet, there is a variety of different machine learning techniques that have not been examined in building retrofit optimization problems. For the purposes of this study, a novel Bagging Regression Trees (BRT) approach is proposed and its performance is evaluated.

5.2 Ensemble Learning Overview

EL combines the predictions of multiple base estimators built given a learning algorithm, in order to improve generalizability and robustness over a single estimator [55]. Despite the fact that EL is relatively simple technique, it shows state-of-the-art performance in machine learning problems [10] making it a reliable option in different applications. EL algorithms can be categorized in two main categories: bootstrap aggregating (bagging) and boosting.

5.2.1 Bagging Algorithms

Bagging, introduced by Breiman [7] in 1996, is one of the earliest, yet effective, EL algorithms. Given a training dataset, bagging algorithm samples N items from X observations with replacement and trains M learners from M bootstrap samples. In the final stage, bagging algorithm combines the output of each learner by averaging their prediction or by using weighted majority voting mechanisms [55].

5.2.2 Boosting Algorithms

Unlike bagging, boosting algorithms emphasize the training instances in the weak models, aiming to produce a powerful ensemble.

In bagging algorithms all instances selected to train individual classifiers have equal probability of being chosen for the training set. However, in boosting algorithms the training dataset for each hypothesis focuses on instances that yielded less accurate results in previous hypotheses. At each iteration, the outputs of each hypothesis are weighted based on their accuracy and the final prediction is based on weighted majority voting [55].

5.3 Bagging Regression Trees

Regression trees is a classic supervised learning approach in data mining and machine learning. Classification and Regression Tree (CART) [8] analysis automatically decides on the splitting points, the splitting variables and the topology that the tree should have based on a greedy algorithm. In each level, the tree is split in one or more branches so that the model achieves better fit (minimize the error). This process occurs recursively until a stopping criterion is met [25].

Suppose there is a partition into M regions $R_1, R_2, ..., R_M$ and the model's output in each region is constant c_M.

$$f(x) = \sum_{m=1}^{M} c_m I(x \in R_m) \tag{5.1}$$

Adopting the sum of squares minimization criterion it is obvious that the best $\hat{c}_m$ is the average of y_i in region R_M.

$$\hat{c}_m = ave(y_i|x_i \in R_m) \tag{5.2}$$

Starting with the full dataset, the greedy algorithm considers a splitting variable j and splitting point s to define two half-planes.

$$R_1(j,s) = \{X|X_j \leq s\} \;\; and \;\; R_2(j,s) = \{X|X_j \geq s\} \tag{5.3}$$

Then the algorithm seeks for the values of j and s that minimize the following:

$$min_{j,s}\left[min_{c_1} \sum_{x_t \in R_1(j,s)} (y_i - c_1)^2 + min_{c_2} \sum_{x_t \in R_2(j,s)} (y_i - c_2)^2\right] \tag{5.4}$$

In each of the two regions the process is being repeated and the tree starts growing. The length of the tree is important as too large trees might overfit the data, while a small tree may not be able to capture the whole structure of the dataset. Regression tree length is a tuning parameter that governs the models complexity. Usually, when further splits do not give additional information in the model or the amount of data in a node is less than a predefined threshold the tree growing stops [25].

BRT is an efficient way to improve the estimation results of a single Regression Tree prediction. Several regression trees are trained based on the aforementioned methodology from bootstrap sampled data. Each bootstrap tree will differ in terms of properties, such as number of nodes, slitting point etc. The bagged estimate is the average estimate of the different trees, increasing the accuracy of the model.

5.4 Evaluation Metric

In order to validate the accuracy of the proposed BRT models, the Mean Absolute Percentage Error (MAPE) was adopted to quantify the percentage deviation of the models outputs compared to the validation data.

MAPE is defined as:

$$MAPE = \frac{1}{N} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \tag{5.5}$$

where A_t is the actual value and F_t the predicted output of the model.

5.5 Stratified Random Sampling

Sampling efficiently within a population is important, as accurate sample can incorporate fully representative information regarding the nature of the data. Inaccurate sampling, on the other hand, may yield misleading samples that vary significantly from the actual population.

Based on prior information the DM must identify efficient sampling techniques on the target population. There are several sampling techniques developed, covering simple random, systematic, compromise, stratified sampling etc. Further discussion of each sampling technique is beyond the scope of this work. Interested readers are referred to [22] for detailed description of the methods.

After plotting the energy consumption of the office building, large "steps" were observed when the chiller input was changed (Figure 5.1).

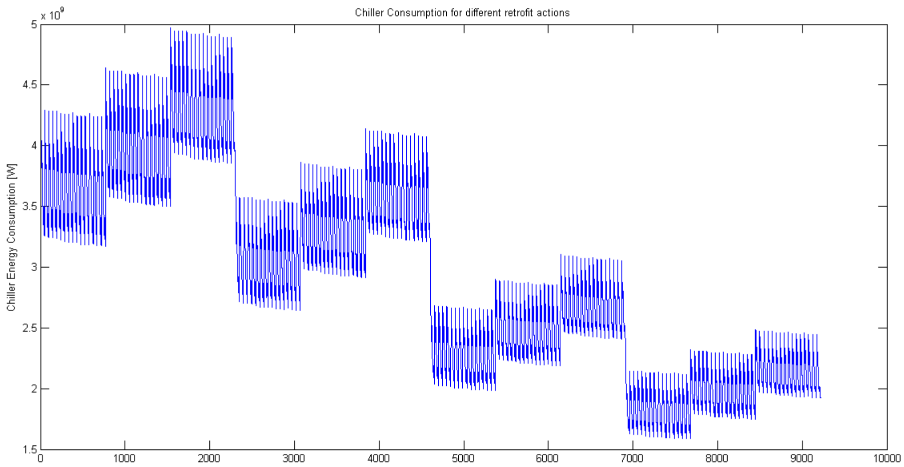

Figure 5.1: Chiller Consumption for different retrofit actions (Office building)

Instead of applying simple random or systematic sampling, the population is divided into sub-populations based on the chiller COP value, and stratified random sampling (SRS) is applied. By this approach, homogeneity in each stratum is ensured, allowing the DM to achieve acceptable precision with a smaller sample than in simple random or systematic.

CHAPTER 6

Results & Discussion

6.1 Description of Optimization Approach

The optimization framework proposed in this study can be summarized in Figure 6.1. After identifying the specifications of BAU models, the building model (.idf file) and the Abu Dhabi weather file (.epw file) act as inputs for the EnergyPlus simulation. The process is repeated for all the identified combinations of retrofits (9216 cases). Instead of resorting in existing software for the parametric runs (e.g. GenOpt), a MATLAB-EnergyPlus coupling scheme was developed. The privilege of calling EnergyPlus and altering the model's parameters directly from MATLAB gives additional flexibility to the researchers for future studies. Then, a representative sample of the parametric runs is obtained through Stratified Random Sampling (SRS). The sample is used to train EL-based Bagged Regression Tree models to predict the building's chiller annual electric power consumption, chiller size and lights electric power consumption. The models are then validated using 3000 inputs different from the ones included in the training dataset. Finally, the GA evaluates the less computational expensive EL-based objective function(s), rather than the heavy EnergyPlus simulation and yields the problem solution in both SOO and MOO. For the SOO case, the results are compared with the results of the exhaustive search space simulation and the BRT models' performance is evaluated.

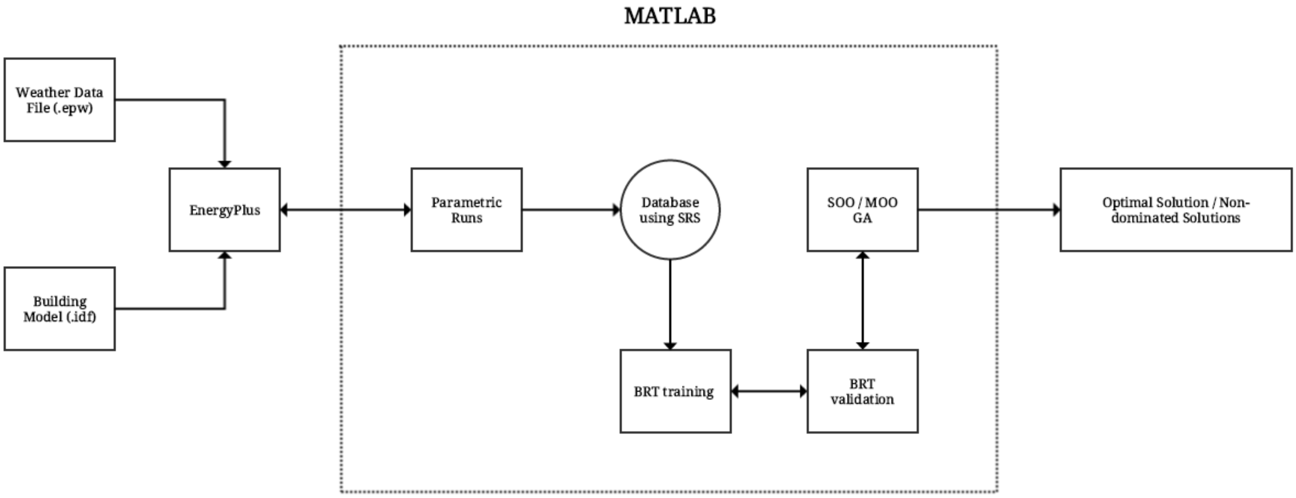

Figure 6.1: Optimization Framework

6.2 Bagging Regression Trees Model Building

In this section, the way the BRT ensembles were built is discussed. Three different models were developed, to predict the three variables of interest, namely chiller electric consumption, lights electric consumption and chiller size. A sensitivity analysis was performed in the properties of each model to identify the optimal number of learners. The results revealed that a model with *150* trees is suitable for chiller energy consumption and chiller size, whereas a model with *100* trees is sufficient to capture the information related to lighting energy consumption. This can mainly be attributed to the fact that lighting consumption is affected only be one parameter (overhang length) and it is easier for the model to capture the dynamics of the data with less complexity.

The fraction of the training data to be resampled for each weak learner was set to 1, so that each learner consists information from the whole range of the dataset.

Regarding the sample size used to train the models of each case study, a sensitivity analysis was performed for each one of them. Sampling sizes ranging from 1000 to 6000 were tested and their predictive performance was evaluated. As all models performed excellent in predicting the lighting load, the model selection is made based on their predictive performance on chiller energy consumption and size.

6.3 Life Cycle Analysis Approach

For each one of the following case studies, a LCA is attempted by means of NPV. The investment cost, replacement cost and energy savings will be assessed for each possible retrofit plan and the one that yields maximum NPV will be identified. Chiller's lifetime is 19 years, thus a discounted replacement cost is added in the 19th year of buildings' operation.

The study for each building type was conducted for 25 years, under the assumption of 7% discount rate on the energy savings.

The search space is comprised of $4 * 3 * 4 * 4 * 4 * 4 * 3 = 9216$ scenarios. After simulating each scenario with the aid of the developed MATLAB-EnergyPlus coupling scheme, the results were tabulated and the NPV was calculated. Then, the GA-EL optimization framework was implemented to locate the same solution with a less complex and time consuming approach.

6.4 Multi-Objective Optimization Approach

In this approach two conflicting objectives were simultaneously optimized, namely the investment cost of the retrofit action and the annual energy footprint of the building. The non-dominated solutions give the DM flexibility to decide on the optimal plan based on their needs.

MATLAB's Global Optimization Toolbox supports only continuous search space for MOO. Thus, instead of the default creation, mutation and crossover functions, customized functions were applied. With this approach, only integer genes were allowed to proceed in the next population, forcing the algorithm to restrict in integer values.

The illustrated Pareto-optimal sets, can be translated in rankings for several building energy performance rating systems. Estidama and LEED base their rankings in a more generalized idea of sustainable buildings, including water system efficiency, indoor air quality and building management system. In this case, the DM may identify the cost-optimal solution to add several points in the building's mechanical system performance.

On the other hand, the European Energy Efficiency Directive ranks the building based on its energy usage compared to a pre-defined baseline building. In this aspect, each of the Pareto-optimal solutions could be ranked, revealing the most cost-effective way to achieve a certain energy performance category.

6.5 Case Study: Villa Building

6.5.1 BRT Predictive Performance Evaluation

Several sampling sizes were obtained from the original dataset and BRT models were trained. Figure 6.2 shows the predictive performance of the BRT models for the chiller electric consumption and size. It can be observed that sample sizes above 2000 yield relatively accurate results, with average prediction error below 2.5% for both outputs.

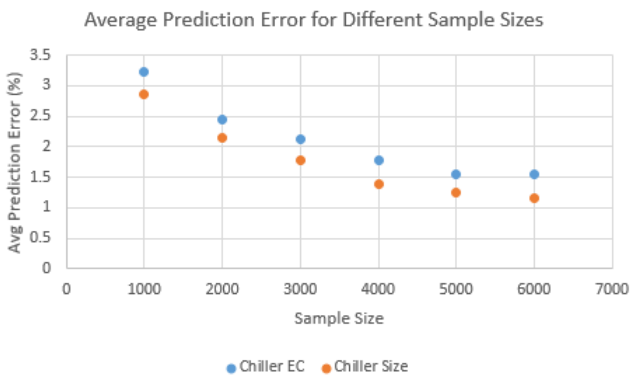

Figure 6.2: Average Prediction Error for Different Sample Sizes, Villa Building

For the purpose of this study, sample size of 2000 was used. As it will be discussed later, the villa BRT models fail to obtain the optimal solution. They manage to accurately predict the real optimal, but they overpredict other solutions, yielding a false optimal NPV. 2000 sample based models, yield solutions that are close to the optimal in terms of retrofit action characteristics, thus these models were incorporated in the study.

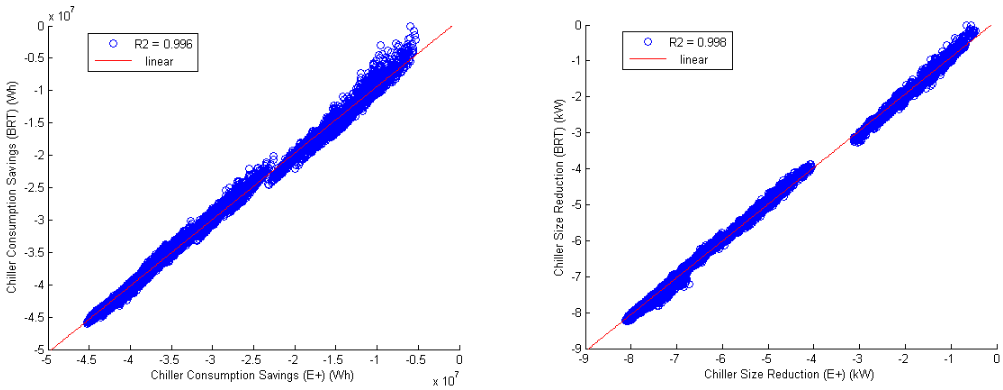

Figure 6.3: Predictions of BRT versus EnergyPlus, Office Building

As observed in Table 6.1, the villa BRT models yield predictions with MAPE around 2.5%. The maximum error reaches 13% in chiller electric consumption and 10% in chiller size which

$MAPE$	$\leq 5\%$	$\leq 2\%$	$\leq 1\%$	$Avg\ Fitting\ Error$	$Avg\ Prediction\ Error$	$Max\ Prediction\ Error$
$EC_{chiller}$	87.63%	53.20%	29.46%	1.87%	2.45%	12.91%
EC_{lights}	100%	100%	100%	0.01%	0.01%	0.09%
$ChillerSize$	91.83%	58.13%	31.63%	1.65%	2.14%	10.16%

Table 6.1: Villa Building BRT validation

is the reason of the overprediction mentioned above. The majority of the predictions are predict with over 95% accuracy, with some of them reaching levels of 98 and 99%.

6.5.2 Life Cycle Analysis

In this section the LCA for the villa building is performed. The search space of the experiment consists of 9216 discrete scenarios, as mentioned above. The optimal NPV of each action is calculated and tabulated, under the assumption of 7% interest rate for a study period of 25 years.

$Villa$	$x_{chiller}$	$x_{airtight}$	x_{wall}	x_{roof}	x_{win}	x_{over}	$x_{coolroof}$	$NPV(AED)$
$Tabular$	5	0.75	0.0254	0.0762	0	0	0.8	54034
$GA\text{-}EL$	5	0.75	0.0508	0.1016	0	0	0.8	58629
							$Deviation$	7.9%

Table 6.2: Villa Building NPV Optimization

Table 6.2 shows the optimal NPV obtained from both the data tabulation and the GA-EL framework. Replacement of the chiller as well as mild insulation of walls and roof appear to be the measures that yield higher NPV in the study period. Although chiller's replacement cost, the energy savings achieved with high-efficiency chiller make it an attractive retrofit. On the other hand, air tightness, window replacement, overhangs and roof painting does not contribute in the maximization of the NPV.

The GA-EL failed to target the optimal solution in this case study. The BRT models of the villa building were the less accurate, compared to the other case studies. Despite the fact that the model predicts the real optimal with accuracy of 99.9%, it overpredicts another solution, setting it as the optimal output.

The Internal Rate of Return (IRR) for the retrofit investment in the villa building is estimated to be 15.45%. Regarding the effectiveness of the retrofit action in the villa building's footprint, significant reduction of 53.8% has been achieved as can be observed in Figure 6.4.

It can be observed that the energy needed to cover the cooling load, especially during the

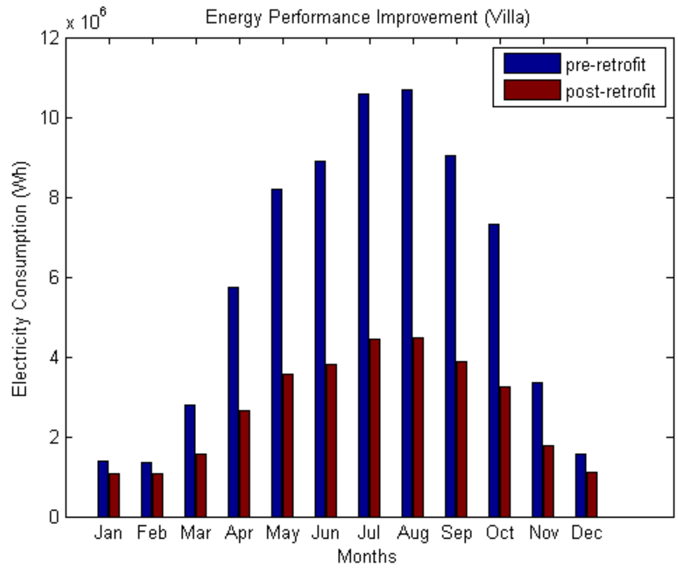

Figure 6.4: Energy Performance Improvement, Villa building

summer months, is significantly less than the baseline case, highlighting the effect of efficient chillers in reducing the overall impact of the building.

6.5.3 Multi-Objective Optimization

This section covers the MOO approach for the villa building. Figure 6.5 depicts the distribution of Pareto optimal solutions for the villa building.

Each individual solution along with the respective investment cost and annual energy consumption is shown in Table 6.3.

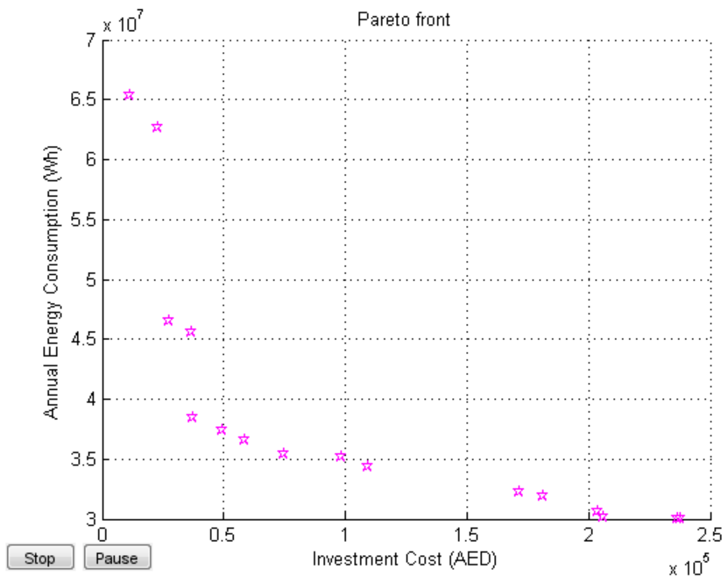

Figure 6.5: Pareto front, Villa building

Further observation of Figure 6.5 reveals that the non-dominated solutions can be classified mainly according to the chiller efficiency in each set. The influence of the chiller replacement in the decision making process is more significant than the other variables. For low-cost solutions, variables such as wall and roof insulation, windows and window overhang retrofits are not considered as optimal, but as the investment cost increases they become part of the solutions, yielding more lower annual energy consumption.

$x_{chiller}$	$x_{airtight}$	x_{wall}	x_{roof}	x_{win}	x_{over}	$x_{coolroof}$	$InvestmentCost(AED)$	$EnergyConsumption(Wh)$
2	0.45	0	0	0	0	0.8	11060	65433565
2	0.15	0	0	0	0	0.6	22928	62687764
3	0.45	0	0	0	0	0.8	27368	46581720
3	0.15	0	0	0	0	0.8	36445	45582557
4	0.45	0	0	0	0	0.8	37228	38438276
4	0.45	0.0254	0	0	0	0.6	49215	37432625
4	0.15	0.0254	0	0	0	0.6	58230	36658545
4	0.15	0.0508	0.1016	0	0	0.8	74797	35422473
4	0.45	0.0508	0.0762	0	1.2	0.6	98244	35198746
4	0.15	0.0508	0.1016	0	1.2	0.6	108901	34393530
5	0.75	0.0254	0.0762	1	0.6	0.6	171655	32290850
5	0.45	0.0254	0.0762	1	0.6	0.6	181301	31977015
5	0.45	0.0762	0.0762	1	1.2	0.6	203814	30589435
5	0.45	0.0762	0.1016	1	1.2	0.4	206037	30209160
5	0.45	0.0762	0.1016	1	2.4	0.6	236713	30110998
5	0.45	0.0762	0.1016	1	2.4	0.4	237618	30014587

Table 6.3: Pareto-optimal solutions, Villa building

6.6 Case Study: Office Building

6.6.1 BRT Predictive Performance Evaluation

A sensitivity analysis was performed among several sample sizes to determine the most appropriate for the office building retrofit optimization problem. Figure 6.6 illustrates the average prediction error for the chiller energy consumption and the chiller size. Sample sizes larger than 3000, yield predictions with in the region of 1% MAPE for both variables. Furthermore, models based on different sample sizes were included in the GA-EL optimization scheme, and models with sample size above 3000 managed to obtain the real optimal solution.

Thus, a 3000 sample based BRT model was used to feed the GA-EL scheme and its predictive performance is illustrated in Table 6.4

Based on the findings depicted in 6.4 it is obvious that the BRT office model is very accurate in its predictions. The maximum prediction error reach 6% and 5% for chiller consumption and

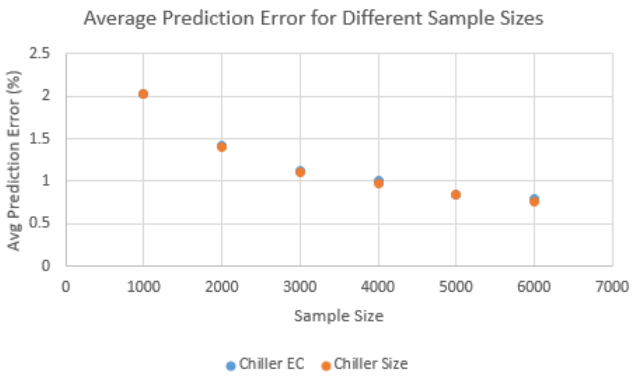

Figure 6.6: Average Prediction Error for Different Sample Sizes, Office Building

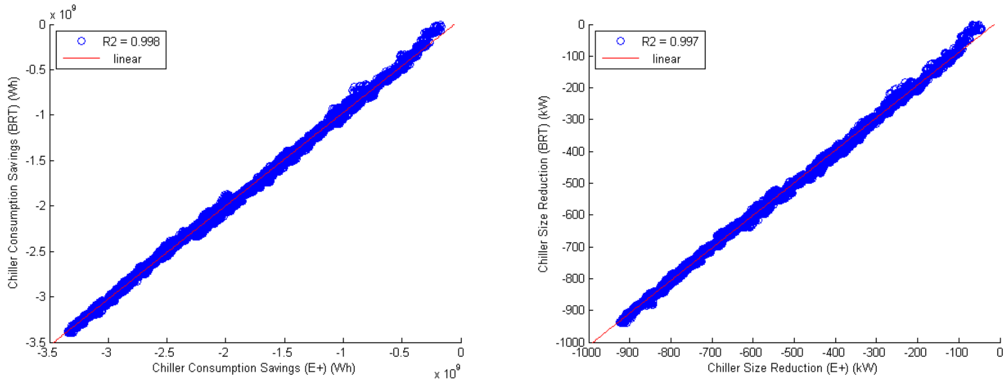

Figure 6.7: Predictions of BRT versus EnergyPlus, Office Building

MAPE	$\leq 5\%$	$\leq 2\%$	$\leq 1\%$	*Avg Fitting Error*	*Avg Prediction Error*	*Max Prediction Error*
$EC_{chiller}$	99.60%	83.33%	54.06%	0.90%	1.13%	6.05%
EC_{lights}	100%	100%	100%	0.02%	0.03%	0.24%
ChillerSize	100%	84.93%	55.70%	0.88%	1.10%	4.88%

Table 6.4: Office Building BRT validation

size respectively, whereas more than 80% of the predictions achieve accuracy higher than 98% for both variables.

6.6.2 Life Cycle Analysis

This section covers the LCA for the office building, taking into consideration two different electricity pricing frameworks. First, the office building is studied as a governmental building, with electricity tariff of 0.293 $^{AED}/_{kWh}$. Secondly, the building is studied under electricity tariff of 0.16 $^{AED}/_{kWh}$, which corresponds to commercial buildings.

Tables 6.5 and 6.6 show the optimal retrofit plans for office buildings, under different electricity pricing, by means of NPV maximization.

Office	$x_{chiller}$	$x_{airtight}$	x_{wall}	x_{roof}	x_{win}	x_{over}	$x_{coolroof}$	$NPV(AED)$
Tabular	5	0.1	0	0	0	0	0.8	2936269
GA-EL	5	0.1	0	0	0	0	0.8	3055300
							Deviation	3.9%

Table 6.5: Office governmental building NPV Optimization

Office	$x_{chiller}$	$x_{airtight}$	x_{wall}	x_{roof}	x_{win}	x_{over}	$x_{coolroof}$	$NPV(AED)$
Tabular	2.5	0.5	0	0	0	0	0.8	0
GA-EL	2.5	0.5	0	0	0	0	0.8	25172
							Deviation	–

Table 6.6: Office commercial building NPV Optimization

From Table 6.5 it can be observed that measures related to the HVAC system and the air tightness of the building result the higher NPV. The GA-EL approach manages to predict not only the optimal solution set, but also the final NPV with very good precision.

Table 6.6 shows the results of the LCA for the office building under commercial electricity pricing. The results show that under such low-pricing framework no retrofit action pays back its investment cost within the period of study (25 years). The GA-EL based optimization identified the optimal solution, but not an estimate close the optimal NPV. This is reasonable as even small inaccuracies in the energy consumption predictions predict different results than the baseline, accounted as savings.

The comparison between the two pricing frameworks raises the question of how subsidized electricity prices act as barrier in energy efficient buildings. It is clear that under different electricity prices the cost-effectiveness of a retrofit plan changes significantly and subsidized prices does not give the incentive to the DM to deeply retrofit their building.

The IRR of the investment is 11.42% for the optimal retrofit solution. Figure 6.8 illustrates the improvement achieved in terms of energy savings when retrofitting the office building. Significant decrease in the building's overall energy consumption can be observed, with the improvement reaching 40% of the initial consumption.

6.6.3 Multi-Objective Optimization

Figure 6.9 illustrates the Pareto front obtained for the office building and Table 6.7 presents the cost and electricity consumption values for each Pareto-optimal solution.

The Pareto front of Figure 6.9 shows high diversity. Clusters of solutions can be identified based on the chiller COP. Retrofitting the building's air tightness is often a cost-effective solu-

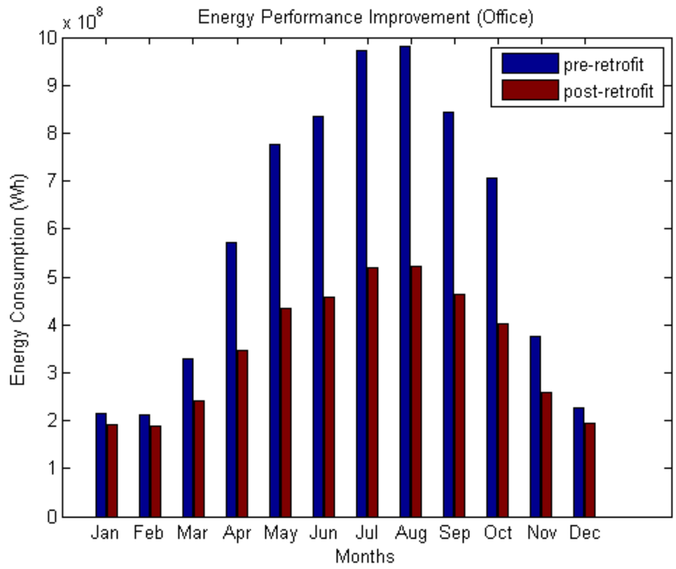

Figure 6.8: Energy Performance Improvement, Office building

$x_{chiller}$	$x_{airtight}$	x_{wall}	x_{roof}	x_{win}	x_{over}	$x_{coolroof}$	$InvestmentCost(AED)$	$EnergyConsumption(Wh)$
2.5	0.3	0	0	0	0	0.8	891840	6614413392
2.5	0.1	0	0	0	0	0.8	1707840	6306775716
2.5	0.1	0.0508	0.1016	0	0	0.8	2184784	6287009822
3	0.3	0	0	0	0	0.8	2870968	5899405060
3	0.3	0	0.0762	0	0	0.8	3099436	5896160178
3	0.1	0.0508	0.1016	0	0	0.6	4063470	5582730926
4	0.3	0	0	0	0	0.8	4270233	4900063254
4	0.3	0.0508	0.1016	0	0	0.6	4773814	4894369965
4	0.1	0.0508	0.1016	0	0	0.6	5375225	4699592708
5	0.3	0	0	0	0	0.8	5713304	4352071814
5	0.3	0.0508	0.1016	0	0	0.6	6224738	4336709179
5	0.1	0.0254	0	0	0	0.8	6399174	4188276052
5	0.1	0	0	0	0.6	0.8	7504078	4151890827
5	0.1	0.0508	0.1016	0	0.6	0.6	7986608	4122710216
5	0.1	0.0254	0	0	1.2	0.6	8893859	4068958572
5	0.1	0.0508	0.1016	0	1.2	0.6	9208095	4040571879

Table 6.7: Pareto-optimal solutions, Office building

tion, whereas replacing the windows with more efficient ones is never part of the Pareto-optimal solutions. Slight reduction in the roof's absorptivity is an effective measure, but reduction to the values of 0.4 is not recommended. This can be attributed to the fact that the effect of coolroof in energy consumption reduction is not significant in multi-story buildings, like the one under study. Finally, window overhangs of different lengths are included in the high-cost solutions, further reducing the energy consumption of the building.

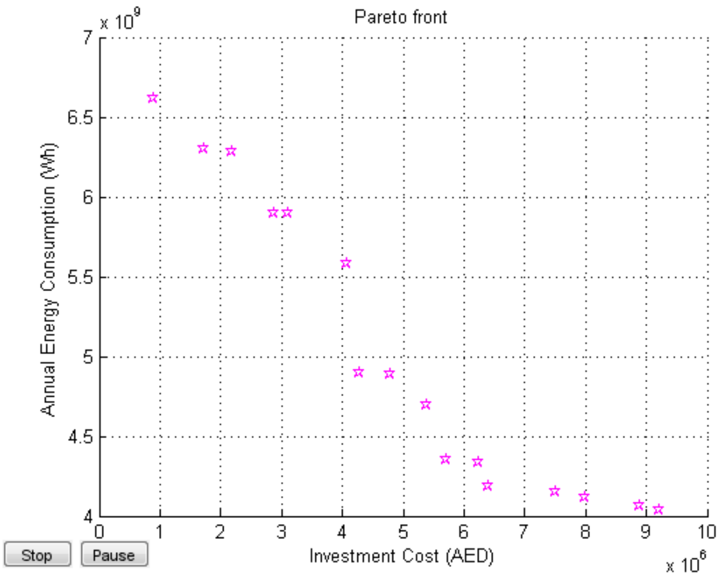

Figure 6.9: Pareto front, Office building

6.7 Case Study: Residential Building

6.7.1 BRT Predictive Performance Evaluation

Similarly to the previous case studies, sampling sizes ranging from 1000 to 6000 were used to train BRT models and their performance was evaluated. In Figure 6.10, one can see the average prediction error of the residential building BRT model for different sample sizes. Sample sizes higher than 2000 samples yield predictions with less than 2.5% MAPE for the chiller energy consumption and size. Sizes above 3000 show a stabilization of the model's prediction error in the region of 1.5%.

Both sample sizes of 2000 and 3000 were able to find the real optimal solution. The 1000 sample-based model yielded a solution close to the optimal,slightly underpredicting the optimal chiller. A 3000 stratified random sampled based model was chosen for this case study, to make sure that the BRT model will predict accurate outputs for all measures and will identify both the optimal NPV and the non-dominated solutions in the MOO.

The predictive performance of the model is illustrated in Table 6.8. Although the maximum prediction error for chiller size and consumption exceeds 10%, 91% and 93.8% of the predictions respectively present errors less than 5%. The average prediction error for both variables is less than 2%.

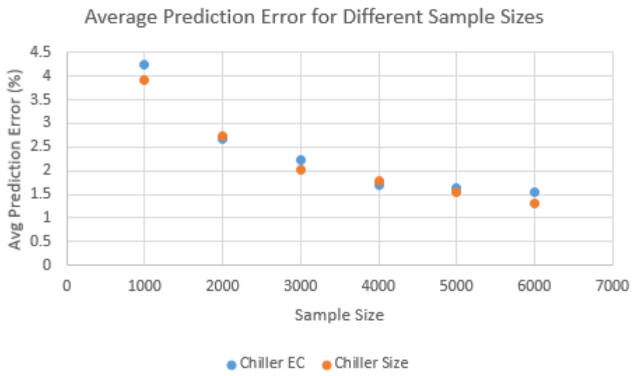

Figure 6.10: Average Prediction Error for Different Sample Sizes, Residential Building

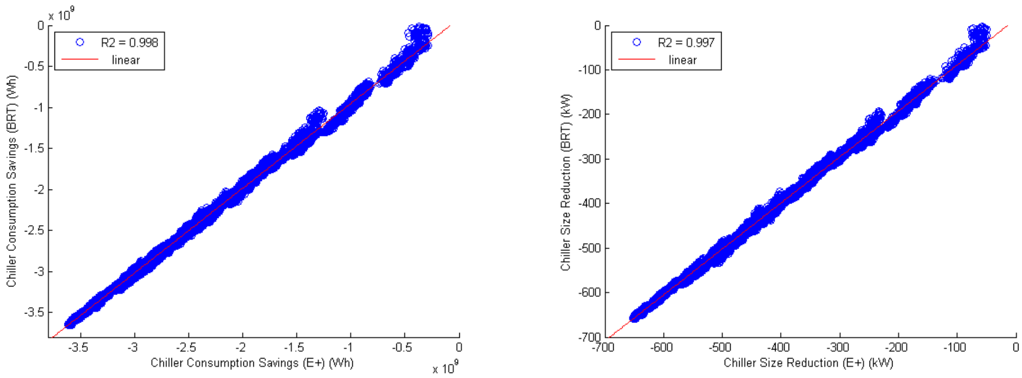

Figure 6.11: Predictions of BRT versus EnergyPlus, Residential Building

MAPE	$\leq 5\%$	$\leq 2\%$	$\leq 1\%$	*Avg Fitting Error*	*Avg Prediction Error*	*Max Prediction Error*
$EC_{chiller}$	91.00%	56.07%	30.70%	1.75%	2.22%	13.19%
EC_{lights}	100%	100%	100%	0.008%	0.009%	0.09%
$ChillerSize$	93.77%	60.03%	31.73%	1.59%	2.01%	11.61%

Table 6.8: Residential Building BRT validation

6.7.2 Life Cycle Analysis

In this section a LCA is performed for the residential building. The maximum NPV found from the data tabulation corresponds to the output of the GA-EL optimization, as illustrated in Table 6.9.

Residential	$x_{chiller}$	$x_{airtight}$	x_{wall}	x_{roof}	x_{win}	x_{over}	$x_{coolroof}$	$NPV(AED)$
Tabular	5	0.15	0	0	0	0	0.4	2164110
GA-EL	5	0.15	0	0	0	0	0.4	2262018
							Deviation	4.5%

Table 6.9: Residential building NPV Optimization

Similarly to the office building, HVAC and air tightness interventions yield the higher NPV for residential buildings. Retrofitting the chiller and improving the air tightness of a residential building is a cost intensive operation, but the energy savings obtained through such action make it a tempting option for profit making in the long run.

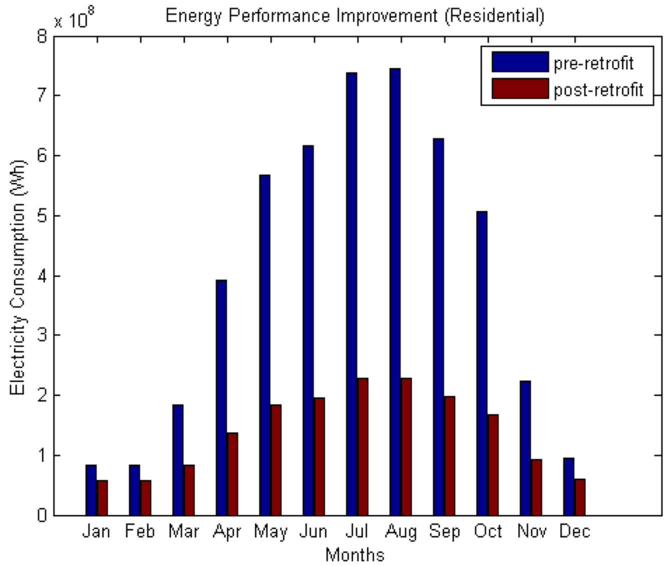

Figure 6.12: Energy Performance Improvement, Residential building

Figure 6.12 illustrates the improvement achieved in the residential building's energy performance after applying the aforementioned retrofits. An overall improvement of 65.2% can be achieved after retrofitting, with significant savings during the months that the HVAC system is continuously used. The IRR of the retrofitting investment for the typical residential building is 12.77%

6.7.3 Multi-Objective Optimization

This section covers the MOO approach for simultaneous optimization of investment cost and annual energy consumption for the typical Abu Dhabi residential building.

Observing the Pareto front of the residential building (Figure 6.13), the non-dominated solutions can be clustered mainly over the chiller and the building's air tightness. A group of solutions is formed from COP 3 chiller, 0.45 ACH air tightness and additions in the wall insulation layer. The same group, but with COP 4 chillers, show an increased investment cost but is still included in the Pareto front. The larger group of non-dominated solutions is governed by high-efficiency chillers and low infiltration rates. The solutions closest to the higher investment cost include the addition of both wall and roof insulation and overhangs of different lengths. Interesting fact is that window replacement is not included in none of the Pareto-optimal so-

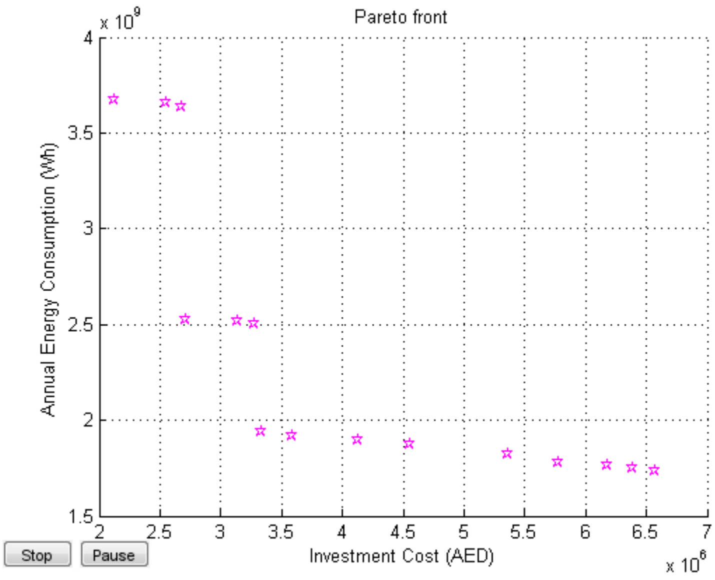

Figure 6.13: Pareto front, Residential building

lutions, as the high investment cost of efficient windows does not compensate with adequate energy consumption reduction.

$x_{chiller}$	$x_{airtight}$	x_{wall}	x_{roof}	x_{win}	x_{over}	$x_{coolroof}$	$InvestmentCost(AED)$	$EnergyConsumption(Wh)$
3	0.45	0	0	0	0	0.8	2116494	3674721070
3	0.45	0.0254	0	0	0	0.8	2542929	3660703747
3	0.45	0.0508	0	0	0	0.8	2669032	3641120111
4	0.45	0	0	0	0	0.8	2713200	2530499633
4	0.45	0.254	0	0	0	0.8	3139128	2520926810
4	0.45	0.0508	0	0	0	0.8	3268406	2505372658
4	0.15	0	0	0	0	0.8	3335873	1938723790
4	0.15	0	0.0762	0	0	0.6	3586457	1921404393
4	0.15	0.0508	0.0762	0	0	0.6	4127527	1899604841
4	0.15	0	0	0	0.6	0.8	4553074	1875834282
4	0.15	0.0508	0.1016	0	0.6	0.6	5357237	1828025345
4	0.15	0	0	0	1.2	0.8	5769524	1782826711
4	0.15	0.0254	0	0	1.2	0.8	6174740	1763564655
4	0.15	0.0254	0.0762	0	1.2	0.8	6379764	1752088645
4	0.15	0.0508	0.1016	0	1.2	0.6	6571138	1738309546

Table 6.10: Pareto-optimal solutions, Residential building

6.8 Case Study: Commercial Building

6.8.1 BRT Predictive Performance Evaluation

In this section different sampling sizes are tested in order to identify the ones that construct a model to accurately predict the building's energy behavior. Figure 6.14 illustrates the model's

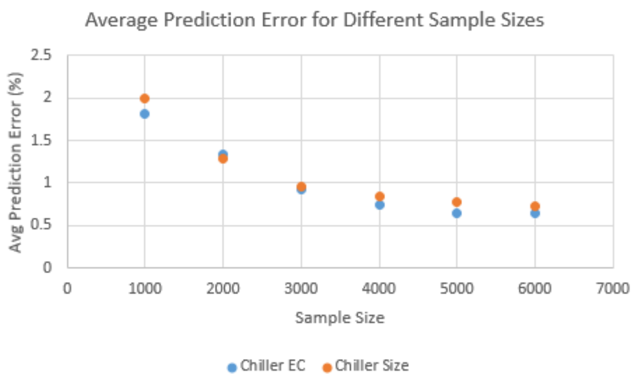

Figure 6.14: Average Prediction Error for Different Sample Sizes, Commercial Building

average prediction error for different sample sizes.

Figure 6.14 shows that the commercial BRT model achieves high predictive performance even with small sample sizes. It can be observed that sample sizes higher than 3000 yield predictions of less than 1% MAPE for both variables (chiller energy consumption, chiller size).

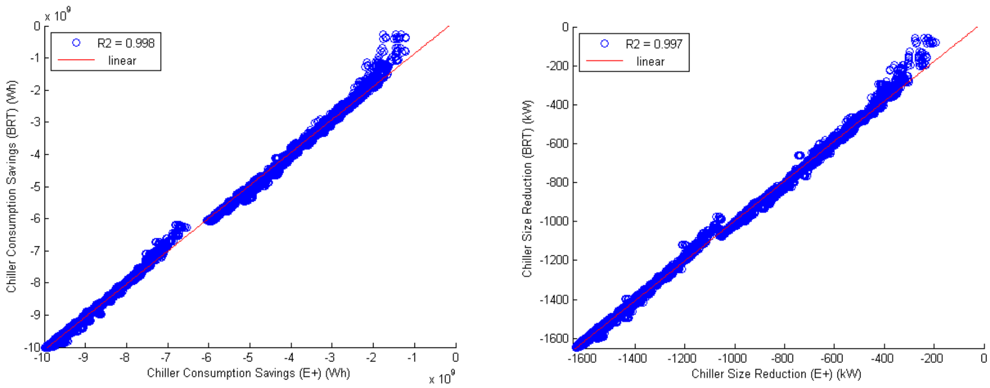

Figure 6.15: Predictions of BRT versus EnergyPlus, Commercial Building

Thus, the BRT model used in this study was trained with 3000 observations and its detailed performance is depicted in Table 6.11.

MAPE	$\leq 5\%$	$\leq 2\%$	$\leq 1\%$	*Avg Fitting Error*	*Avg Prediction Error*	*Max Prediction Error*
$EC_{chiller}$	99.60%	89.23%	66.77%	0.73%	0.92%	5.88%
EC_{lights}	100%	100%	100%	0.002%	0.003%	0.02%
$ChillerSize$	99.83%	89.90%	63.76%	0.77%	0.95%	5.62%

Table 6.11: Commercial Building BRT validation

The average prediction error for both chiller energy consumption and size is below 1%. Furthermore, almost 90% of the predictions yield errors less than 2%, making the model's predictions very solid. Finally, the maximum prediction errors do not exceed 6% for both consumption and size.

6.8.2 Life Cycle Analysis

In this part of the analysis, a LCA for the typical commercial building of Abu Dhabi is discussed. Table 6.12 reveals that the GA-EL based optimization accurately finds the real optimal solution. The NPV estimate of GA-EL is also very close to the real one, deviating only by 2.2%.

Commercial	$x_{chiller}$	$x_{airtight}$	x_{wall}	x_{roof}	x_{win}	x_{over}	$x_{coolroof}$	$NPV(AED)$
Tabular	5	0.5	0	0	0	0	0.4	6751542
GA-EL	5	0.5	0	0	0	0	0.4	6603135
							Deviation	2.2%

Table 6.12: Commercial building NPV Optimization

Chiller retrofitting and roof absorptivity reduction appear to be the most cost-effective retrofits in the long run. Due to the heavy occupancy during the whole day, commercial buildings require extensive usage of HVAC. So, high efficiency chillers can be a cost-effective investment, despite the high investment and replacement cost. Painting the roof would also be a profitable retrofit for commercial building. The low cost along with the cooling reduction impact, mainly in the building's top floor, can generate significant profits in the long run.

It is interesting that in all case studies HVAC retrofitting to its maximum value is included in the optimal solution. In hot and humid climates, like Abu Dhabi, cooling load covers significant part of the buildings' overall energy consumption. Other studies have demonstrated that a minimum chiller performance standard corresponding to annual COP greater than 5 is justified for buildings located in UAE (Qureshi et al.[43]), strengthening the findings of the current research.

The improvement in the energy performance of the commercial building is plotted in Figure 6.16. The high lighting and equipment intensity of such building types restrains improvements as high as in other building types discussed previously. However, there is still significant energy reduction, mostly during the summer months. The overall improvement achieved for the retrofitted commercial building is 24.6% and the IRR of the investment is estimated to 13.86%.

6.8.3 Multi-Objective Optimization

In this section the MOO of the conflicting objectives of investment cost and annual energy consumption for the commercial building is discussed.

Based on Figure 6.17, the non-dominated Pareto solutions can be classified based on the chiller and window retrofit. Solution involving no retrofitting action in the chiller are of low investment cost, but the building's energy consumption remains in high levels. As the chiller

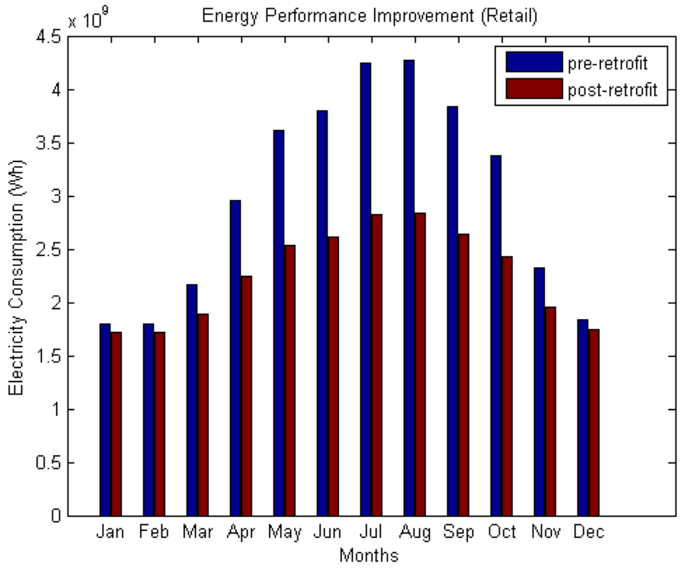

Figure 6.16: Energy Performance Improvement, Commercial building

efficiency increases the investment cost increases gradually, resulting more efficient energy consumption. Solutions involving high investment cost include window replacement and overhangs in the retrofit plan.

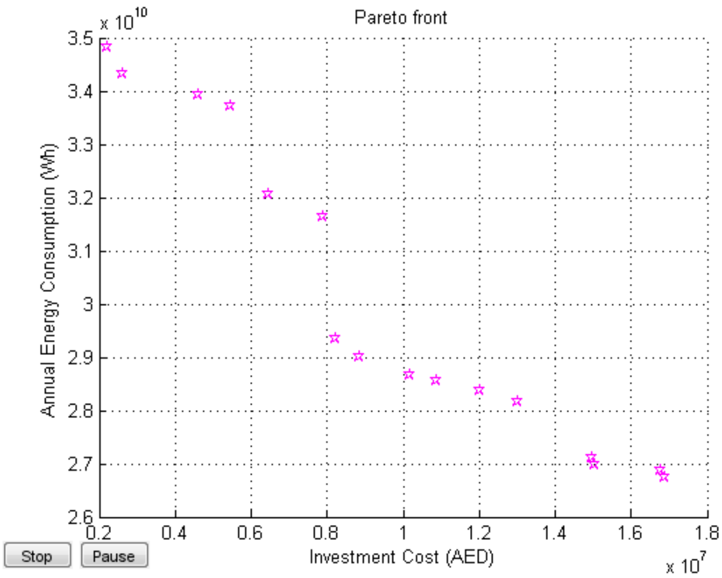

Figure 6.17: Pareto front, Commercial building

$x_{chiller}$	$x_{airtight}$	x_{wall}	x_{roof}	x_{win}	x_{over}	$x_{coolroof}$	$InvestmentCost(AED)$	$EnergyConsumption(Wh)$
2.5	0.3	0	0	0	0	0.8	2185008	34841897246
2.5	0.3	0.0254	0	0	0	0.6	2591463	34333691023
2.5	0.1	0	0	0	0	0.6	4590663	33923762494
2.5	0.3	0	0.1016	0	0.6	0.6	5452133	33724947660
3	0.3	0.0508	0	0	0	0.6	6443418	32058336952
3	0.3	0	0.0762	0	0	0.8	7879276	31649246338
4	0.3	0	0	0	0	0.8	8223272	29347103033
4	0.3	0.0508	0	0	0	0.6	8840958	29007110681
4	0.3	0	0.0762	0	0	0.8	10152706	28682350772
4	0.3	0.0254	0.0762	0	0.6	0.6	10883698	28554434859
4	0.1	0	0.0762	0	0	0.8	11991609	28371102426
4	0.1	0.0508	0.1016	0	0	0.6	13021396	28175252649
5	0.5	0.0254	0.0762	1	0.6	0.6	14960524	27116652480
5	0.5	0.0508	0.0762	1	0.6	0.4	15038565	26987755154
5	0.3	0.0254	0.0762	1	0.6	0.6	16780719	26886887296
5	0.3	0.0508	0.0762	1	0.6	0.4	16886072	26746143505

Table 6.13: Pareto-optimal solutions, Commercial building

CHAPTER 7

Sensitivity Analysis

In Chapter 6, the retrofit set yielding the optimal NPV for typical building types was identified. In this Chapter a sensitivity analysis is performed, in order to examine the sensitivity of the obtained solutions to the following parameters' change: electricity tariff, discount rate and study period length. Additionally, the fluctuation in variables such as the investment's NPV and building's energy consumption is discussed based on the change in the aforementioned parameter values.

7.1 Sensitivity of Optimal Solution to Electricity Tariff

The optimal retrofit solution demonstrates relatively low sensitivity to the electricity price for the governmental office building. As can be observed in Table 7.1, after 20% increase in the electricity tariff, the cool roof option is included in the optimal solution. Pricing schemes ranging from 60-150% of the current price, include intervention in the walls' insulation thickness, decreasing the annual energy usage by 0.86%. In terms of NPV, it is obvious that higher electricity tariffs yield higher NPVs, as the value of saved energy is increased.

In the case of commercial office building (Table 7.2), electricity tariffs up to 20% above the current one, act as a barrier to potential retrofit investment, making none of them cost-effective. Increasing the tariff, significant interventions form the optimal solution (i.e. chiller replacement and air tightness improvement). NPV is altered significantly, it cannot be expressed as a percent-

Office (Governmental)	*price*	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*LCOE*	*LCOE(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	0.293	5	0.1	0	0	0	0	0.8	2936269	0	0.229	0.00	4223153	0.00
10%	0.3223	5	0.1	0	0	0	0	0.8	3981923	35.6	0.229	0.00	4223153	0.00
20%	0.3516	5	0.1	0	0	0	0	0.4	5028264	71.2	0.229	0.00	4214670	-0.20
30%	0.3809	5	0.1	0	0	0	0	0.4	6077063	107.0	0.229	0.00	4214670	-0.20
40%	0.4102	5	0.1	0	0	0	0	0.4	7125863	142.7	0.229	0.00	4214670	-0.20
50%	0.4395	5	0.1	0	0	0	0	0.4	8174662	178.4	0.229	0.00	4214670	-0.20
60%	0.4688	5	0.1	0.0508	0	0	0	0.4	9224823	214.2	0.2319	1.27	4187180	-0.86
70%	0.4981	5	0.1	0.0508	0	0	0	0.4	10283814	250.2	0.2319	1.27	4187180	-0.86
80%	0.5274	5	0.1	0.0508	0	0	0	0.4	11342805	286.3	0.2319	1.27	4187180	-0.86
90%	0.5567	5	0.1	0.0508	0	0	0	0.4	12401797	322.4	0.2319	1.27	4187180	-0.86
100%	0.586	5	0.1	0.0508	0	0	0	0.4	13460788	358.4	0.2319	1.27	4187180	-0.86
110%	0.6153	5	0.1	0.0508	0	0	0	0.4	14519780	394.5	0.2319	1.27	4187180	-0.86
120%	0.6446	5	0.1	0.0508	0	0	0	0.4	15578771	430.6	0.2319	1.27	4187180	-0.86
130%	0.6739	5	0.1	0.0508	0	0	0	0.4	16637762	466.6	0.2319	1.27	4187180	-0.86
140%	0.7032	5	0.1	0.0508	0	0	0	0.4	17696754	502.7	0.2319	1.27	4187180	-0.86
150%	0.7325	5	0.1	0.0508	0	0	0	0.4	18755745	538.8	0.2319	1.27	4187180	-0.86

Table 7.1: Office(Governmental) Building, Sensitivity on electricity price

age though, as its initial value is zero. Regarding the energy consumption, significant reductions can be observed ranging from 26-40%, highlighting once again the fact that subsidized prices prevent transition of energy efficient buildings.

Office (Commercial)	*price*	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*LCOE*	*LCOE(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	0.16	2.5	0.5	0	0	0	0	0.8	0	-	0	-	7043401	0
10%	0.176	2.5	0.5	0	0	0	0	0.8	0	-	0	-	7043401	0
20%	0.192	2.5	0.5	0	0	0	0	0.8	0	-	0	-	7043401	0
30%	0.208	4	0.5	0	0	0	0	0.8	228134	-	0.215	-	5175094	-26.53
40%	0.224	4	0.1	0	0	0	0	0.8	670080	-	0.218	-	4763630	-32.37
50%	0.24	4	0.1	0	0	0	0	0.8	1131662	-	0.218	-	4763630	-32.37
60%	0.256	5	0.1	0	0	0	0	0.8	1615818	-	0.229	-	4223154	-40.04
70%	0.272	5	0.1	0	0	0	0	0.8	2186824	-	0.229	-	4223154	-40.04
80%	0.288	5	0.1	0	0	0	0	0.8	2757829	-	0.229	-	4223154	-40.04
90%	0.304	5	0.1	0	0	0	0	0.8	3328835	-	0.229	-	4223154	-40.04
100%	0.32	5	0.1	0	0	0	0	0.8	3899841	-	0.229	-	4223154	-40.04
110%	0.336	5	0.1	0	0	0	0	0.8	4470847	-	0.229	-	4223154	-40.04
120%	0.352	5	0.1	0	0	0	0	0.4	5041852	-	0.228	-	4214669	-40.16
130%	0.368	5	0.1	0	0	0	0	0.4	5615305	-	0.228	-	4214669	-40.16
140%	0.384	5	0.1	0	0	0	0	0.4	6188028	-	0.228	-	4214669	-40.16
150%	0.4	5	0.1	0	0	0	0	0.4	6760752	-	0.228	-	4214669	-40.16

Table 7.2: Office(Commercial) Building, Sensitivity on electricity price

Observing the sensitivity of the optimal solution to electricity price for the residential building, one can claim that the solution is not sensitive to pricing change, as even if the price is increased by 150% (Table 7.3), the solution will not change. Such finding boosts the claim that chiller and airtightness retrofitting are among the most important ones in hot climate regions. The NPV shows an increasing trend as the electricity price increases.

Residential	*price*	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*LCOE*	*LCOE(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	0.16	5	0.15	0	0	0	0	0.4	2164110	0	0.115	0	1686985	0
10%	0.176	5	0.15	0	0	0	0	0.4	2806520	29.7	0.115	0	1686985	0
20%	0.192	5	0.15	0	0	0	0	0.4	3448929	59.4	0.115	0	1686985	0
30%	0.208	5	0.15	0	0	0	0	0.4	4091339	89.1	0.115	0	1686985	0
40%	0.224	5	0.15	0	0	0	0	0.4	4733749	118.7	0.115	0	1686985	0
50%	0.24	5	0.15	0	0	0	0	0.4	5376158	148.4	0.115	0	1686985	0
60%	0.256	5	0.15	0	0	0	0	0.4	6018568	178.1	0.115	0	1686985	0
70%	0.272	5	0.15	0	0	0	0	0.4	6660977	207.8	0.115	0	1686985	0
80%	0.288	5	0.15	0	0	0	0	0.4	7303387	237.5	0.115	0	1686985	0
90%	0.304	5	0.15	0	0	0	0	0.4	7945796	267.2	0.115	0	1686985	0
100%	0.32	5	0.15	0	0	0	0	0.4	8588206	296.8	0.115	0	1686985	0
110%	0.336	5	0.15	0	0	0	0	0.4	9230615	326.5	0.115	0	1686985	0
120%	0.352	5	0.15	0	0	0	0	0.4	9873025	356.2	0.115	0	1686985	0
130%	0.368	5	0.15	0	0	0	0	0.4	10515434	385.9	0.115	0	1686985	0
140%	0.384	5	0.15	0	0	0	0	0.4	11157844	415.6	0.115	0	1686985	0
150%	0.4	5	0.15	0	0	0	0	0.4	11800253	445.3	0.115	0	1686985	0

Table 7.3: Residential Building, Sensitivity to electricity price

In the case of the villa building, the optimal solution does not change for increase in the electricity tariff up to 50% (Table7.4). Above this threshold retrofits like wall insulation and cool roof are included in the optimal solution. It is worth mentioning that the contribution of cool roof is more significant that the office building studied earlier. A reduction of 1.87% in the annual energy usage of the villa building is observed, versus a 0.2% reduction in the office building, highlighting the efficiency of cool roof as a ECM in low-rise buildings.

Villa	*price*	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*LCOE*	*LCOE(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	0.21	5	0.75	0.0254	0.0762	0	0	0.8	54034	0	0.164	0.00	32697	0.00
10%	0.231	5	0.75	0.0254	0.0762	0	0	0.8	66726	23.49	0.164	0.00	32697	0.00
20%	0.252	5	0.75	0.0254	0.0762	0	0	0.8	79418	46.98	0.164	0.00	32697	0.00
30%	0.273	5	0.75	0.0254	0.0762	0	0	0.8	92109	70.46	0.164	0.00	32697	0.00
40%	0.294	5	0.75	0.0254	0.0762	0	0	0.8	104801	93.95	0.164	0.00	32697	0.00
50%	0.315	5	0.75	0.0254	0.0762	0	0	0.8	117493	117.44	0.164	0.00	32697	0.00
60%	0.336	5	0.75	0.0254	0.0762	0	0	0.4	130326	141.19	0.167	1.83	32084	-1.87
70%	0.357	5	0.75	0.0254	0.0762	0	0	0.4	143180	164.98	0.167	1.83	32084	-1.87
80%	0.378	5	0.75	0.0508	0.0762	0	0	0.4	156096	188.88	0.17	3.66	31543	-3.53
90%	0.399	5	0.75	0.0508	0.0762	0	0	0.4	169094	212.94	0.17	3.66	31543	-3.53
100%	0.42	5	0.75	0.0508	0.0762	0	0	0.4	182093	237.00	0.17	3.66	31543	-3.53
110%	0.441	5	0.75	0.0508	0.0762	0	0	0.4	195092	261.05	0.17	3.66	31543	-3.53
120%	0.462	5	0.75	0.0508	0.0762	0	0	0.4	208090	285.11	0.17	3.66	31543	-3.53
130%	0.483	5	0.75	0.0508	0.0762	0	0	0.4	221089	309.17	0.17	3.66	31543	-3.53
140%	0.504	5	0.75	0.0508	0.0762	0	0	0.4	234087	333.22	0.17	3.66	31543	-3.53
150%	0.525	5	0.75	0.0508	0.0762	0	0	0.4	247085	357.28	0.17	3.66	31543	-3.53

Table 7.4: Villa Building, Sensitivity to electricity price

In the case of the typical commercial building, increase in the electricity tariff yield inclusion of further wall insulation in the optimal solution. Despite the significant increase in the investment's NPV (due to the increase on the tariff), the annual energy consumption of the building does not change significantly, as can be observed in the Energy Use (%) column (Table7.5).

Commercial	*price*	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*LCOE*	*LCOE(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	0.16	5	0.5	0	0	0	0	0.4	6751542	0	0.1084	0.00	27137746	0.00
10%	0.176	5	0.5	0	0	0	0	0.4	8546131	26.58	0.1084	0.00	27137746	0.00
20%	0.192	5	0.5	0.0254	0	0	0	0.4	10346500	53.25	0.1092	0.74	27062627	-0.28
30%	0.208	5	0.5	0.0254	0	0	0	0.4	12156297	80.05	0.1092	0.74	27062627	-0.28
40%	0.224	5	0.5	0.0254	0	0	0	0.4	13966094	106.86	0.1092	0.74	27062627	-0.28
50%	0.24	5	0.5	0.0508	0	0	0	0.4	15779304	133.71	0.1095	1.01	27042508	-0.35
60%	0.256	5	0.5	0.0508	0	0	0	0.4	17593174	160.58	0.1095	1.01	27042508	-0.35
70%	0.272	5	0.5	0.0508	0	0	0	0.4	19407044	187.45	0.1095	1.01	27042508	-0.35
80%	0.288	5	0.5	0.0508	0	0	0	0.4	21220915	214.31	0.1095	1.01	27042508	-0.35
90%	0.304	5	0.5	0.0508	0	0	0	0.4	23034785	241.18	0.1095	1.01	27042508	-0.35
100%	0.32	5	0.5	0.0508	0	0	0	0.4	24848655	268.04	0.1095	1.01	27042508	-0.35
110%	0.336	5	0.5	0.0508	0	0	0	0.4	26525284	292.88	0.1095	1.01	27042508	-0.35
120%	0.352	5	0.5	0.0508	0	0	0	0.4	28336760	319.71	0.1095	1.01	27042508	-0.35
130%	0.368	5	0.5	0.0508	0	0	0	0.4	30148237	346.54	0.1095	1.01	27042508	-0.35
140%	0.384	5	0.5	0.0508	0	0	0	0.4	32104137	375.51	0.1095	1.01	27042508	-0.35
150%	0.4	5	0.5	0.0508	0	0	0	0.4	33918008	402.37	0.1095	1.01	27042508	-0.35

Table 7.5: Commercial Building, Sensitivity to electricity price

7.2 Sensitivity of Optimal Solution to Discount Rate

As can be observed in Tables 7.6,7.7,7.8,7.9,7.10, discount rate is not a variable that affects significantly the optimal solution in the building retrofit optimization problem. More detailed observation of the Tables show that the only case that discount rate alters the energy behavior of the building significantly is in the residential building, where for discount rate of 9%, chiller retrofit option does not reach its upper bound (COP 5), causing the building to consume 17.58% more energy in an annual basis. In terms of NPV, as the discount rate increases the NPV decreases, making the investment less cost-effective.

Villa	*Discount Rate*	*chiller*	*airtigh*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	7%	5	0.75	0.0254	0.0762	0	0	0.8	54034	0	32697	0
	5%	5	0.75	0.0254	0.0762	0	0	0.8	74038	37.02	32697	0
	9%	5	0.75	0.0254	0.0762	0	0	0.8	38745	-28.30	32697	0

Table 7.6: Villa Building, Sensitivity to discount rate

Commercial	*Discount Rate*	*chiller*	*airtigh*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	7%	5	0.5	0	0	0	0	0.4	6751543	0	27137746	0
	5%	5	0.5	0.0254	0	0	0	0.4	9235719	36.79	27062627	-0.28
	9%	5	0.5	0	0	0	0	0.4	4839139	-28.33	27137746	0

Table 7.7: Commercial Building, Sensitivity to discount rate

Residential	*Discount Rate*	*chiller*	*airtigh*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	7%	5	0.15	0	0	0	0	0.4	2164110	0	1686985	0
	5%	5	0.15	0	0	0	0	0.4	3225640	49.05	1686985	0
	9%	4	0.15	0	0	0	0	0.8	1403038	-35.17	1983546	17.58

Table 7.8: Residential Building, Sensitivity to discount rate

OfficeCom	*Inflation*	*chiller*	*airtigh*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	7%	2.5	0.5	0	0	0	0	0.8	0	0	7043401	0
	5%	2.5	0.5	0	0	0	0	0.8	0	0	7043401	0
	9%	2.5	0.5	0	0	0	0	0.8	0	0	7043401	0

Table 7.9: Office(Commercial) Building, Sensitivity to discount rate

OfficeGov	*Inflation*	*chiller*	*airtigh*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	7%	5	0.1	0	0	0	0	0.8	2936269	0	4223153	0
	5%	5	0.1	0	0	0	0	0.4	4411757	50.25	4214669	-0.20
	9%	5	0.1	0	0	0	0	0.8	1796645	-38.81	4223153	0

Table 7.10: Office(Governmental) Building, Sensitivity to discount rate

7.3 Sensitivity of Optimal Solution to Study Period

Study period is another parameter that does not affect the problem's optimal solution significantly. Exemption is the residential building, where for study period of 20 years, the optimal chiller COP reduces from 5 to 4, increasing the building's annual energy consumption by 16.57%. This might be attributed to the chiller replacement cost during the 19th year of operation. Finally, it is obvious that as the study period increases, the NPV of the investment will increase.

Villa	*period*	*chiller*	*airtigh*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	25	5	0.75	0.0254	0.0762	0	0	0.8	54034	0	32697	0
	20	5	0.75	0.0254	0.0762	0	0	0.8	43406	-19.67	32697	0
	30	5	0.75	0.0254	0.0762	0	0	0.8	61611	14.02	32697	0

Table 7.11: Villa Building, Sensitivity to study period

Commercial	*period*	*chiller*	*airtigh*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	25	5	0.1	0	0	0	0	0.4	6751542	0	27137746	0
	20	5	0.1	0	0	0	0	0.4	5248813	-22.26	27137746	0
	30	5	0.5	0	0	0	0	0.4	7822967	15.87	27137746	0

Table 7.12: Commercial Building, Sensitivity to study period

Residential	*period*	*chiller*	*airtigh*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	25	5	0.15	0	0	0	0	0.4	2164110	0	1686985	0
	20	4	0.15	0	0	0	0	0.4	1671723	-22.75	1966458	16.57
	30	5	0.15	0	0	0	0	0.4	2547648	17.72	1686985	0

Table 7.13: Residential Building, Sensitivity to study period

OfficeCom	*period*	*chiller*	*airtigh*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	25	2.5	0.5	0	0	0	0	0.8	0	0	7043401	0
	20	2.5	0.5	0	0	0	0	0.8	0	0	7043401	0
	30	2.5	0.5	0	0	0	0	0.8	0	0	7043401	0

Table 7.14: Office(Commercial) Building, Sensitivity to study period

OfficeGov	*period*	*chiller*	*airtigh*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*
BAU	25	5	0.1	0	0	0	0	0.8	2936269	0	4223153	0
	20	5	0.1	0	0	0	0	0.4	2060673	-29.82	4223153	0
	30	5	0.1	0	0	0	0	0.4	3560556	21.26	4223153	0

Table 7.15: Office(Governmental) Building, Sensitivity to study period

CHAPTER 8

Insights for Future Work

As observed in the results obtained in Chapter 6, window replacement is rarely a cost-effective ECM for typical Abu Dhabi buildings. An alternative retrofit worth examining in future study is the addition of a window film on the top of the existing windows. Moreover, overhangs placed in the Southwest side of the building, receiving the most intense solar radiation might make the retrofit a cost-effective one. Furthermore, generalizing the meta-model in the continuous space of decision variables could potentially yield higher energy savings and NPV. The results of such an attempt are discussed in following section.

8.1 Window Films

Window films prevent the ultra-violet sun rays by entering the building, regulating the levels of heat and light passing through the glazing. The impact of window films on building's energy consumption is twofold. While it contributes in the cooling load reduction, it reduces the visible light transmittance in the building's interior. The performance of window films as potential retrofits for existing buildings and the overall change in the buildings' behavior is assessed in this chapter.

For the purpose of this analysis, an R-20 SR CDF film was studied, similar to DeBusk [15]. The cost of the measure is significantly less than window replacement, at $120 AED/m^2$, according to the same study.

Tables 8.1, 8.2, 8.3, 8.4 demonstrate the effect of window films on the optimal solution's NPV and energy consumption for all four building types.

Commercial	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV (AED)*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*	*Energy Savings (kWh)*	*Energy Savings (%)*
BAU	5	0.5	0	0	0	0	0.4	6751542	0	27137746	0	8857339	0
WindowFilm	5	0.5	0	0	0	0	0.4	8032900	18.98	26779000	-1.32	9216085	4.05

Table 8.1: Commercial Building, Window Film Impact on Optimal Solution

Office	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV (AED)*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*	*Energy Savings (kWh)*	*Energy Savings (%)*
BAU	5	0.1	0	0	0	0	0.8	2936269	0	4223153	0	2820375	0
WindowFilm	5	0.1	0	0	0	0	0.8	3265600	11.22	4174200	-1.16	2869328	1.74

Table 8.2: Office Building, Window Film Impact on Optimal Solution

Residential	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV (AED)*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*	*Energy Savings (kWh)*	*Energy Savings (%)*
BAU	5	0.15	0	0	0	0	0.4	2164110	0	1686985	0	3173062	0
WindowFilm	5	0.15	0	0	0	0	0.4	2748400	27.00	1368600	-18.87	3491447	10.03

Table 8.3: Residential Building, Window Film Impact on Optimal Solution

Villa	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV (AED)*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*	*Energy Savings (kWh)*	*Energy Savings (%)*
BAU	5	0.75	0.0254	0.0762	0	0	0.8	54034	0	32697	0	38145	0
WindowFilm	5	0.75	0.0254	0.0762	0	0	0.8	62110	14.95	28782	-11.97	42060	10.26

Table 8.4: Villa Building, Window Film Impact on Optimal Solution

In the case of residential and villa building, the impact of window film on energy consumption reduction is significant (12 and 19% respectively). On the other hand, the reduction observed in the office and commercial building is around 1-1.3% annually. This difference could be attributed to the fact that both office and commercial buildings operate on a more intense lighting schedule, especially during the daytime. The window films block the sun radiation along with the visible light, increasing the need for artificial lighting. Thus, in building types with intense lighting profiles, the savings incurred in the cooling load are counterbalanced by the increase in the lighting load. On the contrary, villa and residential buildings' lighting schedule is almost zero during the daytime, as they are not usually occupied.

Moreover, significant improvement in the NPV of all buildings is observed, ranging from 11-27%. The low cost of window film makes it a cost-effective measure for energy consumption reduction. An important aspect that has not been included in this study, is how window films affect the overall comfort of the occupant and would be interesting to address in future research.

8.2 Overhangs in the South-West Facade

Relevant studies for application of overhangs in the UAE region highlight the potential of overhangs in the reduction of occupant's thermal and visual discomfort, rather than improving the energy performance of the building [18]. Following the findings of El Sherif [18], each building was simulated with three different overhang configurations, namely: no overhangs, overhangs in all four sides of the building and overhangs in the South-West sides. Setting as baseline the ”All Sides” scenario, significant increase was not observed in the building's energy consumption compared to ”South-West” overhangs. Office and Residential buildings, that have higher WWR, show a difference of 0.7-0.85% in the annual energy consumption (Tables 8.5, 8.6. In the Villa building, the deviation is even smaller (0.3%) (Table 8.7) and in the Commercial building the performance remains almost the same, as the reduction achieved in cooling load is substituted by more intense lighting usage. Thus, for the purpose of this analysis, it can be assumed that the performance of the building is the same under ”All Sides” and ”South-West” scenario and calculate the NPV of the retrofit investment by setting the overhang retrofit cost 50% of the current.

Even after estimating the NPV with half of the initial overhang cost, the result remains the same for all building types, including no overhangs in the solution that yields the higher NPV.

Office (Governmental)	*Light Consumption (kWh)*	*Chiller Consumption (kWh)*	*Total Consumption (kWh)*	*Total Consumption (%)*
All Sides	445983	4835432	6898247	0
South-West	444633	4886424	6947889	0.72
No	444451	4982245	7043401	2.10

Table 8.5: Office Building, Consumption Variation with Different Overhang Configurations

Residential	*Light Consumption (kWh)*	*Chiller Consumption (kWh)*	*Total Consumption (kWh)*	*Total Consumption (%)*
All Sides	290089	4143319	4712342	0
South-West	290021	4183603	4752557	0.85
No	289946	4291915	4860795	3.15

Table 8.6: Residential Building, Consumption Variation with Different Overhang Configurations

	Light Consumption (kWh)	*Chiller Consumption (kWh)*	*Total Consumption (kWh)*	*Total Consumption (%)*
All Sides	4823	59559	70047	0
South-West	4823	59773	70261	0.31
No	4822	60355	70842	1.13

Table 8.7: Villa Building, Consumption Variation with Different Overhang Configurations

	Light Consumption (kWh)	*Chiller Consumption (kWh)*	*Total Consumption (kWh)*	*Total Consumption (%)*
All Sides	16159725	16048261	36006761	0
South-West	16156124	16049070	36003968	-0.01
No	16146911	16051812	35997498	-0.03

Table 8.8: Commercial Building, Consumption Variation with Different Overhang Configurations

8.3 Continuous Space Interpolation

In this section, continuous space interpolation is attempted for all models. The accuracy in the predictions of annual energy consumption and NPV is tested against the re-simulation of the identified optimal solution in EnergyPlus. Plotting the values of each retrofit measure and their respective costs, an almost linear relationship was observed in the data in every variable but the windows. Thus, linear functions were fitted in the decision variables and the optimization problem was formulated in the continuous space.

Commercial	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV (AED)*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*	*Energy Savings (kWh)*	*Energy Savings (%)*
Discrete	5	0.5	0	0	0	0	0.4	6751542	0	27137746	0	8857339	0
Continuous (GA-BRT)	4.63	0.5	0.073	0	0	0	0.5	6781293	0.44	27057592	-0.30	8937493	0.90
Continuous (EP)	4.63	0.5	0.073	0	0	0	0.5	5812207	-13.91	27977765	3.10	8017320	-9.48

Table 8.9: Commercial Building, Continuous Space Interpolation

Office	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV (AED)*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*	*Energy Savings (kWh)*	*Energy Savings (%)*
Discrete	5	0.1	0	0	0	0	0.8	2936269	0	4223153	0	2820375	0
Continuous (GA-BRT)	4.54	0.188	0.07	0.094	0	0	0.8	4207322	43.29	4180954	-1.00	2862574	1.50
Continuous (EP)	4.54	0.188	0.07	0.094	0	0	0.8	2553002	-13.05	4467910	5.80	2575618	-8.68

Table 8.10: Office Building, Continuous Space Interpolation

In Tables 8.9, 8.10, 8.11 and 8.12 it can be observed that continuous space interpolation is not possible in the particular optimization problem context. In all case studies, the GA-BRT model obtains a solution with higher NPV and energy savings in the continuous space compared

Residential	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV (AED)*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*	*Energy Savings (kWh)*	*Energy Savings (%)*
Discrete	5	0.15	0	0	0	0	0.4	2164110	0	1686985	0	3173062	0
Continuous (GA-BRT)	4.53	0.294	0.02	0.01	0	0	0.49	2705239	25.00	1643105	-2.60	3216942	1.38
Continuous (EP)	4.53	0.294	0.02	0.01	0	0	0.49	1369200	-36.73	2047039	21.34	2813008	-11.35

Table 8.11: Residential Building, Continuous Space Interpolation

Villa	*chiller*	*ach*	*wall*	*roof*	*window*	*over*	*coolroof*	*NPV (AED)*	*NPV(%)*	*Energy Use (kWh)*	*Energy Use (%)*	*Energy Savings (kWh)*	*Energy Savings (%)*
Discrete	5	0.75	0.0254	0.0762	0	0	0.8	54034	0	32697	0	38145	0
Continuous (GA-BRT)	4.52	0.49	0.013	0.05	0	0	0.74	60267	11.54	32096	-1.84	38746	1.58
Continuous (EP)	4.52	0.49	0.013	0.05	0	0	0.74	46672	-13.62	35863	9.68	34979	-8.30

Table 8.12: Villa Building, Continuous Space Interpolation

to the discrete one. Simulation of this particular solution in EnergyPlus and calculation of the investment's NPV shows significantly results though. The GA-BRT model predicts a false optimal solution in the continuous space, that is in fact less effective than the discrete one.

The predicted optimal solution's energy performance deviates significantly from the EnergyPlus output, especially in the villa and residential buildings. In the commercial and office building, even if the deviation is smaller, the real output of the identified solution is higher than the discrete one. The error in the energy consumption prediction is depicted on the investment's NPV and in all cases the NPV of the continuous solution is lower than the discrete one, fact that shows the inability of GA-BRT model to be generalized in the continuous search space.

The information used to train the BRT model consisted of 3-4 observations for each variable. Using a wider range of values during the model training stage for the variables with continuous nature (e.g. insulation, infiltration, chiller COP) could give the ability of generalization in the model and it worth studying in future research.

CHAPTER 9

Conclusion & Future Work

9.1 Conclusion

There is no doubt that climate change is one of the major environmental issues nowadays. GHGs emissions could be reduced if energy consumption was more efficient in all sectors. Existing buildings contribute a significant amount in the total electrical energy consumed worldwide, so they constitute a great candidate for energy conservation measures.

In this study four typical buildings of the Emirate of Abu Dhabi were modeled in EnergyPlus based on data obtained from the Urban Planning Council and Abu Dhabi Municipality. Then, several retrofit actions and their respective costs were identified. At this stage 9216 different retrofit combinations were defined.

Following, a coupling scheme was developed between MATLAB and EnergyPlus for automated simulation of different retrofit scenarios. After the simulation of all different scenarios, their outputs were tabulated and used to perform a Life Cycle Analysis in each one of them. The retrofit plan that yielded the higher Net Present Value in the proposed study period was identified for all four building types.

The next step of the study involved a novel meta-model approach based on Ensemble Learning models to accurately represent the buildings' energy performance. More specifically, the method of Bagged Regression Trees was applied to construct the buildings' surrogate models. The BRT models were used as inputs in a Genetic Algorithm-based optimization setup and in the majority of the cases managed to locate the real optimal solution of the LCA discussed above. The findings reveal that BRT models can be reliable alternatives for building retrofit optimization, showing strength in locating the real optimal solution and limiting the simulation time significantly. More specifically, approximately 70% reduction can be achieved in the simulation time without missing the real optimal solution. Even more reduction can be achieved, in cases where the DM process allows some margin of error.

An attempt also was made to move from discrete to continuous space in the decision variables. Although the behavior of most variables was linear, the model could not predict the outputs as accurately as in the discrete space. Thus, the results obtained from this optimization routine would not reflect reality in most of the cases.

Finally, multi-objective optimization was performed for each case study building. The conflicting objectives of investment cost and annual energy consumption were simultaneously optimized using the previously mentioned BRT models and MATLAB's customized NSGA-II. The customization of NSGA-II enabled us to perform mixed-integer optimization, which is the nature of building retrofit optimization problems. Obtaining MOO results by directly coupling of MATLAB and EnergyPlus would not be possible, as the evaluation of the objective function would involve a whole building simulation and each population would take extensive amount of time to be generated. The MOO revealed a set of Pareto-optimal solutions for each individual building, assisting the decision making process based on the DM's needs.

The proposed EL-based approach shows great potential for building retrofit single and multi-objective optimization problems. It can aid the decsion making process and the DM can pick the solutions that satisfy the desired trade-offs or even add meaningful constraints to the existing problem.

Extension of the proposed optimization framework can be used as a basis for building sector policy making in the Emirate of Abu Dhabi. The case studies discussed in the present work can give insights to the policy makers, but in order to form a new policy regional cost data should be used as well as an even wider range of retrofit actions.

9.2 Future Work

Further consideration of a larger range of retrofit choices could yield interesting results and change the trade-offs between the non-dominated solutions. More specifically, retrofits contributing in the reduction of the heat gain through windows could be an interesting field of research. More sophisticated retrofits than overhangs, such as solar screens and window films could be studied. EnergyPlus allows the inclusion of only overhangs and fins as shading devices, but the incorporation of other software, like DesignBuilder, could create construction components to be integrated with the building model as shading devices.

Different objectives can also be assessed in the MOO framework. Occupants' thermal comfort level could be another factor to be optimized along with the investment cost and energy consumption, covering also the social impact of the intervention.

Additionally, more complex EL-based models can be used for this study that are not supported by MATLAB. Python's scikit-learn package incorporates several advanced ensemble learning algorithms, such as random forests, gradient boosting regression trees etc. Developing a coupling scheme between MATLAB and Python would be an interesting endeavor, as well as the inclusion of the aforementioned techniques in building retrofit optimization problems.

Finally, future work should include models that account for the uncertainty in the decision making process. Electricity price, retrofit cost and weather data are some of the uncertainty factors involved in existing building retrofit projects. An uncertainty assessment is crucial to give the DM confidence to proceed in the solution selection.

CHAPTER 10

Abbreviations

IEA International Energy Agency

EIA Energy Information Agency

GHG Greenhouse Gases

DSM Demand Side Management

HVAC Heating, Ventilation and Air-Conditioning

DM Decision Maker

NPV Net Present Value

BAU Business-As-Usual

NREL National Renewable Energy Laboratory

LCA Life Cycle Analysis

MCA Multi Criteria Analysis

MOO Multi Objective Optimization

SOO Single Objective Optimization

GA Genetic Algorithm

EL Ensemble Learning

BPS Building Performance Simulation

ANN Artificial Neural Network

UPC Urban Planning Council

WWR Window to Wall Ratio

SHGC Solar Heat Gain Coefficient

ACH Air Changes per Hour

AED Arab Emirates Dirham

COP Coefficient of Performance

XPS Extruded Polystyrene

VEGA Vector Evaluated Genetic Algorithm

MOGA Multi Objective Genetic Algorithm

SPEA Strength Pareto Evolutionary Algorithm

NSGA Non-Dominated Sorting Genetic Algorithm

NSGA-II Fast Non-Dominated Sorting Genetic Algorithm

BRT Bagging Regression Trees

CART Classification and Regression Trees

SRS Stratified Random Sampling

Bibliography

[1] Afshin Afshari, Christina Nikolopoulou, and Miguel Martin. Life-cycle analysis of building retrofits at the urban scalea case study in united arab emirates. *Sustainability*, 6(1): 453–473, 2014.

[2] Ali Alajmi and Jonathan Wright. Selecting the most efficient genetic algorithm sets in solving unconstrained building optimization problem. *International Journal of Sustainable Built Environment*, 3(1):18–26, 2014.

[3] Ehsan Asadi, Manuel Gameiro da Silva, Carlos Henggeler Antunes, and Luís Dias. A multi-objective optimization model for building retrofit strategies using trnsys simulations, genopt and matlab. *Building and Environment*, 56:370–378, 2012.

[4] Ehsan Asadi, Manuel Gameiro Da Silva, Carlos Henggeler Antunes, and Luís Dias. Multi-objective optimization for building retrofit strategies: a model and an application. *Energy and Buildings*, 44:81–87, 2012.

[5] Ehsan Asadi, Manuel Gameiro da Silva, Carlos Henggeler Antunes, Luís Dias, and Leon Glicksman. Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application. *Energy and Buildings*, 81:444–456, 2014.

[6] Fabrizio Ascione, Nicola Bianco, Claudio De Stasio, Gerardo Maria Mauro, and Giuseppe Peter Vanoli. A new methodology for cost-optimal analysis by means of the

multi-objective optimization of building energy performance. *Energy and Buildings*, 88: 78–90, 2015.

[7] Leo Breiman. Bagging predictors. *Machine learning*, 24(2):123–140, 1996.

[8] Leo Breiman, Jerome Friedman, Charles J Stone, and Richard A Olshen. *Classification and regression trees*. CRC press, 1984.

[9] Luisa Gama Caldas and Leslie K Norford. A design optimization tool based on a genetic algorithm. *Automation in construction*, 11(2):173–184, 2002.

[10] Rich Caruana and Alexandru Niculescu-Mizil. An empirical comparison of supervised learning algorithms. In *Proceedings of the 23rd international conference on Machine learning*, pages 161–168. ACM, 2006.

[11] Andrew Chipperfield, Peter Fleming, Hartmut Pohlheim, and Carlos Fonseca. Genetic algorithm toolbox for use with matlab. 1994.

[12] Abu Dhabi Urban Planning Council. Pearl building: Guide for consultant, 2010.

[13] Kalyanmoy Deb. *Multi-objective optimization using evolutionary algorithms*, volume 16. John Wiley & Sons, 2001.

[14] Kalyanmoy Deb, Amrit Pratap, Sameer Agarwal, and TAMT Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *Evolutionary Computation, IEEE Transactions on*, 6(2):182–197, 2002.

[15] Steve DeBusks. Comparative analysis of retrofit window film to replacement with high performance windows, January 2015. URL `https://www.boma.org/sustainability/info-resources/Documents/WindowFilmWhitePaper.pdf`.

[16] Christina Diakaki, Evangelos Grigoroudis, and Dionyssia Kolokotsa. Towards a multi-objective optimization approach for improving energy efficiency in buildings. *Energy and Buildings*, 40(9):1747–1754, 2008.

[17] Christina Diakaki, Evangelos Grigoroudis, Nikos Kabelis, Dionyssia Kolokotsa, Kostas Kalaitzakis, and George Stavrakakis. A multi-objective decision model for the improvement of energy efficiency in buildings. *Energy*, 35(12):5483–5496, 2010.

[18] Sherihan Khairy El Sherif. The impact of overhangs and side-fins on building thermal comfort, visual comfort and energy consumption in the tropics. 2012.

[19] Flourentzos Flourentzou and C-A Roulet. Elaboration of retrofit scenarios. *Energy and Buildings*, 34(2):185–192, 2002.

[20] Carlos M Fonseca and Peter J Fleming. Multiobjective genetic algorithms. In *Genetic Algorithms for Control Systems Engineering, IEE Colloquium on*, pages 6–1. IET, 1993.

[21] John S Gero, Neville D'Cruz, and Antony D Radford. Energy in context: a multicriteria model for building design. *Building and Environment*, 18(3):99–107, 1983.

[22] Richard O. Gilbert. *Statistical methods for environmental pollution monitoring*. John Wiley & Sons, 1987.

[23] Dirk Gorissen, Ivo Couckuyt, Piet Demeester, Tom Dhaene, and Karel Crombecq. A surrogate modeling and adaptive sampling toolbox for computer based design. *The Journal of Machine Learning Research*, 11:2051–2055, 2010.

[24] Mohamed Hamdy, Ala Hasan, and Kai Siren. Applying a multi-objective optimization approach for design of low-emission cost-effective dwellings. *Building and environment*, 46(1):109–123, 2011.

[25] Trevor Hastie, Robert Tibshirani, Jerome Friedman, T Hastie, J Friedman, and R Tibshirani. *The elements of statistical learning*, volume 2. Springer, 2009.

[26] John H Holland. *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence.* U Michigan Press, 1975.

[27] Climate Initiative. Buildings and climate change. 2009.

[28] Michael Jaggs and John Palmer. Energy performance indoor environmental quality retrofita european diagnosis and decision making method for building refurbishment. *Energy and buildings*, 31(2):97–101, 2000.

[29] Arturas Kaklauskas, Edmundas Kazimieras Zavadskas, and Saulius Raslanas. Multivariant design and multiple criteria analysis of building refurbishments. *Energy and Buildings*, 37 (4):361–372, 2005.

[30] Hisham Khatib. Iea world energy outlook 2011a comment, 2012.

[31] Abdullah Konak, David W Coit, and Alice E Smith. Multi-objective optimization using genetic algorithms: A tutorial. *Reliability Engineering & System Safety*, 91(9):992–1007, 2006.

[32] National Renewalbe Energy Laboratory. National residential efficiency measures database, January 2015. URL http://www.nrel.gov/ap/retrofits/group_listing.cfm.

[33] Mark Levine, Diana Ürge-Vorsatz, Kornelis Blok, Luis Geng, Danny Harvey, Siwei Lang, Geoffrey Levermore, A Mongameli Mehlwana, Sevastian Mirasgedis, Aleksandra Novikova, et al. Residential and commercial buildings. *Climate change*, pages 387–446, 2007.

[34] Ronnen Levinson, Hashem Akbari, Steve Konopacki, and Sarah Bretz. Inclusion of cool roofs in nonresidential title 24 prescriptive requirements. *Energy Policy*, 33(2):151–170, 2005.

[35] Laurent Magnier and Fariborz Haghighat. Multiobjective optimization of building design using trnsys simulations, genetic algorithm, and artificial neural network. *Building and Environment*, 45(3):739–746, 2010.

[36] MATHWORKS. Fitness scaling, January 2015. URL http://www.mathworks.com/help/gads/fitness-scaling.html.

[37] Global Optimization Toolbox MathWorks. Users guide r2011b. *The MathWorks Inc., Massachusetts*, 2011.

[38] Melanie Mitchell. *An introduction to genetic algorithms*. MIT press, 1998.

[39] Sendhil Mullainathan and H Allcott. Behavior and energy policy. *Science*, 327:1204–1205, 2010.

[40] Toke Rammer Nielsen and Svend Svendsen. *Optimization of buildings with respect to energy and indoor environment*. PhD thesis, Technical University of DenmarkDanmarks Tekniske Universitet, Department of Buildings and EnergyInstitut for Bygninger og Energi, 2002.

[41] K Peippo, PD Lund, and E Vartiainen. Multivariate optimization of design trade-offs for solar low energy buildings. *Energy and Buildings*, 29(2):189–205, 1999.

[42] Paola Penna, Alessandro Prada, Francesca Cappelletti, and Andrea Gasparella. Multi-objectives optimization of energy efficiency measures in existing buildings. *Energy and Buildings*, 2014.

[43] OA Qureshi and H Javed. Optimal model-based control of chiller tower fan and cooling water pump. *ASHRAE Transactions*, 120:1W, 2014.

[44] Colin R Reeves and Jonathan E Rowe. *Genetic algorithms: principles and perspectives: a guide to GA theory*, volume 20. Springer Science & Business Media, 2003.

[45] Regulation and Supervision Bureau. New water and electricity tariffs structure, January 2015. URL http://rsb.gov.ae/en/sector/new-water-and-electricity-tariffs-structure.

[46] Emmanuel Rey. Office building retrofitting strategies: multicriteria approach of an architectural and technical issue. *Energy and Buildings*, 36(4):367–372, 2004.

[47] J David Schaffer. Multiple objective optimization with vector evaluated genetic algorithms. In *Proceedings of the 1st International Conference on Genetic Algorithms, Pittsburgh, PA, USA, July 1985*, pages 93–100, 1985.

[48] Adam Sieminski. International energy outlook 2013. *US Energy Information Administration (EIA) Report Number: DOE/EIA-0484*, 2013.

[49] Bram Smeets and Ali Bayar. The sustainability of economic growth in abu dhabi–a dynamic cge approach. 2012.

[50] Nidamarthi Srinivas and Kalyanmoy Deb. Muiltiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary computation*, 2(3):221–248, 1994.

[51] Thomas Stocker, Dahe Qin, Gian-Kasper Plattner, M Tignor, Simon K Allen, Judith Boschung, Alexander Nauels, Yu Xia, Vincent Bex, and Pauline M Midgley. *Climate change 2013: The physical science basis*. Cambridge University Press Cambridge, UK, and New York, 2014.

[52] Bo Wang, Xiaohua Xia, and Jiangfeng Zhang. A multi-objective optimization model for the life-cycle cost analysis and retrofitting planning of buildings. *Energy and Buildings*, 77:227–235, 2014.

[53] Weimin Wang, Radu Zmeureanu, and Hugues Rivard. Applying multi-objective genetic algorithms in green building design optimization. *Building and environment*, 40(11):1512–1525, 2005.

[54] Wei Yu, Baizhan Li, Hongyuan Jia, Ming Zhang, and Di Wang. Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design. *Energy and Buildings*, 88:135–143, 2015.

[55] Cha Zhang and Yunqian Ma. *Ensemble machine learning*. Springer, 2012.

[56] Eckart Zitzler and Lothar Thiele. Multiobjective evolutionary algorithms: a comparative case study and the strength pareto approach. *evolutionary computation, IEEE transactions on*, 3(4):257–271, 1999.