MODEL BASED BUILDING ENERGY OPTIMIZATION USING META-HEURISTICS

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submitted by **MURAT ALTUN** in partial fulfillment of the requirements for the degree of **Master of Science in Civil Engineering Department, Middle East Technical University** by,

Prof. Dr. Gülbin Dural Ünver _____________________
Dean, Graduate School of **Natural and Applied Sciences**

Prof. Dr. Ahmet Cevdet Yalçıner _____________________
Head of Department, **Civil Engineering**

Asst. Prof. Dr. Aslı Akçamete Güngör _____________________
Supervisor, **Civil Engineering Dept., METU**

Examining Committee Members:

Prof. Dr. M. Talat Birgönül _____________________
Civil Engineering Dept., METU

Asst. Prof. Dr. Aslı Akçamete Güngör _____________________
Civil Engineering Dept., METU

Prof. Dr. Gökhan Arslan _____________________
Civil Engineering Dept., Anadolu University

Assoc. Prof. Dr. Rıfat Sönmez _____________________
Civil Engineering Dept., METU

Asst. Prof. Dr. Çağla Meral _____________________
Civil Engineering Dept., METU

Date: 31.08.2015

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name: Murat Altun

Signature :

ABSTRACT

MODEL BASED BUILDING ENERGY OPTIMIZATION USING META-HEURISTICS

Altun, Murat

M.S., Department of Civil Engineering

Supervisor: Asst. Prof. Dr. Aslı Akçamete Güngör

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Energy efficiency plays a key role in minimizing energy usage cost and its environmental impacts. Life cycle thinking guides decision makers to develop energy-efficient solutions in building early design stage; however, in practice, energy analysis is done according to technical specifications' limits due to inefficient tools and lack of methodologies to response frequent changes in design. Therefore, alternative design solutions with different objectives cannot be generated. In this study, two energy optimization models are developed to solve existing energy analysis problems in practise. In the first model, a graphical user interface called EnrOpt that can be fast and flexible enough to be applied to multiple multi-objective problems and any building types is developed by strengthening weaknesses of practically applied TS 825 Turkish Thermal Standard. The metaheuristics with different position update strategies such as Differential Evolution, Particle Swarm Optimizer and Modified Cross Entropy Method are used to provide a flexible model. In the second model, Dynamo based BIM integrated energy simulation optimization model is proposed. This model offers effective communication between stakeholders to avoid possible problems encountered in early design while providing efficient energy analysis by updating frequent changes in design. Performance of energy optimization models are tested by case studies and Pareto optimal results are obtained. Parametric analysis of design parameters that affect energy model or optimization model on EnrOpt are performed. Results indicates that elaboration in climate and geometric data and energy use scheduling influences building energy estimation significantly. These two models can be applied to different building types by analyzing a vast of alternative designs using different meta-heuristics.

Keywords: Building Energy Optimization, Building Energy Estimation, Metaheuristics, BIM, Dynamo

ÖZ

SEZGİSEL ÜSTÜ ALGORİTMALARI KULLANARAK MODEL TABANLI BİNA ENERJİ OPTİMİZASYONU

Altun, Murat

Yüksek Lisans., İnşaat Mühendisliği Bölümü

Tez Yöneticisi: Yrd. Doç. Dr. Aslı Akçamete Güngör

Haziran 2015, 206 sayfa

Enerji verimliliği, enerji kullanım maliyetinin ve onun çevresel yan etkilerinin azaltılmasında önemli bir rol oynamaktadır. Yaşam döngüsü düşüncesi, binanın erken tasarım aşamasında karar vericilerin enerji tasarruflu çözümler geliştirmelerine rehberlik etmektedir; ama, uygulamada kullanılan araçların verimsiz olması ve tasarımda sürekli değişiklere hızlı reksiyon gösteren bir metodolojik yaklaşımdan yoksun olunmasından dolayı enerji analizleri sadece teknik şartnamelerde belirtilen sınırlara göre yapılmaktadır. Çok yönlü ve alternatifli tasarım değerlendirmeleri yapılamamaktadır. Bu çalışmada, sezgisel üstü optimizasyon yöntemleri kullanılarak enerji analizi uygulamalarındaki mevcut sorunların çözümüne yönelik iki enerji optimizasyon yöntemi geliştirilmiştir. İlk yöntemde, pratikte kullanılan TS 825 Türk Yalıtım Standardının zayıf kalan yönleri geliştirilerek birden fazla çok amaçlı problem analizini seri bir şekilde yapabilen, hızlı ve her türlü binaya uygulabilen, esnek bir enerji optimizasyon modeli bir grafik arayüzü kullanılarak EnrOpt adı ile geliştirilmiştir. Esnek bir model oluşturulmasından dolayı üç farklı pozisyon güncelleme yaklaşımları olan Diferansiyel Gelişim, Parçacık Sürüsü Eniyileştirici ve

Geliştirilmiş Çapraz Dağıntı yöntemleri kullanılmıştır. İkinci yöntemde, Dynamo adlı görsel programlama aracılığıyla Yapı Bilgi Modellemesi araçlarıyla bütünleşik çalışan enerji simulasyon programından oluşan bir enerji optimizasyon yöntemi geliştirilmiştir. Bu yöntem, tasarımdaki yapılan sürekli değişimlerin güncellenip enerji analizinin daha etkin yapılmasını sağlarken, bina projesi paydaşları arasında etkili bir iletişim sağlayarak erken tasarım sürecinde karşılaşılabilecek sorunları da ortadan kaldırmaktadır. Enerji optimizasyon modelleri örnek binalarla test edilmiş ve Pareto optimal çözümler elde edilmiştir. EnrOpt arayüz programına etki eden enerji ve optimizasyon yönteminde yer alan parametrelerin parametrik analizi yapılmıştır. Sonuç olarak iklimsel ve geometrik verilerin detaylandırılmasının ve enerji kullanım takvimi geliştirilmesinin bina performans tahmini büyük ölçüde etkilediği görülmektedir. Bu iki model, farklı sezgisel üstü optimizasyon yöntemleri uygulanarak, çok geniş alternatiflerin analiz edilerek farklı bina tiplerine uygulanabilir.

Anahtar Kelimeler: Bina Enerji Optimizasyonu, Bina Enerji Tahmini,Sezgiselüstü Optimizasyon Yöntemleri, Yapı Bilgi Modellemesi, Dynamo

Dedicated to my beloved family…

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TABLE OF CONTENTS

APPENDICES

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ABBRREVIATONS

AAC	Aerated Autoclaved Concrete
ANN	Artificial Neural Network
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BA	Brainstorming Algorithm
BB-BC	Big Bang Big Crunch
BIM	Building Information Modeling
CEM	Cross Entropy Method
CFD	Computational Fluid Dynamics
DE	Differential Evolution
DHW	Domestic Heating Water
EnrOpt	Energy Optimizer
EPS	Expanded Polystyrene
GA	Genetic Algorithm
GBS	Green Building Studio
GSA	Gravitational Search Algorithm
GUI	Graphic User Interface
GW	Glass wool
GWP	Global Warming Potential
HVAC	Heating, Ventilating and Air Conditioning
LPD	Lighting Power Density
LC	Life Cycle
LCC	Life Cycle Cost
LCEI	Life Cycle Environmental Impact
MCEM	Modified Cross Entropy Method
MODE	Multi-objective Differential Evolution

ND	Non-dominated
NPV	Net Present Value
NSGA-II	Non-dominated Sorted Genetic Algorithm
PSO	Particle Swarm Optimizer
PVC	Polyvinyl Chloride
SA	Simulated Annealing
SEOA	Social Emotional Optimization Algorithm
SVM	Support Vector Machine
TS	Turkish Standard
XPS	Extruded Polystyrene
WCA	Water Cycle Algorithm

CHAPTER 1

INTRODUCTION

Energy is essence of human's life. It is consumed continuously as it is required for all aspects of life quality, from the food embodied energy to energy used to produce and utilize the tools that ease human life to vehicles used for our transportation needs. Similarly, energy is also essential for countries' development. It is an indispensable component of economic survival as well as development of countries in many sectors of modern economies. The world energy statistics (2014) support this idea that most of the energy in the world is consumed in the countries with higher level of economic activities or in energy exporting countries that have abundance of energy sources.

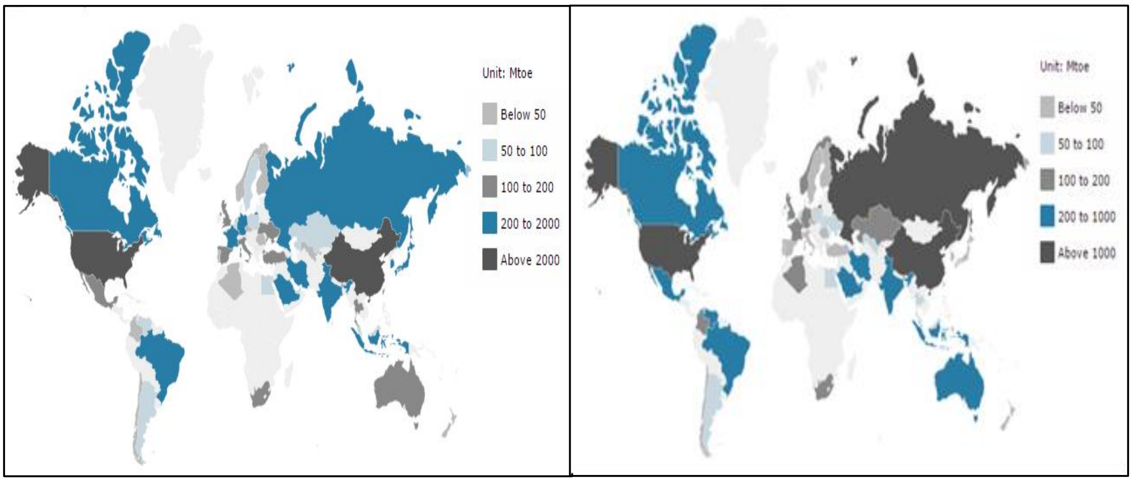


Figure 1.1. World Energy Consumption (a) and Production (b) (Enerdata 2014)

In the last half century, world energy consumption has risen significantly in an exponential trend (see Figure 1.2.a) which has caused significant depletion of non-renewable energy sources such as oil, natural gas, coal and increase in concentration of greenhouse gases in atmosphere that traps radiated heat from Earth surface and causes change in the climate also called global warming potential (GWP) (Panwar et al. 2011). Moreover, energy is a political card used time to time by energy exporting countries to manipulate world politics and persuade other energy importing players with energy reduction threats to take their sides (Cameron 2008). Therefore, energy importers must develop energy strategies to minimize the adverse effect of their energy exports. The simple but efficient strategies are (i) to increase role of domestic energy resources by increasing share of renewable energy with improvement in renewable technologies and (ii) to maximize energy efficiency by developing energy efficient solutions.

Renewable energy resources are alternative domestic resources to reduce share of the imports in the energy demand of a country. Thus, governments, especially developed key players in world politics, give incentives to renewable energy technologies and support Research & Development projects in the renewable technologies to increase renewables' effect on energy demand met. For instance, Germany targets to increase the share of renewable energy in its electricity production by %35 in 2020 and by 80% in 2050 whereas the share of renewables in its total energy consumption is planned to be 18% in 2020, 30% in 2030 and 60% in 2050 (Klaus et al. 2010). Similarly, the role of renewable energy sources such as solar, wind, biomass, and hydropower is forecasted to increase its share in the energy consumption in the following years (Figure 1.2.b) and consequently decrease the greenhouse release by increasing clean energy usage.

The energy statistics are required to be examined in detail to develop energy strategies. In terms of energy consumption, the statistical results point out that energy use is concentrated in three sectors: industry, transportation and buildings (residential and non-residential ones). The buildings are responsible for 40 % of total energy consumption and 30% of CO_2 emission in the world (Shaikh et al. 2014).When building energy consumption is reviewed in detail , it is observed that energy demand on heating and cooling of the buildings seizes the lion's share. The statistics (2008) for European countries indicates that the share of space heating varies from 50% to 70% of total building final energy consumption- the energy supplied to doors of the final consumers as seen in Figure 1.3. Similarly, the space heating and cooling in the buildings consume nearly 70% of the final energy in Turkish residential sector (Turkish Contractors Association 2014).

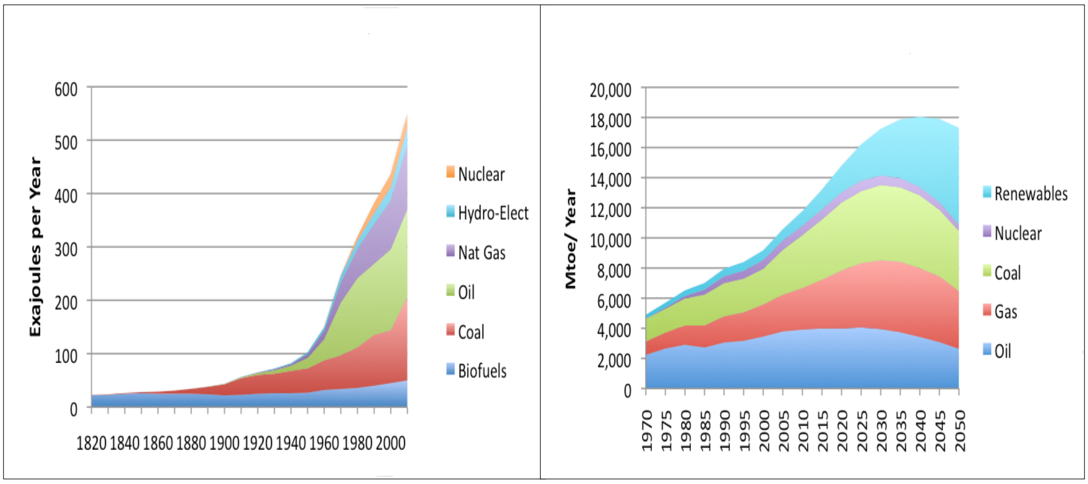


Figure 1.2. World energy consumption (a) in years and (b) forecasted

The exponential increase in the energy demand warns decision makers in energy importing countries to take precautions to control and govern energy demand due to its significant effect on international relations in terms of energy politics and energy security. Therefore, countries should use their energy and economic resources efficiently for both providing energy security and decreasing energy costs. Besides domestic non-renewable resources and renewable potentials, one of the energy efficient strategies is efficient management of potential energy savings. In the building sector, Shaikh et al. (2014) summarizes from different studies that the United States can reduce their building energy consumption up to 20% whereas this value can go up to 30% in European Union and Turkey. In order to provide energy efficiency in the buildings and use building energy savings potential effectively, first, the barriers in front of energy efficient buildings should be analyzed and energy efficient strategies needs to be developed as a solution to remove the barriers. The next section focuses on investigating barriers to energy efficient buildings and discussing efficient energy strategies in the buildings.

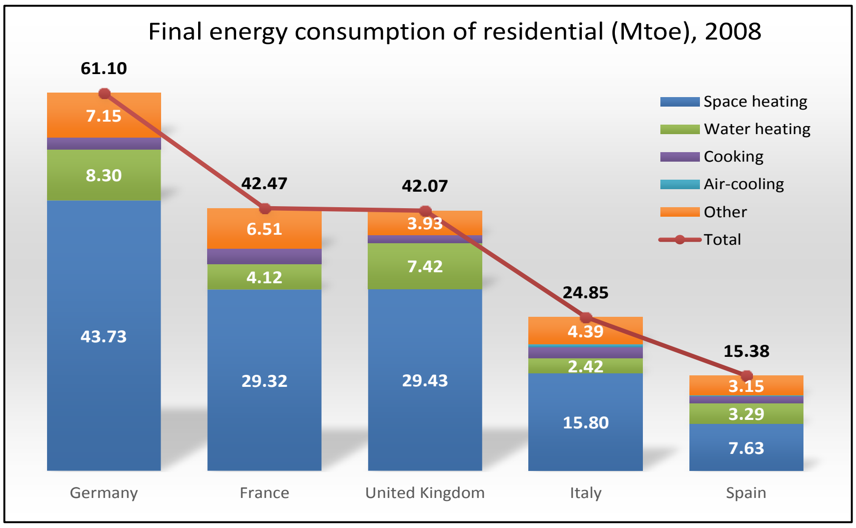


Figure 1.3. Final energy consumption of households (Mtoe), 2008 (Enerdata 2008)

1.1. Energy Efficiency in Buildings

Energy efficiency means using less amount of energy resource while providing the same service. It is one of the fundamental steps to develop sustainable buildings. Energy efficiency increases the value of the buildings by providing energy cost control and improving environmental drawbacks of energy consumption; however, in most building design practices, energy analysis in design phase is neglected or the designer dabbles at energy analysis by only applying legal limits on building energy analysis. Therefore, this insufficient or ignored step in building design process decreases building's whole life cycle value. Moreover, the precautions taken in the next steps of the building life cycle are not as efficient as the ones in the early design process in terms of both energy efficiency and cost-effectiveness as seen in Figure 1.4. The reason for this is that more alternative scenarios can be evaluated in early design process with lower constraints in the projects compared to next steps in the building life cycle.

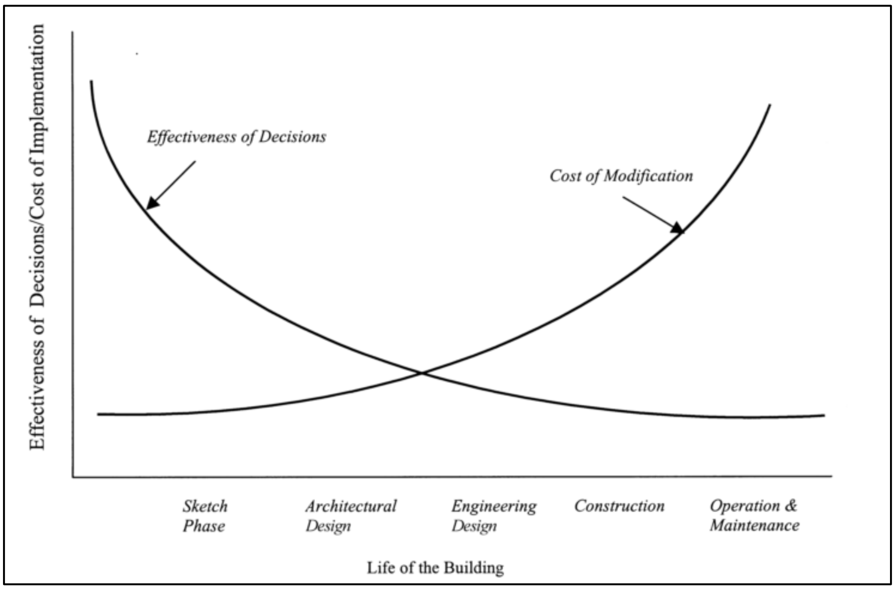


Figure 1.4. Decision cost and its impact during life cycle of building

The reasons for having barriers in front of energy efficient solutions in the building, vary in building design process. The barriers in front of energy efficient buildings are explained in detail below:

- ✓ *Poor scope definition:* Improper or incomplete scope of the project leads to frequent changes in the project. Thus, re-evaluation of all project design in each design change is required which may cause ineffective energy design due to reduction effect on building performance as project progresses. Moreover, energy performance of the buildings is analyzed after all necessary architectural and construction documents are prepared. This process is just followed to show the results of existing project design's energy performance.

Thus, it is resulted in lost opportunity in the evaluation of any other energy based design alternatives. The main reason of this improper process is that traditional CAD-based design and planning tools are not adequate for energy performance evaluation. All stakeholders of the project make their designs in terms of their views and this results in lack of integration in design stage (Cho et al. 2009). Addition to energy analysis prominence negligence, lack of integration in the stakeholders' designs also causes inefficient energy-based design in the buildings.

- ✓ *Lack of life cycle thinking/knowledge*: In traditional view, designer and the contractor generally focus on minimization of initial investment of building design and construction by providing all necessary design and construction details explained in the technical specifications of the building project. However, minimizing initial investment of the project does not add value to the building as higher operational energy costs exist which increase building life cycle costs and decrease its long-term cost-effectiveness. Therefore, building whole life cycle cost from early design stage to demolition of the building should be evaluated in determination of design details.

- ✓ *Lack of Legal Sanction or Incentives:* In building design and construction practice, legal sanctions on energy efficiency enforce the designer and the contractor to produce energy efficient solutions in practice. Otherwise, gaps or recommendations in the mandatory codes, unfortunately, direct the designer or the contractor to develop solutions to minimize initial investment cost with short-term thinking in project profit. Similarly, incentives to energy efficient building are not seen sufficient enough to motivate construction companies to construct energy efficient buildings. Instead, the renowned construction companies construct symbolic energy efficient buildings that can be counted by fingers of the hand, to increase their prestige. However, share of smaller size companies on energy efficient building constructions decreases significantly due to their cost minimization strategy. As the small-size companies dominate construction market, energy efficient practices become rare.

A set of strategies are required to increase energy efficiency in the buildings. The following strategies can be followed to increase the energy efficiency:

- ✓ *Mandatory codes/certificates:* One of the most efficient approaches to increase energy efficiency is the legal obligation for the buildings. Mandatory codes related with energy efficiency should be re-written to increase energy efficiency when it is seen inefficient in practice. Moreover, all necessities related with building energy efficiency should be clarified in the codes by filling all the gaps in the practice. Thus, this both increases the efficiency in the buildings and provides standardization in the practice. In order to reduce inefficiency of the recommendations on energy efficiency, minimum energy efficiency level for whole building, building components or building energy processes/operations should be set. Similarly, building certification programs such as LEEDS, BREEAMS or Energy Star or equivalent country indigenous certification programs may be used as mandatory programs to provide both energy efficient and sustainable solution and increase the minimum energy efficiency level in the buildings. For instance, in the United States, LEED certification has become mandatory application in the governmental buildings to incentivize efficiency and sustainability in the building via governmental hand.

- ✓ *Incentives to life cycle thinking:* In general, the aim of a construction project is to complete the project within minimum project cost within pre-determined technical specifications that include mandatory codes; however, incentive programs are required to generate more efficient solutions than the ones limited by mandatory codes. Therefore, the decision makers should prepare incentive programs for short-term period to deal with short-term profit thinking in the construction projects. Green tax reduction to reward building energy efficiency and provision of lending facilities for energy efficient projects and easiness in procedural details of building registers of certificated buildings and prestigious opportunity value addition on the building sales of certification motivate the construction sector in short-term period. Moreover, educational programs for life-cycle thinking increase the awareness in the society and long-term cost effectiveness in the buildings provide an increase in the building sale prices.

- ✓ *Incentives to renewable energy technologies:* The rising awareness in global warming potential and depletion of non-renewable energy resources due to high level of energy consumption and forecasted trend in energy demand increase, directs the governments or social organizations to find alternatives to reduce greenhouse gas emission and energy depletion. The renewable energy resources are alternatives to reduce undesired effect of the non-renewable ones; however, the resources cannot compete with traditional energy resource in terms of cost. Therefore, the renewable sources must be incentivized by the governments to compete with the non-renewable ones. Carbon green taxes for the non-renewable energy usage or subsidy for renewable resources can be a solution to enable fair competition between alternatives. Moreover, the disadvantages of renewable resources and technologies such as higher initial cost in solar energy, 40% efficiency of solar panels, discrete energy/electric production in wind and solar energy due to permanent change in wind speed or low wind speed, day and night effect on solar energy performance, social and economic adverse effect of small hydropower plants, and wide installation area requirement to produce in high amount energy of solar energy must be considered as trade-off parameters on the strategic decision making process on energy resources. The efficiency based parameter is expected to be improved in near future; however, the problems due to nature of renewable sources need to be considered as a constant parameter. Therefore, greenhouse and cost effect of renewable sources should trade-off with their adverse effect. Moreover, during economic crises such as in 2008, the incentives for renewable technologies are decreased as seen in Germany. On the other hand, renewable energy usage decreases foreign-source dependency in a considerable amount.

- ✓ *Building energy control system:* Building energy control system provides measurement of energy consumption of whole building system or different components of the buildings and analyzes energy performance of each component to re-design building components or reuse the results of the analysis in equivalent buildings. Using smart building applications such as building management systems, instantaneous energy consumption in the building components can be control by adjusting the performance of the required tools to environmental conditions. For instance, redundant lightening can be controlled by sensors or thermostatic setting in building can be automated to specific temperature controls. Moreover, direction/angle of the solar panel in the building is changed according to solar radiation to get higher energy from the Sun (Karagol 2013).

- ✓ *Wieldy energy analysis process:* Energy estimation tools should be easy to use and applied to building energy performance. The response of the tools for design changes should be effective in terms of time and accuracy to update energy analysis.

1.2. Building Energy Performance Estimation

In building energy based design, accurate energy performance simulation for the building guides decision makers to develop energy efficient solutions in design stage. Various energy estimation tools or methods have been proposed to predict amount of energy required to meet building needs for a specific time period. The performance of energy estimation tools varies based on their methodologies. Energy estimation methods used in the literature are explained in detail in Chapter 2.

Building energy performance, in general, can be estimated by engineering calculations or measured by using special devices or methods. In calculation based energy analysis, the accuracy of building performance estimation depends on details available for energy model. As the building is modeled in more detail building performance analysis get more realistic, however simulation time of the building analysis increases exponentially. On the other hand, measurement based energy estimation require huge amount of energy usage data. As details in measured data increase or energy measurement interval gets smaller, cost of measurement increases in an incremental order. Therefore, in energy estimation, decision makers consider trade-off between estimation cost, energy estimation accuracy, and simulation run time.

Measured data are only available for existing buildings. Therefore, it is expected to be evaluated in retrofit projects. On the other hand, measured data in similar environmental conditions and building envelop can be used as a reference in the evaluation of newly designed buildings. In general practice, engineering calculations are more appropriate to estimate building performance in early design stage if measured data with similar conditions does not exist or is not reliable.

1.3. Building Information Modeling (BIM) and BIM Integrated Energy Analysis

Building Information Modeling (BIM) is data-enriched parametric representation of physical and functional characteristic of a facility that provides shared information for its life-cycle to be exchanged between the stakeholders (Eastman et al. 2011). BIM can also be used as communication and coordination tool to solve possible disputes encountered in construction process between stakeholders (Krygiel and Nies, 2008). The model can be used as main communicator in the evaluation of building performance criteria from different perspectives such as esthetics, structural reliability, and energy performance in an integrated model. The model provides design alternatives and tests the performance of the design solution for each performance criteria.

Building information modeling helps to analyze energy performance of the buildings with integration of simulation tools. The building is modeled virtually in BIM tool, then, energy model is exported into dynamic simulation tool as input file, and the performance of the energy model is estimated by energy simulation tool by adding default tool specific information. In the second approach, the performance of the building model can be tested through an add-in energy simulation tool in BIM environment such as Green Building Studio. Moreover, visual programming tools such as Dynamo can be used to change building element properties and automate building energy performance analysis in BIM tool via GBS.

Dynamo integrated BIM tool is appropriate to evaluate multiple design alternatives in automation. In BIM integrated dynamic simulation energy analysis, the exported energy model needs to be updated by changing building elements manually to get accurate results. Whenever, energy model is exported once all design alternatives are determined in dynamic simulation tools, the dynamic model cannot inherit parametric relationship between building elements and prone to errors in energy model. On the other hand, in Dynamo based BIM tool integrated analysis, alternatives are applied to building model and associated energy performances are tested. At each design update, building model and energy model are updated by model in Dynamo. The automated building energy analysis in Dynamo overcomes disadvantages of two alternative approaches mentioned above. However, there is no commercially available or fully developed Dynamo based BIM energy optimization method to best of all knowledge.

1.4. Building Life Cycle Energy Optimization

In early design stage of the building projects, effective energy based design of the building both provides cost-effective solution and also reduces environmental adverse effect of higher energy use in building operational process. However, to make the design effective, all stages of the building life cycle needs to be evaluated. For instance, minimization of wall insulation thickness decreases initial investment on the building whereas in the building operational process, high amount of energy is required for cooling and heating the building. Therefore, decision makers evaluate the trade-off between initial investment for wall insulation and extra energy cost due to reduction in insulation thickness, to minimize total cost of the energy based design. Moreover, inadequate insulation design in early design stage will require retrofits in building operational period to increase building energy efficiency and reduce existing life cycle energy cost of the building. However, decision making process by taking permits from all residents may take long time for insulation retrofits in multi-family dwellings. Therefore, early decision making improves performance and value of the buildings.

In early design stage, decision makers want energy analyst to calculate life cycle energy performance of multiple alternative design solutions and evaluate all alternatives to select most appropriate design combination in building construction process. If number of design alternatives can be counted by fingers of the hands, energy analyst can run each design alternative and reports the results to decision maker; however, a great many design alternatives may not be solved one by one. In such conditions, optimization techniques are applied to test the energy performance of multiple design alternatives.

Building energy performance can be optimized on single objective criterion to find optimum design combination or evaluated according to multiple objective criteria by generating multiple Pareto optimal design alternatives depending on decision makers' expectations.

1.5. Motivation of the Study

Researchers have been working on improving building energy estimation accuracy and optimizing building energy performance to maximize energy based cost savings and minimize environmental adverse effects. However, in real life, energy performance of existing building stocks are questionable due to inefficient design limits in previous thermal standards. In newer versions of thermal standards, more energy efficient design limits are set to provide improvement in building heat losses. Therefore, retrofit projects have been implemented to improve existing building performance, especially in developed countries. On the other hand, in Turkey, Turkish Contractors Association (2014) indicates that only 15 % of existing building stocks meets the minimum energy efficiency level in Turkish insulation standard TS 825, "Thermal insulation requirements for buildings" standard which regards insulation as an energy efficient solution. Therefore, Grand National Assembly of Turkey legislated for a law called "Law 5627 Energy Efficiency" to increase insulated dwelling stock with incentives and penalties. The Law forces residents to get energy ID card for the buildings which will be used for calculating the tax rates for the buildings and could provide advantages and prestige for energy efficient solutions. Moreover, significant number of existing buildings are planned to be renewed by urban renewal projects. During renewal projects and in new constructions, development of energy efficient solutions in early design stage of the buildings provide significant improvement in energy cost, resource use and environmental adverse effects.

In the first part of this thesis, a flexible energy optimization framework is constructed to optimize building life cycle energy performance according to multiple objective combinations analyzed within a reasonable time. The aim is to provide enriched energy data analysis for decision maker to evaluate more design alternatives in a broader perspective. Thermal insulation standard TS 825 is modified to overcome its weaknesses that are explained in literature for achieving more accurate energy estimation. This rapid comprehensive energy optimization analysis can be applied to practical real life problems through a user-friendly interface.

In the second part of the thesis, energy optimization model is constructed on a visual programming tool to automate BIM integrated optimization process by adjusting design to changes fast and efficiently aiming to provide effective communication between stakeholders. The visual programming tools offer built-in nodes and custom nodes for non-programmers to construct the model easily.

1.6. Research Questions

This thesis is based on finding solutions to answer following research questions:

- ✓ How do climate data parameters change building energy performance estimation? Which parameters should be updated to obtain more accurate simulation results in TS 825 standard methodology?

- ✓ How do design alternatives influence building performance results? How can the building be designed to optimize building energy performance?

- ✓ How can life cycle approach be applied in energy optimization model? Which parameters make trade-off in life cycle analysis?

- ✓ How can a flexible energy optimization model be constructed to optimize energy performance of the building in multi-objective perspective such as cost, environmental effects, and payback period?

- ✓ How are BIM tools integrated into energy optimization model to provide effective communication?

- ✓ What are differences in energy optimization applications between steady state energy estimation and BIM-based energy simulation?

1.7. Research Goals/Objectives

The objective of this thesis is to develop a flexible and wieldy case-free framework called Energy Optimizer (EnrOpt) to optimize single or multi-objective building life cycle energy performance according to life cycle cost savings, life cycle environmental improvements and payback periods by using meta-heuristic optimization techniques to contribute the literature.

Another objective of this thesis is to propose visual programming based BIM integrated multi-objective building energy optimization framework to simulate building operational life cycle energy performance in the model and make efficient decisions in early design stage with respect to simulated models. Finally, energy estimation methodology and energy optimization models of the steady state methods based energy estimation and dynamic simulation based energy estimation are compared with each other according to EnrOpt and Dynamo based BIM integrated energy analysis.

1.8. Scope of the Study

In this thesis, thesis chapters are organized as follows:

Chapter 1 introduces problems in energy optimization, motivation of the study and objectives of this thesis.

Chapter 2 presents literature review on energy estimation methods and optimization applications on building energy performance. In this chapter, methodology of each energy estimation method is explained in detail with previous studies to discuss which energy estimation method can be applied to different case studies. The optimization techniques applied to building energy estimation studies are introduced and categorized.

Chapter 3 explains energy estimation methods used in the energy optimization models. Details of TS 825 standard and Green Building Studio are introduced.

Chapter 4 introduces single and multi-objective optimization. The reasons for applying meta-heuristic optimization techniques on optimization problems are explained. The meta-heuristic algorithms Differential Evolution, Particle Swarm Optimizer, and Modified Cross Entropy Method are introduced and how the meta-heuristic algorithms are applied to energy optimization model is discussed.

Chapter 5 presents energy optimization models: EnrOpt and Dynamo based BIM integrated life cycle energy optimization frameworks. The modifications in energy models and assumptions in energy optimization model in EnrOpt are explained with detailed design alternatives in optimization procedure. The implementation process of the interface is explained with design variables and optimization objectives. In the second part of Chapter 5, how Dynamo based BIM integrated life cycle energy optimization model is implemented is discussed. The details of the case studies for each energy optimization model are explained.

Chapter 6 presents energy performance results of the case studies. Parametric analysis results of both energy models and optimization models are reported and discussed separately. Lastly, the energy optimization methodologies in the two energy optimization models applied are compared and evaluated.

Chapter 7, finally, concludes major research findings and discusses the limitations of the study and explains possible future research studies.

CHAPTER 2

LITERATURE REVIEW

In this chapter, energy estimation methods in the literature are introduced. Design alternatives and objectives in multi-objective building energy optimization studies are investigated. Optimization techniques used in these studies are presented.

2.1. Building Energy Estimation Methods

Building energy performance estimation plays a key role to get accurate energy performance results for proposing energy-efficient solutions in the buildings. Researchers have been working on energy estimation methods for the last fifty years. In the literature, energy estimation techniques are categorized in various ways.

ASHRAE Handbook (2009) classified the methods into two approaches as forward approach and inverse approach. In forward approach, design alternatives are entered as inputs to mathematical expression that describes physical behavior of building system and output of the mathematical expression indicates building energy performance. Whereas in data-driven approach, design alternatives are known and building energy performance is measured; however, mathematical relationship between design alternatives and performance results are unknown. Data-driven approach develops mathematical description to estimate building performance according to different design alternatives.

Pedersen (2007) divided load and energy predictions into three groups such as statistical approaches/regression analyses, energy simulation programs and intelligent computer systems. Statistical approaches use measured hourly energy consumption data as output of building energy estimation system whereas design parameters are set as input to maximize mathematical correlation between design alternatives and energy consumption by linear and multi-variate regression analysis. The correlation quality between design parameters and measured energy data indicates whether the regression analysis is accurate enough in building energy predictions. Energy simulation programs model and simulate all building energy models in two different calculation approaches such as response function method and numerical method. Response function method calculates building energy performance with respect to time invariant linear differential equations whereas numerical methods include time variance in the calculation where the model gets more complex and realistic by simultaneous equation solving. Lastly, intelligent computer systems such Artificial Neural Network interpret mathematical expression intrusively between given input and output data such as climate and energy performance data and testify the performance of the constructed model by training data among inputs and outputs.

Foucquier et al. (2013) categorized energy estimation methods into three approaches such as white box, black box and green box approaches. White box approach, also called physical model, constructs building energy model and solves thermal behavior equations in the model according to design parameters to estimate building energy performance. Thermal building behavior is simulated according to three different approaches such as Computational Fluid Dynamics (CFD), zonal approach and nodal approach. CFD decomposes a building zone into numerous control volumes and thermal transfers in the building zone are modeled in detail whereas zonal and nodal approaches simplify the building zone details compared to CFD. In black box approach, statistical approaches and intelligent computer systems in Pedersen (2007) study are combined. ANN, SVR, GA and linear multi-variate regression analysis interpret design data and energy performance data to construct a model to estimate alternative design performance. Genetic Algorithm is proposed as complimentary technique for machine learning techniques to optimize ANN and SVR analysis parameters for minimizing difference between measured energy data and modeled energy data. Grey box approaches integrate white and black box approaches in building performance estimation.

Wang, Yan, and Xiao (2012) quantified existing building energy use in three approaches such as calculation based energy analysis, measurement based energy analysis and hybrid approach. Building energy performance of the building is formulized in a mathematical expression according to its relation with external environment and internal heat loads in calculation based energy analysis whereas previous measurements in different buildings are used to estimate energy performance of the similar type of the building in equivalent environment in measurement based energy analysis.

Wang, Yan, and Xiao (2012) divided calculation based energy analysis in two main parts as steady state and dynamic energy analysis. Steady state energy analysis simplifies building operations by assuming all properties and variables in building energy model constant for each calculation period condition by ignoring building and HVAC system dynamics whereas dynamic simulation models show continuous time dependent building operation and variation in a system. Quasi-steady state models combine simple part of dynamic model into steady state model by adding transient effect due to weather conditions and internal environment of the buildings.

Typical steady state models are degree-day method, bin method and equivalent full load methods. The details of steady state methods are as follows:

Degree-day method is single-measure steady state method developed to calculate heating energy demand of buildings (Al-Homoud 2001). Except outdoor dry bulb temperature and design heat loss, heating equipment efficiency, all other effects are ignored in the method. Heating degree-day and cooling degree-day values for the building are calculated according to given internal thermostat temperature and outdoor temperature difference. The annual or monthly average temperature data are used in the calculation by assuming continuous heating in that period. The method is modified by adding correction coefficient to decrease the difference between method results and actual building performance. Moreover, variable-base degree-day method is improved from fix-base degree-day method considering temperature balance of the buildings by adding interior heat gains and solar gains in the calculation in addition to degree-day methodology in the balanced temperature calculation.

Bin method, temperature frequency, is also single measure steady state method developed to improve building energy estimation to calculate heating and cooling energy consumption of the buildings where the degree-day method is insufficient. In bin method, day is divided into pre-determined intervals and average temperature values for those periods are considered in calculation. Occupied and unoccupied conditions are also considered in the internal gain calculation procedure which makes the method more accurate than degree-day method. In modified bin method, instead of peak loads, diversified load profile characterized by average solar and internal gain profile is used.

Equivalent full-load hour method, is a single–measure method to calculate approximated annual energy requirement especially for cooling session. It calculates number of hours an air-conditioner works at full load with equal energy consumption. It is generally used to get a rough energy use estimate.

Dynamic energy models simulate energy consumption in detail by dividing time interval into small pieces with hourly or sub-hourly data. Dynamic changes in building energy loads and building system due to the external weather and response of plant used as energy converter to meet energy requirement of the building are reflected to analysis simultaneously. The simulation tools for energy analysis are generally based on three modeling such as load model, system model, and plant model. The load model analyzes thermal behavior of all building system including building envelope, internal heat loads, and infiltration to determine heat requirement to the building system. The system model calculates thermodynamic effects of air-side system such as air handling equipment, fans and terminal units, and system needs on HVAC plant. Lastly, plant model analyzes building loads and energy converters to balance energy requirement into system. Commonly, these three models are linked to another one in a sequence in the order of building load calculation, system modeling, and plant analysis. The load analysis is generally based on two approaches such as weighted factor method and heat balance method. In weigh factor approach, the weight factor that is used for convective heat gains of building components over whole building heat gains is pre-calculated before energy simulation according to material properties of building components. On the other hand, heat balance method calculates instantaneous building loads based on heat balance for each zone based on conductive, convective, and radiative heat flux in building zone.

Energy calculations in dynamic simulation models are based on simulation programs. Input parameters in simulation programs can be entered directly or exported from BIM tools. In direct simulation programs, all input data and drawings are entered according to nature of simulation program whereas in BIM-based programs, the building is modeled via any BIM software such as Revit and ArchiCAD. Then, the output of BIM software is converted to input data for simulation programs and missing parts of building energy model is filled by the user and then the simulation runs.

Energy simulation programs vary depending on details in the modeling and differences of country–specific approaches. Nguyen, Reiter, and Rigo (2014) investigated utilization intensity of building simulation programs in the literature in Scopus engine for the years of 2000-2013. The results indicate that the most commonly used simulation programs in optimization studies are Energy-Plus, TRNSYS, DOE-2. The detailed information about these simulation programs are presented below:

DOE-2 is a powerful and widely used to predict energy performance of different types of buildings. Building layout, constructions, scheduling details, HVAC and lightening details and utility rate are entered as inputs and by using weather data through an hourly simulation it calculates utility bills and energy use. It uses weighting factor method to calculate energy loads between spaces and zonal approach in thermal simulation by simplifications. VisualDOE, eQUEST and PowerDOE, are examples of DOE-2 based simulation tools. Moreover, Green Building Studio integrated with Revit BIM tool uses DOE-2.2 in energy performance calculations.

EnergyPlus is a new generation simulation engine that uses basic structures of DOE-2 in the simulation whereas heat balance method is used to calculate thermal loads. It can be applied to various complicated buildings with its advance futures. It provides flexibility in the design of HVAC system controls; however, its interface is not user friendly enough for direct design; therefore, the buildings are modeled in third party tools and exported as input file into simulation engine.

TRNSYS is a simulation program to perform thermal behavior of transient systems. It is commonly applied to solar systems, low energy buildings and HVAC systems, renewable energy systems, cogeneration and fuel cells. TRNSYS divides each simulation stakeholders into components and manage and integrates all the process with calculation platform for simulation. Compared to EnergyPlus and DOE-2, thermal load calculations are simpler whereas HVAC design is more advanced.

Measurement based energy analysis is founded on energy performance estimation according to measured energy data. This type of energy estimation is effective to forecast energy consumption of the existing building using its previous energy performance. Moreover, measurement based energy calculation can be applied to new buildings by using similar environmental conditions and building properties; however, extensive energy database for the buildings and their environment is required to get accurate results. This process may require higher initial investment and it is labor-intense while achieving accurate estimation. Therefore, it would be effective for governmental organizations to use an extensive database including all country's energy efficiency data. On the other hand, for private sector and residents, it is cost-inefficient and labor-intensive. Therefore, in new building designs, calculation based energy estimation is more preferable. Energy estimation of existing building can be forecasted by using its previous energy bills and this would be much more cost effective. Alternatively, special equipment can be used for all building components to monitor their energy use, which is expected to be expensive but gives more accurate result. Therefore, the decision maker should consider the trade-off between opportunity of energy estimation accuracy and cost of energy estimation method.

Wang (2012) categorized measurement based energy estimation into two main parts such as energy bill disaggregating and monitoring based energy estimation. Energy bill disaggregating is a methodology that portions out total energy consumption in the bill into end-use equipment or systems. This method provides cost-effective and time efficient solution; however, the accuracy of energy consumption distribution on appliances is questionable. On the other hand, energy consumption in each appliance and system can be controlled by metering. Monitoring based energy estimation gives more accurate energy results; however, it is expensive for residential buildings (Wang et al. 2012).

Hybrid energy estimation models combine measured data with calculation based energy analysis. Wang, Yan, and Xiao buildings (2012) classify hybrid approaches as calibrated simulation and dynamic inverse models.

Calibration simulation models try to minimize difference between simulated energy estimation and measured data by changing details of the input parameters for simulation programs. The simulated energy results direct decision maker to change details of input parameters. Moreover, effect of each design parameters as inputs in simulation programs can be measured easily by comparing simulated energy performance with measured data in the rank of design parameters.

Dynamic inverse modeling is another hybrid energy estimation technique where a model is constructed by using training data that come from building measurements to determine the relationship between inputs such as equipment or any design parameters, process like building load calculation and energy use as output. The modeling covers dynamic effects of thermal mass to get more accurate calculation; however, the relationship between system stakeholders is complex and the method requires more detailed measurements to get more accurate results. One of the examples of dynamic modeling is Artificial Neural Network that is constructed between input parameters such as weather conditions, HVAC system, building properties and output parameter such as energy use of the building. Some of these data are used to construct relationship between measured data and input parameters as training data whereas the others are used to control the accuracy of the results by comparing the results of the model with measured data. The model constructs the relationship by using its modeling approach and the results are compared with the measured ones to determine its accuracy level for deciding whether to detail the input parameters more or not. If reasonable results can be held, the energy estimation of other new or existing buildings can be done via the model.

2.2. Multi-objective Optimization in Building Energy Performance Analysis

Optimization aims at improving building energy performance by changing design alternatives according to pre-defined calculation methodology in a reasonable run time. Details of building design, number of alternative design solutions and run time of energy model determine the limits of the optimization process. Therefore, in energy optimization models, trade-off between energy model accuracy and its run time are required to generate optimization process in a right way. Among energy estimation methodologies, Foucquier et al. (2013) explained that CFD is most comprehensive method to estimate thermal performance of the building in a most accurate way; however, single analysis of the building with CFD takes multiple minutes. Therefore, time-consuming simulation decreases the efficiency of all process. Due to this reason, multiple simulation tools used in literature such as EnergyPlus and TRNSYS use zonal approach which is the simplest version of CFD approach. On the other hand, since the real energy model is simplified more, the accuracy of energy estimation gets more questionable.

Multi-objective optimization process generates solutions to provide extensive enriched data for decision makers to take a decision on building early design stage or in retrofit projects. Basically, performance of alternative designs is evaluated according to decision maker's expectations. If decision maker pre-determines importance of each design objectives clearly before optimization process, all objectives can be combined together to find the optimum design solution according to decision maker's expectation. Conversely, in post-decision making process, optimization method generates alternative solution sets which cannot dominate each other in at least one of the alternative evaluation methodologies. Therefore, all of design alternatives are candidates of optimum design depending on decision making process.

In multi-objective optimization problems, researchers evaluate building energy performance by generating alternatives solutions that considers trade-off between objectives in the studies as tabulated in Table 2.1. General focus on energy optimization studies are based on investment on better design alternatives to minimize building energy use and cost. On the other hand, lightening and thermal comfort in the building are evaluated with building energy use and initial investment cost to generate alternative design approaches in decision making process. Moreover, life cycle awareness has increased in latest optimization studies whereas life cycle cost and environmental impact has a trade-off with initial investment. Life-cycle thinking approach provides significant decrease in life cycle emissions and other environmental adverse effects with a huge amount of energy cost savings. Furthermore, studies compare life cycle performance of the building and initial investment by minimizing payback period of initial investment with a trade-off between annual energy reduction with initial investment.

In multi-objective studies, building performance is tested by changing design parameters in energy models. Design variables in optimization studies in the literature are summarized in Table 2.2. In general view of the literature, optimization process presents heat loss reduction solutions with passive energy efficient approaches. The basic solution approach in energy optimization studies is changing insulation materials and their thicknesses to minimize heat loss in different building components. Secondly, window systems with different geometry and glazing properties present heat-loss reduction solutions. In some of the studies, HVAC system of the buildings are re-designed to improve building performance whereas interventions in appliances are used to minimize energy and electric usage. In some of the studies, solar collectors are added as renewable design alternatives to improve domestic heat water performance of the building. Additionally, in some cases, occupancy of people and equipment are evaluated in building energy performance estimation.

In building energy optimization literature, nonlinear and mixed integer linear programming (Karmellos et al. 2015b; Aria & Akbari 2014; Antipova et al. 2014) are modeled to optimize building performance. Tchebycheff distance as efficient multi-objective approach are one of the commonly used solutions in the literature (E. Asadi et al. 2012a, 2012b; Diakaki, Grigoroudis, and Kolokotsa 2013; Diakaki et al. 2010). Meta-heuristic optimization techniques are in trends in building energy optimization. Different versions of Genetic Algorithm are the mostly presented optimization techniques (Asadi et al. 2014; Boithias et al. 2012; Yang et al. 2014; Oh et al. 2011; Asadi et al. 2013; Yu et al. 2015a; Penna et al. 2014). Moreover, Harmony Search (Asadi 2014; Fesanghary et al. 2012), Ant Colony Optimization (Yuan et al. 2010; Asadi et al. 2012), Differential Evolution (Wang et al. 2014) and Particle Swarm Optimizer (Liu et al. 2015; Karaguzel et al. 2014) are studied in literature.

Table 2.1. Objectives in Multi-objective Studies in Literature

Study	Energy Cost	Energy Use	Initial Investment	LCC	LCEI	Energy Payback Period	Thermal Comfort	Lightening
Antipova et al. (2014)				+	+			
Aria & Akbari (2014)	+	+						
Asadi et al.(2012)	+		+				+	
Asadi et al. (2012)	+		+					
Asadi et al.(2014)	+		+				+	
Asadi (2014)				+	+			
Ascione et al.(2014)		+					+	
Asl et al. (2014)		+						+
Asl & Zarrinmehr (2013)	+							+
Boithias et al. (2012)		+					+	
Chen & Gao (2011)		+	+					
Diakaki et al.(2008)		+	+					
Diakaki et al.(2010)	+	+	+					
Diakaki et al.(2013)		+	+					

Table 2.1. Objectives in Multi-objective Studies in Literature (continued)

Study	Energy Cost	Energy Use	Initial Investment	LCC	LCEI	Energy Payback Period	Thermal Comfort	Lightening
Eisenhower et al.(2012)		+					+	
Fesanghary et al. (2012)				+	+			
Futrell et al.(2015)		+						+
Karaguzel et al. (2014)				+				
Karmellos et al.(2015a)		+	+					
Liu et al. (2015)				+	+			
Malatji et al. (2013)	+					+		
Oh et al. (2011)		+					+	
Penna et al.(2014)		+		+			+	
Salminen & Palonen (2012)	+		+					
Sisman et al.(2007)	+		+			+		
Wang et al.(2014)		+		+		+		
Welle et al. (2011)								
Wu et al. (2014)		+	+			+		

Table 2.2. Design Variables in Multi-objective Studies in Literature

Study	Window	Insulation	Renewables	Occupancy	HVAC	Orientation	DHW	Shades	Lightening
Antipova et al. (2014)	+	+	+						
Aria & Akbari (2014)	+	+		+	+				+
Asadi et al.(2012)	+	+	+						
Asadi et al. (2012)	+	+	+						
Asadi et al.(2014)	+	+	+	+					
Asadi (2014)	+	+							
Ascione et al.(2014)	+	+			+				
Asl et al. (2014)	+								
Asl & Zarrinmehr (2013)	+								
Boithias et al. (2012)	+			+	+				
Chen & Gao (2011)	+					+			
Diakaki et al.(2008)	+	+							
Diakaki et al.(2010)	+	+			+		+		
Diakaki et al.(2013)	+	+			+		+		
Eisenhower et al.(2012)					+		+		

Table 2.2. Design Variables in Multi-objective Studies in Literature

Study	Window	Insulation	Renewables	Occupancy	HVAC	Orientation	DHW	Shades	Lightening	Intervention
Fesanghary et al. (2012)	+	+								
Futrell et al.(2015)	+							+		
Karaguzel et al. (2014)	+	+								
Karmellos et al.(2015a)	+	+			+		+		+	
Liu et al. (2015)	+	+					+			
Malatji et al. (2013)					+				+	
Oh et al. (2011)	+									
Penna et al.(2014)	+	+			+					
Salminen & Palonen (2012)	+	+			+				+	
Sisman et al.(2007)		+								
Wang et al.(2014)					+				+	+

In literature, both forward approach to estimate building performance directly and black box approaches that predict the relations between design parameters and building performance in minimum variance with measured energy consumption have been studied. The simplest version of the forward optimization approach is building energy load minimization (Diakaki et al. 2008). In degree-day steady state method, building energy use is calculated by adding climate data and energy efficiency of heating/cooling systems (Diakaki et al. 2010; Futrell et al. 2015; Murray et al. 2014; Asadi et al. 2014). Besides steady state methods, building is modeled in more complexity in dynamic simulation models. In literature, EnergyPlus (Oh et al. 2011; Ascione et al. 2014; Asadi 2014; Fesanghary et al. 2012; Griego et al. 2012; Karaguzel et al. 2014; Futrell et al. 2015) and TRNSYS (Antipova et al. 2014; Asadi et al. 2012; Penna et al. 2014) are most commonly used simulation tools. In black box approach studies, design parameters and measured consumption data are used to construct engineering models to evaluate different design alternatives by using ANN (Boithias et al. 2012). Moreover, machine learning techniques such as ANN (Yu et al. 2015b; Futrell et al. 2015; Asadi et al. 2014) and SVR (Eisenhower et al. 2012) are used to simulate optimization process of dynamic simulation models to accelerate optimization run time. Complex energy models are simulated in dynamic simulation tools more than one minutes and detailed parameter design process requires reasonable number of function evaluations such as at least 5000 to obtain stimulating data for decision maker. Therefore, in a proper optimization process, the model runs in 3.5 days. In the literature studies, 3.5 days may be tolerated for once; however, in real life energy analysis, it is practically inapplicable. Therefore, machine learning tools are used to reduce all simulation time down to one or two hours by reducing difference between simulated energy analysis results and tested model results. The black box model is constructed according to pre-determined number of data and optimization algorithm is changing parameters in ANN layers. At the end of each update, performance of the constructed model is tested with simulated or measured test data. In literature studies, test data is one-tenth of training data (Magnier & Haghighat 2010; Asadi et al. 2014). After the model is constructed, the forward approach is applied to optimize building performance by using the constructed model as engineering calculation methodology in the model. Although deviation in the constructed model is more than the measured data or simulation data, it provides rapid optimization process in practice.

2.3. BIM Based Multi-objective Optimization in Building Energy Performance Analysis

Building Information Modeling provide integration with energy estimation tools and communicate with all project stakeholders to avoid possible differences in building projects due to inconsistent designs for different disciplines. BIM based energy analysis process provides extensive data exportation from BIM tools to simulation tools where interface of simulation tools is not user friendly enough. In optimization process, BIM tools can be used in three different approaches explained one by one below.

In the first approach, building is modeled in BIM tool and then exported to simulation tool. Simulation tool completes missing data in the exported energy model with its default values. Then, it simulates building performance. In optimization process, design parameters are changed in simulation models and optimized. Oh et al.(2011) studied on BIM-based optimization of a library building. The authors, first, modeled the building in Revit and then exported it into EnergyPlus 6.0 using a proposed Matlab based gbXML-IDF converter file. Performance of the building is optimized by minimizing thermal discomfort and energy consumption using GA by changing window glazing type and cavity gas in EnergyPlus input files. At each iteration, GA writes updated design parameters into EnergyPlus input and EnergyPlus runs simulation and gives objective fitness values. The rest of optimization process continues with respect to GA methodology in Matlab.

In second approach, building is modeled in BIM tool and multiple design alternatives are created by changing some design details of the building model. Performance of each design alternative is tested via energy simulation tool within the BIM environment. After simulating all alternative design models, a black box model is proposed to express implicit mathematical relationship between design alternatives and simulation results. The constructed black box model is used to optimize building performance. Chen and Gao (2011) modelled two-story academic building and exported building model to IES/VE simulation tools for 40 different alternative designs by changing building orientation and window-wall ratio in the building. After obtaining simulation results with heating and cooling details, the authors constructed mathematical model for heating, cooling energy use and initial investment by using simulation results and design alternatives for regression analysis. The regressed model is optimized by Genetic Algorithm in Matlab environment by minimizing energy consumption and initial investment on building.

In first two approaches, BIM tool is just used in the initial building modeling to give input parameters to simulation models; however, in this case, parametric relationship between building elements are ignored and all parameters are updated in simulation models or black box model. Ignorance of parametric property of BIM tool can be prone to geometric update errors. Therefore, in BIM integrated updates, consideration of parametric relations among building elements provides more accurate energy model construction. In BIM integrated optimization models, the building is modeled in BIM tool and exported to simulation tools to calculate building energy performance. Optimization algorithm evaluates simulated building performance values to generate new design. The new design parameters are updated in BIM tools and then exported to simulation tools. This loop continues until termination criteria are satisfied (Asl & Zarrinmehr 2013). Thus, this provides more flexibility to the resulting energy model and increases the accuracy of the model thanks to automated parametric update of all components, which avoids possible errors in manual updates in BIM software and/or updates in simulation tools.

Automation in BIM based energy modeling leads up studies on optimization of BIM-based building performance analysis. In the literature, researchers have worked on multiple BIM tool and simulation program combinations. Asl and Zarrinmehr (2013) developed a plug-in to Revit called Revit to Green Building Optimization (Revit2GBSOpt) that provides automatic link between Revit BIM tool and cloud based simulation program GBS to optimize building energy use and lightening. Asl et al. (2014) studied same problem concept with visual programming tool Dynamo, to update building elements in BIM tools Revit and Vasari, by using Non-dominated Sorting Genetic Algorithm-II (NSGA-II) for minimizing energy use and maximizing suitable day lighting level in the resident. They make use of visual programming that provides a graphical user interface to construct programming relationships without coding, to ease BIM information use for the analysis. Welle et al. (2011) proposed an automated BIM based energy analysis methodology called ThermalOpt to calculate thermal and lightening performance of the buildings in multi-criteria problems. Similarly, Liu et al.(2015) developed BIM integrated Ecotect based optimization framework to optimize life cycle performance of office building in terms of lightening and thermal performance of the building by changing building wall type, window wall ratio, window glazing properties, and external sun shades.

2.3. Discussion of Literature View

After a general look in energy optimization literature, decision maker needs to evaluate different energy optimization methods by evaluating the trade-off between simulation run time, cost-effectiveness of energy optimization model, and accuracy of energy estimation in the model. In real life, cost effective solutions with high accuracy achieved in a reasonable time is looked for. On the other hand, the decision maker may want to evaluate design alternatives in terms of different perspectives such as initial investment, environmental impact, payback period, energy use, life cycle analysis among others. Therefore, flexible and rapid energy optimization model is required to provide extensive data for decision maker in order to evaluate design alternatives in broad perspective. In this study, practically applicable and user-friendly energy optimization methodology is developed based on TS 825 Turkish thermal insulation standard, commonly used in building design practice. However, the performance accuracy of existing TS 825 standard is questionable. Yaman (2009) compared performance of the standard with measured data of campus buildings in Izmir. The results show that TS 825 performance deviates 66% from measured data. In any study, this deviation cannot be tolerated in optimization process. Therefore, energy model is required to be modified by detecting and strengthening the weaknesses of TS 825 model. The previous studies in literature point out the modification requirement for TS 825 methodology. Kürekçi et al. (2012) exchanged the climate temperature data proposed for four degree-day regions by long-term average temperature data for each city. Secondly, Bektas Ekici (2015) explained that solar radiation data in standard deviation are underestimated in the standard. Moreover, Aksoy & Bektas Ekici (2013) changed window geometry to test its performance on energy consumption and it is detected that window geometry also changes building performance; however, in TS 825 standard, average glazing-frame ratio is used for any window geometry. Moreover, campus building study underlines the importance of scheduling for occupancy conditions. However, in TS 825 standard, continuous heating is provided in contrast to real usage conditions. Therefore, these weaknesses of TS 825 methodology are eliminated in the modified energy model used in this study to increase energy estimation accuracy.

Three meta-heuristic optimization techniques with different update strategies are proposed in energy optimization model to provide effective solutions in different case studies whereas the energy optimization framework is constructed for general use instead of case specific solutions.

In the second part of this thesis, visual programming based BIM integrated energy optimization model is constructed to optimize building performance with parametric relations by avoiding possible errors in dynamic simulation models. BIM integrated model provides effective communication and control mechanism to avoid unnecessary and improper design problems encountered in the early design stage.

This thesis contributes steady state energy analysis literature by improving the performance of TS 825 energy estimation methodology. Moreover, the developed flexible energy optimization interface called EnrOpt provides variety in objectives and design variables in optimization process with multiple meta-heuristics developed for multi-objective energy optimization problems with different optimization strategy. In addition, besides Particle Swarm Optimizer and Differential Evolution as commonly used meta-heuristics in previous studies, a newly developed meta-heuristic, Modified Cross Entropy Method, is modified for multi-objective optimization problems as a contribution to literature. Finally, visual programming based BIM integrated energy optimization framework eliminates the difficulties for BIM based automated energy analysis for non-programmers in the previous studies and fills the gap in BIM based life cycle energy optimization for non-programmers by developing Dynamo visual programming based BIM integrated energy optimization framework with efficient optimization strategy in an efficient meta-heuristic algorithm.

CHAPTER 3

ENERGY ESTIMATION

In this chapter, energy estimation methods used in energy optimization model are introduced.

3.1. Energy Estimation by Modified TS 825 Thermal Insulation Standard

In building energy performance improvement process, the most prominent approach to develop efficient solution is to construct building energy model that gives accurate building performance result compared to real life building performance. As the accuracy of the building performance estimation increases, the optimization process gives more accurate and reliable energy efficient solutions. In this study, TS825 Standard "Thermal insulation requirements for buildings" as a commonly used energy estimation method in Turkey is applied for heating energy requirement estimation in buildings. The weaknesses of the building energy model are strengthened in the constructed building energy optimization model to provide more reliable solutions. The details of building energy estimation model are explained in the following paragraphs.

TS825 Standard "Thermal insulation requirements for buildings" is a steady state energy estimation methodology based on degree-day approach used as static energy calculation method. This method is accepted as the main thermal insulation standard for calculation of heating energy requirement of a building in Turkey since 1998. The standard TS 825 is modified two times in 2008 and 2013 to incent more energy efficient buildings with higher insulation levels in order to decrease heat loss in the buildings. The methodology in the standard is based on static and average calculation values. In the standard, climate data, building internal heat gain, solar effects on building heat gain are examples of calculation with static data. The calculation details are explained below:

In building energy performance, climate data plays a key role to calculate level of heating energy requirement and it also shapes the details of TS 825 standard. According to TS 825 standard, Turkey is divided into degree-day regions according to similar climate conditions based on heating degree days and monthly average climate data used in heat loss calculation. According to five degree-day regions figured in Figure 3.1, the level of heat loss is calculated based on difference between monthly average outdoor temperature and building internal balance temperature depending on building types, and construction material properties and thickness values.

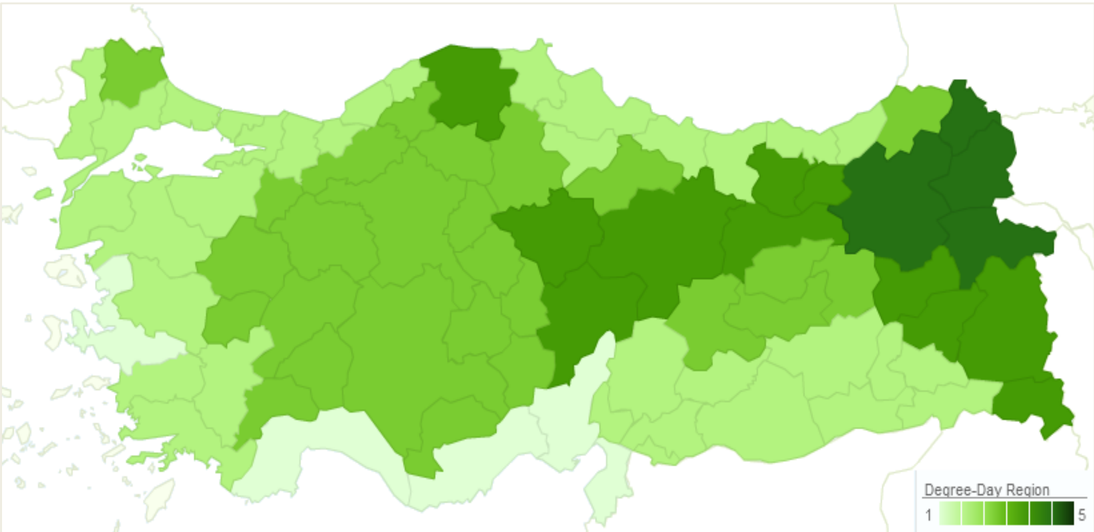


Figure 3.1 Degree-day Regions

In TS 825 standard, annual heating energy requirement (Q_{year}) of a building is calculated by summing up the monthly average energy requirements (Q_m) with respect to given building internal (θ_i) and monthly outdoor ($\theta_{e,m}$) temperature difference, building specific heat loss (H) and heat gains as a result of internal conditions (ϕ_i) and solar effect (ϕ_s).

$$Q_m = [H(\theta_i - \theta_{e,m}) - \eta_m(\phi_{i,m} + \phi_{s,m})]\, t \tag{3.1}$$

$$\eta_m = 1 - e^{\frac{\max(0,\, H(\theta_i - \theta_{e,m})}{\phi_{i,m} + \phi_{s,m}}} \tag{3.2}$$

$$Q_{year} = \sum Q_m \tag{3.3}$$

where η_m represents monthly average utilization factor for gains and t is time in seconds.

Heat Loss in Buildings:

Heat loss in the building caused by convection, transmission and ventilation processes is called specific heat loss. Building specific heat loss is calculated by summing up heat loss by transmission and convection (H_T) and ventilation (H_v) regarding the following formulas:

$$H = H_T + H_V \tag{3.4}$$

$$H_T = \sum AU + IU_I \tag{3.5}$$

$$\mathrm{U}_I = bU_{TB} + \xi \tag{3.6}$$

$$\sum AU = U_{ew}\mathrm{A}_{ew} + U_w\mathrm{A}_w + U_{ed}\mathrm{A}_{ed} + 0.8U_r\mathrm{A}_r + U_f\mathrm{A}_f + 0.5U_b\mathrm{A}_b + 0.5U_{lt}\mathrm{A}_{lt} \tag{3.7}$$

where I and U_{TB} represent length and thermal transmittance of thermal bridge . The heat loss (Equation 3.5) by heat transmission and convection between environments with different temperatures is calculated by multiplication of thermal transmittance and area of the building components with the reduction factor (if exists) given in the Equation 3.7 such as external wall, window, external door, roof, basement, floor connect to external environment and the building component neighbor to lower temperature environment.

Thermal transmittance of any building component is calculated according to following formulas:

$$U = \frac{1}{R_e + \sum_i \frac{d_i}{\lambda_{h,i}} + R_i} \tag{3.8}$$

where d_i and $\lambda_{h,i}$ are thickness and thermal conductivity values of element i of the building component and R represents thermal resistance of the component. Internal and external thermal resistance (R_i , R_e) of the building component are obtained from Table 1 in TS 825 standard.

Heat loss by ventilation is calculated according to ventilation types such as natural and mechanical ventilation. The ventilation discharge rate is calculated in different formulas for the ventilation types. In natural ventilation, heat loss calculation depends on air density (ρ) and specific heat (c), ventilated building volume (V_h) and ventilation rate (n_h) in the building as seen in Equation 3.9-3.10 where V_h and n_h is taken 0.7 in default. On the other hand, in mechanical ventilation, ventilation discharge is calculated in more details such that average ventilation rate in working system (V_f) and additional discharge rate due to air passage (V_x) depending on ventilated volume, air entrance and existing discharge rate (V_S, V_E) and building openings. Moreover, time working rate (β) and heat recovery rate (η_v) of ventilation system changes heat loss by ventilation in mechanical ventilation systems.

$$H_V = \rho \; c \; V' \tag{3.9}$$

$$V'_n = n_h \, V_h \tag{3.10}$$

$$V'_m = V_0 (1-\beta) + \beta \; (V_f (1-\eta_V) + V_x) \tag{3.11}$$

$$V_x = \frac{V_h \; n_{50} \; e}{1 + \frac{f}{e} \left(\frac{V_S - V_E}{V_h \quad n_{50}} \right)} \tag{3.12}$$

where V_0 and n_{50} represent ventilating discharge rate when the ventilation system is non-working and air exchange rate in 50 Pa pressure difference between indoor and outdoor, e and f are constants depends on building openings and location.

Heat Gains in Buildings

Buildings recover some of their heat losses by their internal heat gains and solar heat gains. Internal heat gains covers the gain thanks to human metabolism effect, cooking and lightening and heat released from electronic tools whereas solar radiation on building windows provides heat gain as solar heat gain. Heat gains in the building are calculated as follows:

In the building, the maximum value of internal heat building is accepted five times of building usage area (A_n) in residential buildings and offices and ten times of building usage area in high interior heat gain buildings such as food and textile factories. The building usage area is taken thirty two percent of gross heated volume of the building as default if it is not specifically calculated.

Solar heat gains (ϕ_s) are calculated according to heat gains from direct solar radiance from building windows in the following formula:

$$\phi_{s,m} = \sum_i r_{i,m}\, g_{i,m}\, I_{i,m}\, A_i \tag{3.13}$$

$$\phi_s = \sum \phi_{s,m} \tag{3.14}$$

$$g_{i,m} = 0.8\, g_{\perp} \tag{3.15}$$

where $r_{i,m}$, $g_{i,m}$ and $I_{i,m}$ represent shading factor, solar transmission factor of glazing and, solar radiation on vertical surface direction in direction i in mth month of year, respectively, and, $g_{\perp}$ and A_i are solar transmission factor for the normal incidence and total window area in direction i.

TS 825 standard limits maximum allowable annual heating energy requirement for buildings (Q_{max}) and upper limit of allowable thermal transmittance level (U_u) for different building component given in Table 3.1 to provide energy savings and incite insulation in the buildings. Therefore, in early insulation based building energy design process, both annual energy requirement level and thermal transmittance level for each building component should be checked whether the design exceeds the given upper limits or not. It is not mandatory rule but provides energy savings for the buildings in its life cycle. Therefore, if any of upper limits given in standard is exceeded, the design materials should be replaced with insulation materials that has lower heating conductivity property or insulation thickness of the design materials should be increased.

Table 3.1. Insulation Limits in TS 825

Degree-Day Region	$U_{u,wall}$	$U_{u,floor}$	$U_{u,roof}$	$U_{u,window}$
1	0.66	0.43	0.66	1.80
2	0.57	0.38	0.57	1.80
3	0.40	0.28	0.43	1.80
4	0.38	0.23	0.38	1.80
5	0.36	0.21	0.36	1.80

3.2. Energy Estimation in Green Building Studio

Green Building Studio (GBS) is a standalone cloud-based service to perform building energy simulation and carbon footprint calculation of the buildings modelled in BIM tools. It is interoperable with Autodesk Revit, Autodesk Vasari, ArchiCAD and Google SketchUp for exporting energy models to gbXML format to be used as input in DOE-2 dynamic simulation engine for hourly energy simulation. It provides whole building energy analysis based on building type geometry and envelope properties, using detailed climate data, HVAC system values, lightening amounts, and fuels and electricity as energy resources.

Energy performance of the building model in Revit can be exported to GBS in three ways. In the first one, building energy performance is calculated conceptually by using "Conceptual Mass" approach that gives an idea about building performance. In second approach, energy performance of the building is analysed in detail by using building elements such as walls, windows, roofs and doors to create Energy Analytical Model in order to update the model into GBS via gbXML file. In the last approach, the building model in BIM tool or a third party tool is exported to gbXML and the file is updated to GBS to run energy performance. Before gbXML exporting, volume by area and room computation should be well-defined to take precautions against possible interoperability errors.

Energy settings of the energy model exported into GBS are adjusted according to common practices in construction companies, ASHRAE standards and Commercial Building Energy Consumption Survey results. The general standards used in GBS energy simulation are as follows:

- ✓ Schedules: California Non-residential New Construction Baseline Study 1999
- ✓ Envelope thermal characteristics, Lighting Power Density, HVAC efficiency: ASHRAE 90.1 2007 and ASHRAE 90.2 2007

- ✓ Equipment power density & Domestic Heating Water loads: California 2005 Title 24 Energy Code
- ✓ Occupancy density, ventilation: ASHRAE 62.1-2007

In energy settings, 34 different building types with different equipment power density, lighting power density, outside air flow rate and infiltration rate in multiple operational schedules can be selected with 30-year average climate data where the location of the building can be selected via Google Maps among 1.6 million virtual data station. The weather data includes global horizontal radiation (wh/m^2), the amount of energy striking, the horizontal surface during the hour, direct normal radiation perpendicular to the sun's rays (wh/m^2), diffuse horizontal radiation (wh/m^2), total sky cover, dry bulb temperature (℃), dew point temperature (℃), relative humidity (%), pressure (mb), wind direction (°) and wind speed (m/s).

Building performance is analysed in GBS web service. The results can be followed via GBS web service or BIM tool integrated graphs. Energy and carbon based results in GBS simulation are as follows:

- ✓ Annual energy cost as a summation of different energy resource costs
- ✓ 30-year life cycle energy cost in terms of Net Present Value
- ✓ Annual CO_2 emission based on different energy resources' emission values
- ✓ Annual energy consumption
- ✓ Life cycle energy consumption

All the results given above can be obtained in Dynamo based BIM integrated energy analysis. Therefore, in this study, some of the simulated energy results and their combinations are used as operational energy performance analysis of the building. By adding initial performance parameters such as initial investment cost in building life cycle cost analysis, whole life cycle energy performance of the building will be able to be calculated

CHAPTER 4

OPTIMIZATION APPLICATION

In this chapter, implemented optimization methodology is introduced. Firstly, the procedures in single and multi-objective problems are presented. Next, different approaches in objective relationships in multi-objective problems are explained in detail and then the approach used in this study is presented. Finally, Meta-heuristic techniques applied to multi-objective energy model are discussed.

4.1. Optimization

Optimization is improvement of a process or a product performance. The mathematical process tries to select the best alternative of available alternative sets. In building life cycle from design stage to building demolition, all stages of the building life cycle offer improvements in building performance for the building occupants. In early design stage, for instance, size of building structural components is optimized to minimize structural cost or weight (Hasançebi et al. 2013). In construction process, resource constrained building construction project schedule is optimized to use resources effectively within given budget and time limitation to avoid from delay penalties (Bettemir & Sonmez 2012). On the other hand, some optimization problems such as building energy optimization take all life cycle of the buildings into consideration. For instance, optimization of building material selection covers initial design process, construction process, performance in operational stage and recyclability of the materials in demolition stage of the buildings. The energy performance of the building components may be optimized to minimize life cycle energy use or many other performance parameters such as energy use, emission, and thermal comfort in building operational phase can be considered all together.

In optimization problems, minimization or maximization of single performance function consideration is called single optimization problems whereas more than two function-optimization problems are solved as multi-objective optimization problems.

In optimization problems, each solution alternative used as an input is called design variable whereas all solution alternatives together are considered as solution space. The mathematical expression of optimization function as maximization/minimization problem called as objective function. The output of optimization process is called as fitness value or fitness values if more than one objective functions are evaluated. The constraints limit the performance of the objective functions.

Optimization problems can be solved by numerous solution techniques. In general, these techniques are divided into two parts: classical optimization techniques and heuristic optimization techniques. Classical optimization techniques such as linear programming, nonlinear programming, integer programming and Newton-Raphson method, search the optimal solution using gradient information of objective function(s) including constraints' effects. In some problems, however, performance of the classical optimization techniques is questionable and solution is found in very long time. Therefore, heuristic optimization techniques are developed to solve optimization problems whenever classical optimization techniques produce inefficient solution(s). The heuristics are generally proposed for a specific problem to increase the efficiency and calculation speed of the problem. Heuristic search does not guarantee optimal solution for the problem but tries to approximate optimal solution. Shortly, heuristics can be called unguaranteed shortcut solution to problems. Moreover, more generalized versions of the heuristics were needed to be proposed to apply heuristic approaches to different kinds of problems. Meta-heuristic optimization methods are appropriate solution approaches to apply them to more problems (Voß 2001).

In the following sections, single and multi-objective optimization techniques are expressed mathematically. Types of multi-objective solution approaches are explained and discussed to determine appropriate solution approach for this thesis. Meta-heuristic optimization techniques are compared with classical techniques and illustrated according to different solution methodology. The meta-heuristic techniques used in this thesis are presented in detail.

4.2. Optimization Problems

The details of a general single and multi-objective optimization problem are given in the following sections 4.2.1 and 4.2.2.

4.2.1. Single Optimization

Single optimization problem is generally represented as follows:

$$\begin{aligned} & min\,/\,max \quad f(x) \\ & subject\ to \\ & \qquad g_j(x) \geq 0 \\ & \qquad \mathrm{h}_k(x) = 0 \\ & x \in S \end{aligned} \tag{4.1}$$

where the design variable set x in solution space vector S try to optimize f, scalar objective function, subjected to g_j and h_k constraints.

4.2.2. Multi-objective Optimization

Multi-objective optimization problem can be formulated in general as follows:

$$
\begin{aligned}
& \mathit{min} / \mathit{max} \quad [\, f_1(\,x\,), f_2(\,x\,)\,, \ldots, f_M(\,x\,)\,] \\
& \mathit{subject\ to} \\
& \qquad g_j(x) \geq 0 \\
& \qquad \mathrm{h}_k(x) = 0 \\
& x \in S
\end{aligned}
\tag{4.2}
$$

where M>1 and the design variable set x in solution space vector S tries to optimize multiple objective function , f_m , together, subjected to g_j and h_k constraints.

In multi-objective optimization problems, all generated solution sets are first tested in terms of feasibility of the solution whether any constraints are violated or not. Then, solutions are compared with each other to determine dominance relation between solutions. Any solution set is called dominated solution if performance of at least one of the other solution sets is better at all objectives than the solution set; otherwise, solution set is called as non-dominated solution.

Optimal solution in multi-objective optimization is not directly calculated as seen in single optimization. Instead of optimal solution, all non-dominated solution sets are kept in special place and these solutions are used to draw an M-dimensional graph to show their relations which is called Pareto optimality curve. The decision maker takes a decision and selects a solution set from Pareto curve according to decision making conditions which depend on weight of the objectives. The Pareto optimal solutions are expressed as weak and strict Pareto optima. The solution is called weak Pareto optima if at least one of the objectives of the solution set is equal to compared Pareto optimal solution and the solution set is dominated in other objectives by the compared Pareto optimal solution. The solution that dominates all Pareto solutions in any objective(s) and dominated by same solution in other objective(s) is called strict Pareto optima.

The relationship between objectives in multi-objective optimization can be formulated in different views to calculate optimal solution(s) as follows:

- ✓ Scalarization technique (weighted sum approach)
- ✓ ϵ-constraints method
- ✓ Goal programming
- ✓ Multi-level programming

Scalarization technique combines all objective functions into a single objective function by giving weight for all objectives. The mathematical expression of scalarization technique can be formulated as follows:

$$
\begin{aligned}
& min\,/\,max \quad \sum \gamma_m f_m(x) \qquad (4.3) \\
& subject\ to \\
& \qquad \sum \gamma_m = 1 \\
& \qquad g_j(x) \geq 0 \\
& \qquad \mathrm{h}_k(x) = 0 \\
& x \in S
\end{aligned}
$$

where γ_m represents weight factor for objective function $f_{m.}$

Alternative optimal solution sets can be generated by changing weight factors for objective functions. Pareto optimal curve is drawn according to different weight factors. The solution set in the Pareto optimal curve is introduced as supported solution whereas the rest of solution sets are considered as unsupported solution sets.

ϵ-constraints method is proposed to focus on one objective by setting targets for all other objectives (Chankong & Haines 1983). The other objective functions are formulated as constraints and the selected objective function is tried to be optimized.

The mathematical expression of ϵ-constraints method for minimization problems are expressed as follows:

$$
\begin{aligned}
& \min \quad f_g \\
& \text{subject to} \\
& \qquad f_h(x) \le \varepsilon_h \quad \forall \mathrm{h} \in \{1,2,...\mathrm{m}\}/\{\mathrm{g}\} \\
& \qquad g_j(x) \ge 0 \\
& \qquad \mathrm{h}_k(x) = 0 \\
& x \in S
\end{aligned}
\tag{4.4}
$$

where f_g is selected objective function to be optimized according to given target limits ϵ_h for each objective function f_h.

Goal programming is developed to reach specific goal fitness value for each objective (Charnes et al. 1955). Therefore, the fitness function for goal programming is formulated regarding the difference between goal objective fitness and solution fitness as seen below in mathematical expression for given 3-objective problem:

$$
\begin{aligned}
& \min \quad \alpha_{s_{1-}} s_{1-} + \alpha_{s_{2+}} s_{2+} + \alpha_{s_{2-}} s_{2-} + \alpha_{s_{3+}} s_{3+} \\
& \text{subject to} \\
& \qquad f_1(x) + s_{1-} \ge v_1 \\
& \qquad f_2(x) + s_{2-} - s_{2+} = v_2 \\
& \qquad f_3(x) - s_{3+} \le v_3 \\
& \qquad s_{1-}, s_{2+}, s_{2-}, s_{3+} \ge 0 \\
& x \in S
\end{aligned}
\tag{4.5}
$$

where goals are given below:

$$f_1(x) \ge v_1,\ f_2(x) = v_2,\ f_3(x) \le v_3$$

where α represents weight factor for slack or surplus variable.

Multi-level programming is another solution approach to find Pareto optimum solution sets. In multi-level programming, M objectives are ordered in a hierarchical order. First, the most important objective is optimized; then, the next one is optimized according to previous results and the process goes on until all objectives are optimized. Multi-level programming is preferred whenever hierarchy between objectives can be constructed. On the other hand, hierarchical optimization may constrain solution sets at last objectives' optimization, as it may find infeasible solutions for the objective functions due to constraint functions.

In this study, fifteen objective functions are evaluated separately and in a combination. For instance, life cycle cost savings of the building performance simulation is optimized as single optimization as well as building life cycle cost savings and life cycle global warming potential savings are both optimized to draw Pareto optimal curve as bi-objective optimization. More than two objectives such as life cycle cost savings, life cycle global warming potential savings, and initial investment are developed as multi-objective optimization problem. Therefore, the optimization approach should be valid for both single and multi-objective optimization problems. The scalarization technique may be effective when optimization technique is applied to bi-objective optimization problem; however, increasing the number of objectives requires exponential increase in the number of weight factors for the problem for constructing Pareto optima curve and that is expected to decrease efficiency of scalarization technique significantly. Combinations of fifteen objective functions bring too much workload to apply on the problem in efficient way. On the other hand, ϵ-constraints method is effective solution approach if the solution focuses on specific objective function and constrains other objective function with pre-determined targets. However, in this study, generalized version of multi-objective optimization approach to apply multiple buildings with different sizes is proposed. Therefore, the objective targets vary depending on building size. The variation in building objective targets makes ϵ-constraints method inefficient. Similarly, goal programming is also inefficient solution approach for the given conditions above. Moreover, the number of objective functions is expected to reduce performance of multi-level programming whenever number of objective functions increases in the optimization process. As discussed, direct use of these four multi-objective optimization solution approaches found to be inefficient to solve problems in this study. Therefore, a new approach that regards conditional statements in the problem model is developed. In this new approach, a prior objective called main objective is determined and solutions are generated according to this main objective while Pareto optimal solutions are also kept. Focusing on main objective may weaken the performance of the algorithm due to less concentration on non-dominated solutions surrounding other optimum designs of other objectives. The weakness of the solution approach is planned to be eliminated by solution approach in meta-heuristic algorithm application in the next section.

4.3. Meta-heuristic Optimization Techniques

Meta-heuristics are developed to solve the complex real life optimization problems where performance of the classical optimization problems is poor on the optimization problems. To eliminate drawbacks of classical optimization techniques, meta-heuristics offer a derivative-free solution approach to eliminate problems due to gradient behavior of the classical methods such as multiple and shark peaks or discontinuous behavior of objective functions that causes sudden change in derivative value (Eskandar et al. 2012). Moreover, in gradient based solution approaches, the performance of the optimization techniques depends on the initial points when multiple local optima values exist in objectives functions. Meta-heuristics are expected to prevent from tackling local optima values by using derivative-free solution approaches applied to discrete, combinatorial and continuous optimization problems. These techniques do not guarantee to reach optimal solutions; however, they offer near optimal solutions. The meta-heuristics are efficient solution techniques when the classical optimization problems cannot reach optimal solution in efficient time. In highly complex problems, they reduce evaluation time by providing near optimal solutions.

Meta-heuristic optimization algorithms are developed by imitating biological, physical or social processes or behaviors. The most known meta-heuristics, Genetic Algorithm (GA) and Differential Evolution (DE) are developed by imitating Darwin's Evolutionary Law of Natural Selection. Particle Swarm Optimizer (PSO), Ant Colony Optimization, Artificial Bee Colony, Cuckoo Search are proposed as products of inspiration of behaviors of animals such as birds, ants, bees and cuckoos respectively (Goldberg 1989; Holland 1992; Storn & Price 1997; Kennedy & Eberhart 1995; Dorigo & Stützle 2004; Karaboga & Basturk 2007; Yang & Deb 2009). Simulated Annealing (SA), Gravitational Search Algorithm (GSA), Water Cycle Algorithm (WCA) and Big Bang Big Crunch (BB-BC) algorithms are developed as simulation of annealing of metals, Newtonian gravity law, water cycle in the Earth and theory of the birth of the universe respectively(Kirkpatrick et al. 1983; Rashedi et al. 2009; Eskandar et al. 2012; Erol & Eksin 2006). Brainstorming Algorithm (BA), League Championship Algorithm and Social Emotional Optimization Algorithm (SEOA) are algorithm examples of social processes or behaviors depending on brainstorming of people, football games and social status of people (Shi 2011; Kashan 2009; Xu et al. 2010).

In meta-heuristic algorithms, constraints of the problem require a modification on the objective function to reflect the constraints' effect on objective function. This constraint handling strategy provides constrained to unconstrained transformation in the problem formulation (Coello Coello 2002). Thus, modified objective functions are directly evaluated in the optimization process. The most known constraint handling strategies are dead penalty and penalty function. In death penalty strategy, feasibility of solution is tested for the constraints. The solution is eliminated directly if any constraints are violated. In the second approach, instead of direct elimination, constraint violation is penalized and added to objective function to worsen fitness value of the solution. Penalty strategies vary depending on fitness value result (positive or negative) and minimization or maximization of objective function. In this study, constraint violating solutions are eliminated by multiplying the objective function with infinitesimally large number.

In multi-objective optimization problems, contrast to single optimization problems, all non-dominated fitness values and position vectors are kept as best fitness and position vector; however, in position update procedure and fitness value calculation of each member, main objective function is taken as reference.

The general procedure in meta-heuristic optimization algorithm can be explained in the following order. First, the algorithm is initialized by random distribution. The distribution type may change depending on the algorithm; however, in general, mostly uniform random distribution between upper and lower limits of design variables are preferred for efficient initialization. Then, the fitness function value for each population member is calculated. Fitness value and solution vector which is called position vector, are kept in memory if position vector of the population member uses its or others' memories for their best fitness value and position vector called local best fitness and local best position vector to update its position vector. Then, the fitness values are sorted and best fitness value and position vector are kept in a special place. The most critical step which differentiates algorithms is the position vector update stage. After position vector is updated, the fitness value for each member is calculated and compared with local best fitness values to update local fitness best and local best position vector for population member. The best local best fitness value is assigned as best fitness and same is done for best position vector. Then, position vector for each member is updated and the algorithm repeats the same steps until the termination criterion is met.

The position update procedure influences the performance of meta-heuristic algorithm significantly as underlined in previous part. The position update procedure or strategy for any algorithm is constructed on the balanced trade-off between exploration (diversification) and exploitation (intensification) in solution search. In exploration search, the algorithm tries to explore new solution in global solution space whereas new solution is searched around global best solution in exploitation stage. In general, the algorithm focuses more on exploration search in early iteration; however, as iteration number increases, the algorithm looks more for new solution around the best solution encountered up to that time. The algorithm performance is expected to decrease if only one of these two search strategies is focused on much more. The exploration causes loss of concentration around best solution whereas much more focus on exploitation search results in pre-mature convergence and trap in local optimal solutions. Therefore, efficient trade-off between exploitation and exploration should be provided to improve algorithm performance.

Performance of meta-heuristic algorithms changes depending on the optimization problems. Therefore, saying that algorithm A performs better than algorithm B by comparing one or two optimization problems will be a subjective decision as performance ranking of algorithms may change depending on optimization problems. In meta-heuristics, position vector update procedures mostly determine the performance of the algorithm. The random number used in position vector updates provides variety in solutions. Therefore, in contrast to classical optimization techniques, meta-heuristics may find different best fitness values at each optimization run. Although more than fifty meta-heuristic algorithms exist, in general, the position vector update procedures for the algorithms can be categorized into three approaches. In the first approach, only local best position vectors of the population are used in optimization procedure. In other words, new position vector of the swarm is located with respect to combination of local best position vector of the population member, local position vector of other population members and population global best position in multiple variation. In the second approach, besides population's local best position vector and global best position vector, position vectors of the population in the previous iteration are used to update population position vector. In the last approach, distributions such as Normal Distribution and Exponential Distribution are used to update position vectors. In the determination of distribution parameters, the latest position vector of the population, local best position vector, global best position vector, elite position vector that is selected among the latest position vectors or local best position vector are used.

In this study, a generalized optimization model that can be applied to optimize buildings in different size and different material combinations is planned to be constructed. The performance accuracy of single optimization algorithm is expected to vary depending on optimization case studies. Therefore, in this study, three different algorithms with different position update strategies are constructed to obtain more accurate optimization performance in different case studies. Meta-heuristic algorithms are classified according to their position update strategies as seen in Table 4.1. Performance of each optimization algorithms are tested with discrete and continuous unconstrained test problems and constrained engineering problems (Liang et al. 2006; Sadollah et al. 2013). Performance of each algorithm is compared with each other within its group. According to performance results, Differential Evolution, Particle Swarm Optimizer, and Modified Cross Entropy Method are selected to be applied to energy optimization model. The details of optimization algorithms are explained in the following sections.

Table 4.1. Algorithm Categorization with respect to Position Update Strategy

Position Update Strategy	Algorithms
Population and population member's best position vector based position update	Artificial Bee Colony (Karaboga & Basturk 2007) , Ant Colony Optimization (Dorigo & Stützle 2004), Backtracking Search Optimization Algorithm (Civicioglu 2013), Bat Inspired Algorithm (Yang 2010), Cuckoo Search (Yang & Deb 2009), Differential Evolution (Storn & Price 1997), Differential Search Algorithm (Civicioglu 2012), Flower Pollination (Yang 2012), Genetic Algorithm (Goldberg 1989) ,Great Salmon Run (Mozaffari et al. 2012), Grey Wolf Optimization (Mirjalili et al. 2014), Harmony Search (Zong Woo Geem et al. 2001), Interior Search Algorithm (Gandomi 2014), Symbiotic Organisms Search (Cheng & Prayogo 2014) and Teaching Learning Based Optimization (Rao et al. 2011)
Previous position vector based position update	Artificial Tribe Algorithm (Chen et al. 2010) , Black Hole (Hatamlou 2013), Colliding Bodies Optimization (Kaveh & Mahdavi 2014), Firefly Algorithm (Yang 2009), Gravitational Search Algorithm (Rashedi et al. 2009), Group Search Optimization (He et al. 2009), Kinetic Gas Molecule Optimization (Moein & Logeswaran 2014), Particle Swarm Optimization (Kennedy & Eberhart 1995), Social Emotional Optimization Algorithm (Xu et al. 2010) , Water Cycle Algorithm (Eskandar et al. 2012)
Distribution based position update	Big Bang Big Crunch Optimization (Erol & Eksin 2006), Cross Entropy Method (Rubinstein & Kroese 2004) , Modified Cross Entropy Method , Simple Optimization (Hasançebi & Azad 2012), Vortex Search Algorithm (Doğan & Ölmez 2015), Water Wave Optimization (Zheng 2015)

4.3.2. Differential Evolution

Differential Evolution is an evolutionary optimization algorithm based on Darwin's Law of Natural Selection. Differential Evolution updates position vector of each individual called agent by crossover, mutation and selection stages (Storn & Price 1997). In crossover stage, it is decided whether position value of agent i in dimension d is kept or changed. In mutation stage, new position vector is constructed. In selection stage, performance of local fitness best of agent i is compared with newly constructed vector's fitness and the one with better fitness is selected. The details of Differential Evolution are introduced step by step below:

Step 1: Initialize position vector for all agents by random distribution according to Equation 4.6. and set iteration t=0.

$$x_i^d(t) = X_{min}^d + r * \left(X_{max}^d - X_{min}^d \right) \quad for\ d = 1, 2, .., m \quad and\ i = 1, N \qquad (4.6)$$

where $x_i^d(t)$ represents i^{th} individual's position on the d^{th} design variable at iteration t within upper and lower boundary limits, X_{max}^d and X_{min}^d and r is uniform random number between 0 and 1.

Step 2: Evaluate objective function fitness value(s) $f_m(x_i(\mathrm{t}))$

Step 3: Construct donor position vector for all agents by different mutation strategies. The alternative mutation strategies are formulated below:

$$y_i^d(t+1) = x_{r_1}^d(t) + F(x_{r_2}^d(t) - x_{r_3}^d(t)) \tag{4.7}$$

$$y_i^d(t+1) = x_i^d(t) + F(x_{r_1}^d(t) - x_{r_2}^d(t)) \tag{4.8}$$

$$y_i^d(t+1) = \mathrm{p}^{g,d} + F(x_{r_1}^d(t) - x_{r_2}^d(t)) \tag{4.9}$$

$$y_i^d(t+1) = x_{r_1}^d(t) + F(x_{r_2}^d(t) - x_{r_3}^d(t)) + F(x_{r_4}^d(t) - x_{r_5}^d(t)) \tag{4.10}$$

$$y_i^d(t+1) = x_i^d(t) + F(x_{r_1}^d(t) - x_{r_3}^d(t)) + F(x_{r_4}^d(t) - x_{r_5}^d(t)) \tag{4.11}$$

$$y_i^d(t+1) = \mathrm{p}^{g,d} + F(x_{r_1}^d(t) - x_{r_2}^d(t)) + F(x_{r_4}^d(t) - x_{r_5}^d(t)) \tag{4.12}$$

$$y_i^d(t+1) = x_i^d(t) + F(\mathrm{p}^{g,d} - x_i^d(t)) \tag{4.13}$$

where y is donor position vector constructed with respect to random position vector of population agents using control parameter F.

In this study, two different position update strategies are proposed with respect to optimization strategy of the decision maker. If the decision maker wants to focus more on the main objective and generate Pareto optimal solution around optimum main objective faster, the position vector of the population is updated according to Equation 3.6. Whereas, the position vector is updated according to Equation 3.14 as global best position for agent i is selected randomly from Pareto optimal solution sets if the decision maker tries to collect all Pareto optimal solutions to gather data for detailed post-optimization evaluation.

Step 4: Construct trial position vector. Select donor position vector if unit random number is less than the predetermined crossover rate, C_r ; otherwise, select existing position vector for the agent i.

$$u_i^d(t+1) = \begin{cases} \mathrm{y}_i^d(t+1) & \text{if } r_j < C_r \\ x_i^d(t) & \textit{otherwise} \end{cases} \tag{4.14}$$

Step 5: Select the position vector with better fitness value among previous position vectors and trial position vectors of each agent.

$$x_i(t+1) = \begin{cases} u_i(t+1) & \text{if } f_1(u_i(t)) < f_1(x_i(t)) \\ x_i(t) & \textit{otherwise} \end{cases} \tag{4.15}$$

Step 6: In single optimization problems, sort local best fitness values of the population. Select position vector of the individual with minimum local fitness value as the best position vector of the population, p^g. In multi-objective optimization problems, set initial individual as best position at t=0, compare objective fitness values with best fitness values. Eliminate position vector of any individual in best solution sets if it is dominated by position vector of individual i. Add into i^{th} individual position vector if its objective fitness values cannot be dominated by the best objective fitness sets.

Step 7: Repeat steps 2-6 until termination criterion is met.

In original DE, global best position vector is updated at each function evaluation and this cause pre-mature converges in the problems. Therefore, to prevent from pre-mature converges, especially in single optimization in this thesis; the global best position vector is updated at the end of each iteration.

4.3.1. Particle Swarm Optimizer

Particle Swarm Optimizer is a population based meta-heuristic optimization algorithm inspired from social behavior of animals like fish schooling, insect swarming, and bird flocking (Kennedy & Eberhart 1995). PSO takes both individual memory of all swarm members and swarm knowledge together. Besides position vector for each individual, velocity vector that is based on previous position vector, local best position vector, and best position vector is also taken into consideration to update position vector of each individual. The details of Particle Swarm Optimizer for minimization problems are outlined as follows:

Step 1: Initialize position and velocity of each particle according to Equation 4.6 and 4.16. Set iteration t=0.

$$v_i^d(t) = X_{min}^d + r*\left(X_{max}^d - X_{min}^d\right) \quad for\ d = 1,2,..,m \quad and\ i = 1:N \tag{4.16}$$

where v represents velocity vector.

Step 2: Evaluate objective function fitness value(s) $f_m(x_i(\mathrm{t}))$.

Step 3: Update local best position for all swarm particles. If iteration is equal to 0, assign position vector of individual as local best position.

$$p_i^l = \begin{cases} x_i(t) & f_1(x_i(t)) \leq f_1(p_i^l) \\ p_i^l & otherwise \end{cases} \tag{4.17}$$

where p_i^l is representation of i^{th} particle's local best position.

Step 4: Apply Step 6 in detailed explanation of Differential Evolution.

Step 5: Update velocity and position vector for all particles.

$$v_i^d(t+1) = \mathrm{w}*v_i^d(t) + c_1 r_1(p_i^{l,d} - \mathrm{x}_i^d(t)) + c_2 r_2(p_i^{\mathrm{g},d} - \mathrm{x}_i^d(t)) \tag{4.18}$$

$$\mathrm{x}_i^d(t+1) = \mathrm{x}_i^d(t)) + v_i^d(t+1) \tag{4.19}$$

where w represents inertia weight of particle to control exploration in the algorithm whereas c_1 and c_2 are constant trust parameters that may change to improve algorithm performance. When focusing on main objective optimization, global best position vector is used in update process whereas in focusing the Pareto optimal strategy, the global best position vector is randomly selected among existing Pareto optimal solutions updated in Step 4.

Step 6: Repeat steps 2-5 until termination criterion is met.

4.3.3. Modified Cross Entropy Method (MCEM)

Modified Cross Entropy Method is an improved version of the distribution algorithm, Cross Entropy Method (CEM) proposed by Altun and Pekcan (2015). MCEM provides balance between exploration and exploitation stages to provide efficient convergence speed and solution result. Compared to BB-BC, another distribution algorithm as a special form of Modified Cross Entropy, MCEM provides higher convergence speed. In Modified Cross Entropy Method, in order to optimize single optimization problems, initial position vectors for each individual are randomly distributed and evaluated in terms of fitness. Then, all individuals are sorted in terms of its objective fitness values and elite samples are categorized for mean and standard deviation parameters of normal distribution. The position vector for each individual is updated according to normal random distribution. In multi-objective optimization problems, random selection of non-dominated solutions are considered as mean value for each individual and standard deviation parameters are calculated as done in single optimization. The step by step explanation of MCEM is detailed as follows:

Step 1: Initially randomly distribute design variable according to Equation 3.6 and set iteration t=0.

Step 2: Evaluate objective function fitness value(s) $f_m(x_i(\text{t}))$

Step 3: Sort objective fitness values and determine position vector set for mean and standard deviation parameters' calculation. In focus on main objective strategy, mean and standard deviation parameters of distribution are updated as follows:

$$\mu^d(t+1) = \frac{\sum_{si=1}^{N_{mean}} x_{si}^d(t)}{N_{mean}} \qquad (4.20)$$

$$\sigma^d(t+1) = \sqrt{\sum_{si=1}^{N_{std}} \frac{(\mu'^d(t) - x_{si}^d(t))^2}{N_{std}-1}} \text{ where } \mu'^d(t+1) = \frac{\sum_{si=1}^{N_{std}} x_{si}^d(t)}{N_{std}} \qquad (4.21)$$

where μ and σ are mean and standard deviation of elite samples whereas N_{mean} and N_{std} represent number of elite individuals for mean and standard deviation. In focus on Pareto optimal strategy, mean vector of the distribution is calculated according to position vector of randomly selected non-dominated solutions updated in Step 6 in DE whereas standard deviation vector is calculated by using same formulation in the previous strategy.

Step 4: Apply Step 6 in detailed explanation of Differential Evolution.

Step 5: Update position vector for each individual. In single optimization, mean value for the distribution is calculated in Step 3; whereas in multi-objective optimization, a random selected non-dominated position vector from Step 4 is used to update position vector.

$$\mathrm{x}_i^d(t+1) = \mu^d(t+1) + \mathrm{randn}()\ \sigma^d(t+1) \qquad (4.22)$$

where randn () is unit random normal distribution with N(0,1).

Step 6: Repeat steps 2-6 until termination criterion is met.

CHAPTER 5

ENERGY OPTIMIZATION MODELS

In this chapter, optimization methodology and energy models used in the developed energy optimization models are introduced. Meta-heuristic techniques applied to multi-objective energy model are presented in detail. The energy models constructed for steady state and BIM integrated energy estimations are explained.

5.1. EnrOpt: Steady-State Life Cycle Energy Performance Optimization Framework

Energy Optimizer is Excel integrated Matlab based graphic user interface to optimize building energy performance. In the interface, meta-heuristic optimization techniques are applied to a modified TS 825 standard based energy model for improving the building performance and getting the Pareto optimal design solutions for decision makers in the early design stage of the building. Energy performance of the building is analyzed comparatively for each design alternative solution set by taking initial energy based design as reference building design and a datum point in quantitative calculations. The general perspective of the interface model is summarized below while the prominent points in summarization of the interface are explained in detail in the following sections one by one.

- ✓ The reference building design parameters are selected initially in commonly used tool Microsoft Excel to provide an easy and practical application for the users.

- ✓ The energy optimization model can be applied to any building types available in TS 825 standard.

- ✓ The building energy estimation model based on TS 825 standard is modified by adding alternative climate data and operational schedule. Moreover, heating degree-day methodology and window system heat loss calculation methodology is elaborated to calculate annual heating energy requirement more accurately.

- ✓ Meta-heuristic optimization techniques are applied to interact with the energy model efficiently and provide flexibility in the interface by applying different techniques on various buildings. Therefore, performance of optimization model in more complex building design can be improved by applying alternative meta-heuristics with different position update strategies.

- ✓ The optimization model can be applied to both single objective and multi-objective building energy performance analysis. In single objective problem, due to the nature of the problem, the algorithm tries to optimize the objective fitness to find single optimum fitness value. In multi-objective problems, the objectives are ranked according to their priority for the decision maker and the most important one is selected as the main objective in the optimization process.

- ✓ In EnrOpt interface, two different optimization strategies, focus on main objective optimization and focus on Pareto optimal solutions, are available to apply in the building performance optimization based on decision maker expectations.

- ✓ In EnrOpt interface, the energy optimization model calculates building performance for a specific period, shortly called semi-life cycle performance analysis. Therefore, in each design solution, cost and environmental impact based trade-offs are considered between initial design cost and environmental performance values, and operational energy cost and environmental impact values for this analysis period.

- ✓ Building performance is analyzed based on cost-effective, payback period minimization and environmental impact minimization based objectives that are listed below. In energy optimization model, any of the listed fifteen objectives can be used to generate Pareto optimal solutions or single optimum design solution for the selected objective can be generated. The objectives in EnrOpt energy optimization model are as follows:

    1. Life cycle cost savings
    2. Life cycle GWP savings
    3. Initial investment cost
    4. Energy cost payback period
    5. Emission payback period
    6. Life cycle air acidification savings
    7. Life cycle water acidification savings
    8. Life cycle ecotoxicity savings
    9. Life cycle air eutrophication savings
    10. Life cycle water eutrophication savings
    11. Life cycle air human health particulate savings
    12. Life cycle human toxicity, cancer savings
    13. Life cycle human toxicity, non-cancer savings
    14. Life cycle ozone depletion savings
    15. Life cycle smog air savings

- ✓ In energy optimization model, wall types, insulation material and thickness combination on different building components such as wall insulation, roof insulation, floor and foundation insulation, and window systems with different frame and glazing types are generated as design alternatives to find Pareto optimal solutions.

- ✓ The commonly used insulation materials in Turkish insulation applications such as mineral wools like glass wool and rock wool, expanded polystyrene (EPS) and extruded polystyrene (XPS) are applied as design alternatives in optimization application. Moreover, horizontal coring and vertically perforated brick walls with different sizes and autoclaved aerated concrete in different thickness alternatives are used as wall type design alternatives.

- ✓ In energy optimization model, natural gas, hard coal, lignite, fuel oil, fuelwood and electricity are offered as energy resource alternatives for heating the buildings. The user can select one of the resources or multiple energy resources with their associated share in heating process.

- ✓ In theory, each building element can be insulated with different insulation materials and thickness combinations; however, it is not applicable in practice. Therefore, building elements with same function should be designed with same design alternative to get more realistic results. Therefore, 23 design variables explained in detail in section 5.1.5 are generated for wall types, insulations, and window systems. Various design alternatives are generated for each design variables whereas the number of design alternatives for each design variable can be limited in the interface depending on decision maker's expectation.

- ✓ In optimization model, cost data are obtained from 2015 Unit Price Database of Republic of Turkey, Ministry of Environment and Urbanization, whereas environmental data are extracted from PE INTERNATIONAL 2012 and Eco-invent 2012 databases via Gabi 6.0 software (Ministry of Environment and Urbanisation 2015;EcoInvent Centre 2012).

5.1.1. Modifications in Energy Model

Accuracy of energy estimation is very important in building performance evaluation and reliable decision making. Therefore, the weaknesses of the TS 825 standard based steady state energy model are overcome with additional detailed information and changes made in the methodology aiming to increase accuracy of the model for getting more reliable results. The modified parts of the energy model and the reasons for the modifications are explained below:

- ✓ In TS 825 standard, five different monthly climate data are available to calculate required energy amount according to degree-day region categorization. Therefore, same two buildings in two different cities in the same degree-day region with different real climate data need same amount of annual heating energy according to energy estimation methodology in TS 825 standard contrast to reality. Hence, city specific climate data are generated from statistics to make the energy analysis more realistic. Hence, two different climate data types such as long-term monthly average climate data and recent short-term climate data are added into energy model. According to Turkish State Meteorological State data (2015), long-term climate data includes fifty five year monthly average temperature data for the years 1950-2014; whereas recent short-term climate data covers monthly average heating degree-days and number of days heating is required for the building that are used to determine monthly adjusted heating degree days for the building types for the years 2007-2014.

- ✓ The most important building components in the building heat loss are walls and windows (Dasdemir 2014). According to TS 825 standard, thermal transmittance of the window system is calculated with respect to frame material and glazing type according to given standard table taken from TS 2164 Principles for the Preparation of the Projects of the Central Heating Systems; however, geometric details of frame and glazing system in the window have not been considered yet. Therefore, in the energy optimization model, thermal transmittance calculation methodology is modified by including shape and width parameters of window frames and glazing system in the calculation formula based on ISO 10077-1:2006 standard. Dividers with same material properties as window frame are added to adjust uncommonly used window shapes. Hence, thermal transmittance of window system is determined by the following formula:

$$U_W = \frac{\sum A_g U_g + \sum A_f U_f + \sum l_g \psi_g}{\sum A_f + \sum A_g} \tag{5.1}$$

$$\psi_g = \begin{cases} 0.00 & U_g \geq 3.2 \\ 0.05 & U_f \leq 2.27 \ \& \ 3.2 \geq U_g \geq 2.0 \\ 0.06 & U_f \geq 2.27 \ \& \ 3.2 \geq U_g \geq 2.0 \\ 0.06 & U_f \leq 2.27 \ \& \ U_g \leq 2.0 \\ 0.08 & U_f \geq 2.27 \ \& \ U_g \leq 2.0 \end{cases} \tag{5.2}$$

where U_w , U_g and U_f represent thermal transmittance of window system, window glazing system, and window frame respectively. Ψ_g and l_g are linear thermal transmittance due to the combined thermal effects of glazing, spacer and frame, and perimeter length of window glazing. In energy optimization model, area and perimeter values for each window shape are entered in Excel sheet and the optimization code directly changes thermal transmittance of window system by changing material properties while keeping geometric details of windows system constant.

- ✓ In TS 825 standard, for solar heat gain calculation, solar radiation values on vertical surface direction in each main direction are valid for any location in Turkey; however, detailed annual solar radiation analysis clears that solar radiation distribution changes depending on the location of the building. Therefore, by taking average solar radiation distribution as reference, an adjustment solar radiation coefficient is generated by dividing annual solar radiation of city A to Turkey's annual solar radiation mean. Therefore, solar radiation on different cities is differentiated to get more reliable results. Moreover, in the standard, solar transmission factor for the normal incidence values is given for limited glazing types. In the energy optimization model, by using Isıcam data set (2015), solar transmission factor for the normal incidence values for each glazing alternatives are set. Furthermore, shading property of the glazing alternatives can also be re-evaluated; however, in TS 825 standard, building surroundings are evaluated to determine glazing shading factor. Therefore, shading factor of glazing system according to Isıcam data set is ignored.

- ✓ One of the most important drawbacks in TS 825 standard is heating operational schedule in the building. The standard assumes continuous heating schedule based on indoor and outdoor monthly temperature difference. Therefore, continuous heating schedule decreases the accuracy of the energy estimation in the building by resulting in higher energy estimation than measured one. Thus, alternative schedule programs are generated to deal with energy overestimation. The building does not need any heating requirement if outdoor average temperature is higher than 15ºC which is used as reference temperature in heating degree-day calculations (Eurostat, 2015). In this study, it is assumed that building is heated up to 15 ºC when it is out of operational schedule in a day. The operational schedule based on number of heating degree-day (HDD) is calculated by the formula given in Equation 5.3 as follows:

$$HDD_m = \begin{cases} a \max(0,\theta_i - \theta_e) + (1-a)\max(0,15-\theta_i) & if\ \theta_e \leq 15\ ºC \\ 0 & otherwise \end{cases} \quad (5.3)$$

where HDD_m and α represent number of heating degree-day in month m and operational schedule time rate in terms of percentage (0,1). In recent short-term climate data evaluation, all the calculations are done same as long-term one; however, HDD values for each month are given by taking internal balance temperature as 18 ºC .Therefore, depending on building type , HDD values are adjusted using both pure HDD values and number of days with less than 15 ºC. Then, the same procedure is followed with long-term climate data.

✓ In this energy optimization model, building wall is insulated as external thermal sheathing. TS 825 claims that thermal bridges in buildings with external thermal sheathing are neglected. In this model, effect of thermal bridge is taken as zero, even in reference building design.

5.1.2. Objectives

In this study, it is aimed at developing a flexible energy modeling interface to solve any combination of objectives together depending on decision maker’s expectations. Therefore, multiple objectives constructed on time, cost and environmental issues are evaluated within this interface. The decision maker selects main objective and other objectives to generate Pareto optimal solutions for providing alternatives for post-evaluation in decision making process. Hence, in this study, fifteen objectives explained in detail below are used in optimization process. The objectives in the energy optimization model and their mathematical expressions are as follows:

Life cycle cost savings considers trade-offs between initial investment cost to improve building energy performance and cost savings due to increase in the building energy efficiency/performance. It provides life-cycle thinking for the decision maker in the early design stage to change the idea of minimizing initial investment cost as short-term profit goal while evaluating design alternatives. In this study, analysis period of the building is determined by the decision maker; therefore, the decision maker can evaluate the performance of the building for different time periods to make a better evaluation. Net Present Value (NPV) approach is used by adding time value of the money in the optimization process to make the evaluation more comparative and clear. In the calculations, the performance of the building is evaluated with respect to reference building. The mathematical expression of life cycle cost savings are as follows:

$$LCCS_d = IC_R - IC_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k p_k w_k)(1+i_{ei})^n}{(1+i_i)^n} \text{ in Turkish Lira} \tag{5.4}$$

where ICR and Q_R represent comparative initial investment and amount of energy need for the reference building whereas $LCCS_d$, IC_d and Q_d symbolize lifecycle cost savings for the design solution compared to reference building, comparative initial investment and amount of energy need for the designed building, respectively. In NPV analysis, energy inflation rate (i_{ei}) and interest rate (i_i) are used to calculate discounted price of energy resource k (p_k) for the next years by adding time value of money into optimization process whereas it is multiplied by energy resource use percentage (w_k) from all energy resources to calculate annual discounted energy price for any year. In EnrOpt interface, energy inflation rate and interest rate are taken 8% and 9.5%, respectively (Deposite Rates 2015; Turkish Statistics 2015). Energy inflation rate is determined by examining last 3-years and 5-years change in energy prices according to Turkish Statistics in terms of Turkish Lira. Although the country imports nearly seventy five percent of its energy needs and U.S. Dollar is mostly used in energy trade, as all the design costs are determined in terms of Turkish Lira, energy prices and energy inflation rate are considered based on change in energy cost in Turkish Lira.

Global warming potential measures heat amount trapped by greenhouse gases in the atmosphere to describe the impact of greenhouse gases on global warming for different time periods. In this study, *life cycle global warming potential (GWP) savings* measures how much kg equivalent CO_2 GWP can be reduced by changing design alternatives in the given analysis period. Similar to cost analysis, in GWP analysis, GWP value of initial design alternatives have a trade-off with relative GWP value due to change in annual energy needs between designed building and reference building. In this study, time value of GWP is also taken into consideration by taking it 3% to underline the importance of taking precautions to reduce GWP in early design stage (Marshall & Kelly 2010). The formula of life cycle GWP savings is given in Equation 5.5 as follows:

$$LCES_d = IE_R - IE_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k GWP_k w_k)}{(1+i_{GWP})^n} \quad \text{kg equivalent } CO_2 \qquad (5.5)$$

LCES, IE and GWP_k represent life cycle global warming savings, initial relative global warming value of design alternatives and global warming potential of energy resource k for unit energy amount, respectively.

Initial investment cost (IIC) measures how much extra investment is required to change initial reference building design. IIC is formulated as follows:

$$IIC_d = IE_d - IE_R \quad \text{kg equivalent } CO_2 \qquad (5.6)$$

Energy cost payback period presents duration to recover relative initial investment by reducing annual energy need in designed building compared to one in the referenced building. If the initial investment on the designed building is less than the one in the referenced building, the payback period in the building is assigned zero. Payback period is calculated by adding cumulative discounted energy cost to investment for each year until the sign of NPV changes. The payback period is determined by interpolation between two following years where the sign of NPV changes in between. The general formula of energy payback period time is as follows:

$$IC_d - IC_R = \sum_{n=1}^{n_c} \frac{(Q_d - Q_R)(\sum_k p_k w_k)(1+i_{ei})^n}{(1+i_i)^n} \tag{5.7}$$

where n_c presents energy cost payback period.

Emission payback period is time period for recovery of initial extra emission coming from difference between designed building and reference building by relative energy need reduction in the designed building. In emission payback period calculation, similar formula in energy payback period calculation is used. The formula of emission payback period is explained in Equation 5.8 below:

$$IE_d - IE_R = \sum_{n=1}^{n_e} \frac{(Q_d - Q_R)(\sum_k GWP_k w_k)}{(1+i_{GWP})^n} \tag{5.8}$$

where n_e presents emission payback period.

The rest of objectives in this study are environmental impact related objectives. They are explained in detail in Table 5.1 and formulated in Equations 5.9-5.18.

Table 5.1. Environmental Impact based Objectives in Energy Optimization Model

Objectives	Interest Rate (%)	Formula
Life Cycle Acidification Air (AA) Savings (kg SO2-Equiv.)	i_{AA} = 0 %	$IAA_R - IAA_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k AA_k w_k)}{(1+i_{AA})^n}$ (5.9)
Life Cycle Acidification Water (AW) Savings (kg SO2-Equiv.)	i_{AW} = 0 %	$IAW_R - IAW_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k AW_k w_k)}{(1+i_{AW})^n}$ (5.10)
Life Cycle Ecotoxicity (ET) Savings (CTUeco)	i_{ET} = 0 %	$IET_R - IET_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k ET_k w_k)}{(1+i_{ET})^n}$ (5.11)
Life Cycle Eutrophication Air (EA) Savings (kg N-Equiv.)	i_{EA} = 0 %	$IEA_R - IEA_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k EA_k w_k)}{(1+i_{EA})^n}$ (5.12)
Life Cycle Eutrophication Water(EW) Savings (kg N-Equiv.)	i_{EW} = 0 %	$IEW_R - IEW_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k EW_k w_k)}{(1+i_{EW})^n}$ (5.13)

Table 5.1. Environmental Impact based Objectives in Energy Optimization Model (continued)

Objectives	Interest Rate (%)	Formula
Life Cycle Human Health Particulate Air (HHPA) Savings (kg PM2,5-Equiv.)	$i_{HHPA} = 0$ %	$IHHPA_R - IHHPA_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k HHPA_k w_k)}{(1+i_{HHPA})^n}$ (5.14)
Life Cycle Human toxicity, cancer (HTC) Savings (CTUh)	$i_{HTC} = 0$ %	$IHTC_R - IHTC_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k HTC_k w_k)}{(1+i_{HTC})^n}$ (5.15)
Life Cycle Human toxicity, non-cancer (HTNC) Savings (CTUh)	$i_{HTNC} = 0$ %	$IHTNC_R - IHTNC_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k HTNC_k w_k)}{(1+i_{HTNC})^n}$ (5.16)
Life Cycle Ozone Depletion Air (ODA) Savings (kg CFC 11-Equiv.)	$i_{ODA} = 0$ %	$IODA_R - IODA_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k ODA_k w_k)}{(1+i_{ODA})^n}$ (5.17)
Smog Air (SA) Savings (kg O3-Equiv.)	$i_{SA} = 0$ %	$ISA_R - ISA_d + \sum_{n=1}^{N} \frac{(Q_R - Q_d)(\sum_k SA_k w_k)}{(1+i_{SA})^n}$ (5.18)

5.1.3. Design Alternatives

In building energy performance based design, insulation property of the design component plays a key role to reduce heat loss in the building. Therefore, decision maker selects appropriate design materials to construct energy efficient solutions. In this study, wall types, insulation materials with different thickness combinations, and window systems with different frame-glazing type combination are presented as design alternatives in energy optimization process to generate Pareto optimal energy efficient solutions with respect to selected objectives. The details of all design alternatives by giving priority to insulation material are explained below.

Insulation materials can be used in new building design or renovation of existing building in different forms such as as batt, roll, foam, board depending on intended use regarding fire protection, material strength, resistance to vapor as per given details in Table 5.2 . In Turkey, mineral wools such as rock wool, glass wool, expanded polystyrene (EPS), and extruded polystyrene (XPS) are commonly used insulation materials for insulation applications in buildings. In building insulation design, the right insulation material with right thickness should be selected to provide energy-efficient and life cycle existing solution. For instance, in building foundation, if the compressive strength of the materials is insufficient to resist on the carried load, insulation material may lose its insulation property faster than intended period due to smash. Therefore, in insulation design, the prior objective should have insulation-effectiveness; however, other properties such as reaction to fire or compressive strength should be also considered in material selection as constraints.

Mineral wool comprises glass wool and rock wool which are produced as boards, mats and filling materials. The main raw materials for rock wool manufacturing are basalt, dolomite and limestone; whereas the glass wool is produced from sand, glass cullets, soda ash and limestone. For these mineral wools, the raw materials are melted at 1500°C as spun fibers that are in a bind together to improve wool properties. The produced mineral wool is then cured at about 200-250°C and cut in the required size and shape. Thermal conductivity of both rock wool and glass wool is 0.04.

Table 5.2. Detailed Information of Most Common Insulation Materials in Turkey

	Mineral Wools		Organic Foam	
	Glass wool	**Rock wool**	**EPS**	**XPS**
Density(kg/m^3)	15-100	40-150	15-35	25-30
Thermal conductivity factor λ (W/Mk)	0.035-0.050	0.035-0.050	0.035-0.040	0.030-0.040
Resistance to vapor diffusion factor	<=1	<=1	20-100	80-250
Reaction to fire	Very good	Very good	Good	Good
Compressive strength (kPa)	0.5-500	0.5-500	30-500	100-1000
Where to use	wall, floor, ceiling, roof	wall, floor, ceiling, roof	wall, floor, ceiling, roof, expansion joints	wall, floor, roof, foundation
How to install	fitted between joists, glued, nailed	fitted between joists, glued, nailed	glued ,nailed	glued ,nailed
Reuse/recyclability	Recyclable; but not practical	Recyclable; but not practical	Recyclable	Recyclable
Waste disposal	No special burden	No special burden	No special burden	Long bio-persistence

EPS is composed of small spheres of polystyrene that are expanded by pentane (C_6H_{12}) with water vapor heat. The expanded beads are cooled, and air diffuses gradually into the pores and replaces residual condensed vapor and pentane gas. Then, the beads are molded in the intended shape and cut in the pre-determined size. Thermal conductivity of expanded polystyrene depends on EPS density (ρ_a). In this study, thermal conductivity values of EPS with various densities such as 16 kg/m$_3$, 20 kg/m$_3$, 30 kg/m$_3$ and 35 kg/m$_3$ are calculated according to EPS thermal conductivity prediction formula of European Manufacturers of Expanded Polystyrene (EUMEPS,2014) given in Equation 5.19.

$$\lambda_{pred} = 0.027174 + 5.1743\ 10^{-5}\rho_a + \frac{0.173606}{\rho_a} \quad (5.19)$$

where λ_{pred} represents predicted EPS thermal conductivity.

XPS is produced from melted polystyrene by adding expansion gas such as HFC, CO_2 or C_6H_{12} where polystyrene mass is extruded through a nozzle with pressure release that provides mass expansion. XPS is produced in continuous lengths and cut after cooling process. Thermal conductivity of extruded polystyrene varies between 0.03 and 0.04. In this study, three different thermal conductivity values such as 0.03, 0.035 and 0.04 are used in the optimization process.

In wall type selection, brick walls and autoclaved aerated concrete walls are offered in common practice. All possible brick walls and AAC wall alternatives are listed according to 2015 Unit Price Database of Republic of Turkey, Ministry of Environment and Urbanization. Thermal resistance of each wall alternative is adjusted according to material list of TS 825 standard.

In window system design, different frame and glazing combinations are created to evaluate more alternatives for better design. Types of frame and glazing systems are determined according to given alternatives in TS 825 standard. Beside this, glazing alternatives are diversified by adding different glazing type combination with different thickness level and different gases such as air and argon between two glasses. Thermal transmittance value of generated glazing types are taken from Isıcam database.
In the determination of design alternative materials and their thickness values, availability of cost and environmental impact based data draw the limits for design alternatives. The cost of each design alternatives is determined according to 2015 Unit Price Database of Republic of Turkey, Ministry of Environment and Urbanization whereas environmental data are extracted from PE 2012 and Eco-invent 2012

databases via Gabi 6.0 software. The general procedure applied in this study for design alternative generation using these data is as follows:

- ✓ Design alternative materials in insulation application of any building component should be used or not is determined according to pre-determined rule whether the insulation material is used in the insulation of that building component in the Unit Price Database. Moreover, all possible wall types in the database are used in the wall design process.

- ✓ Some thickness levels of insulation materials decided to be used in design are given in Unit Price Database; however, alternative thickness values are generated to vary building design by interpolation for intermediate thickness values and extrapolation for the thickness alternatives that is higher than maximum thickness levels in Unit Price Database.

- ✓ In the energy optimization model, insulation thickness alternatives are initially applied to reference building components to eliminate some of alternatives due to causing more heat loss than recommended thermal transmittance value in Table 3.1. In building walls, building wall type is assumed to be fixed according to reference building in elimination process.

- ✓ Insulation design in any building component is done with respect to given insulation and material details in Unit Price Database. Therefore, all complementary materials for insulation application for different building components and waste percent of insulation materials are determined based on this database.

- ✓ In this study, all cost and environmental impact based analyses are done comparatively. Therefore, same material applied in all alternative insulation designs is not taken into consideration.

- ✓ Some of the missing data are supported by complementary data. For instance, environmental impact values for natural gas used in Turkey are not available in database whereas same data is available for Greece, Hungary and European Union. Therefore, missing data is completed by complementary data from the given alternative above in the order of Greece, Hungary and European Union regarding geographical conditions. All of energy resource alternatives are determined according to this procedure.

- ✓ Environmental performance of all insulation materials in Turkey is not available in Gabi 6.0 database. Therefore, existing performance values in the database are taken into consideration for design alternatives. Similar to energy resources, in insulation alternatives, missing environmental impact data of insulation materials are completed with respect to existing database. For instance, environmental performance of EPS 16 kg/m_3 is estimated by interpolation of environmental performance of EPS 15 kg/m_3 and EPS 20 kg/m_3 whereas environmental performance of EPS 35 kg/m_3 is estimated by extrapolation of environmental performance of EPS 25 kg/m_3 and EPS 30 kg/m_3.

- ✓ Environmental performances of insulation and other design alternatives are calculated according to life cycle of materials. However, environmental performance impact due to material logistics is ignored, because a comprehensive database in detail is required for eighty one cities with various materials which needs to include material importing location and distance to local supplier.

- ✓ In the evaluation of environmental performance of brick walls , in real life, the change in the surface area of brick wall changes energy requirement and brick environmental performance; however, in this study, only the weight of the brick is evaluated in the environmental performance calculations due to lack of data in the database. Similarly, in environmental performance evaluation of PVC frames, PVC frames with different hollow chambers are assumed to give same environmental life cycle performance.

In energy optimization model, the decision maker, firstly design reference building and decide which design alternatives can be used in the optimization process. The decision maker can improve the building performance by changing wall types, window frame and glazing type and insulation material and thickness of wall, roof, and floor and foundation. All the possible design alternatives generated in the interface are tabulated in Table 5.3.

5.1.4. Design Variables

In the optimization design process, each building element can be design separately. For instance, walls in each story can be insulated by different material and thickness combination or in each story, different wall type can be used; however, this design approach loses touch with reality in practical applications. Therefore, instead of evaluating each building element separately, in this study, building components are categorized according to their thermal property difference and each building element with same thermal property are insulated by same material and thickness combination. This makes the study more realistic. Wall, roof and floor / foundation component of the building are sub-divided into multiple categories according to their location in the building and window system is diversified according to main directions in the building. The location based design variables in the energy optimization model are tabulated in Table 5.4.

In optimization procedure, firstly, all redundant insulation material/thickness design alternatives that violates recommended insulation levels are directly eliminated. In the elimination procedure, the building elements with same design type and location

Table 5.3. Design Alternatives

Design Type	Design material	Design Alternatives (size, thickness)
Wall Type	Aerated Concrete Wall	7.5 cm, 8.5 cm, 9 cm, 10 cm, 12.5 cm, 13.5 cm, 15 cm, 17.5 cm, 19 cm, 20 cm, 22.5 cm, 25 cm, 30 cm, 35 cm
	Horizontal Coring Brick Wall (HCB)	190 x 85 x 190, 200 x 100 x 200, 250 x 120 x 200, 190 x135 x 190, 250 x200 x 250, 235 x240 x 135, 240 x250 x 190
	Vertically Perforated Brick Wall –W Class	240 x 115 x 235, 240 x 145 x 235, 240 x 175 x 235, 290 x 190 x 235, 240 x 240 x 235, 240 x 250 x 235, 240 x 300 x 235
	Vertically Perforated Brick Wall –W Class	290 x 190 x 135, 290 x 240 x 190, 240 x 290 x 190, 190 x 390 x 190
Wall Insulation	EPS 16 kg/m_3 EPS 20 kg/m_3 EPS 30 kg/m_3 EPS 35 kg/m_3	3 cm to 20 cm by 1 cm interval
	XPS 25 kg/m_3 XPS 30 kg/m_3	3 cm to 20 cm by 1 cm interval
	Rock wool 120 kg/m_3	3 cm to 20 cm by 1 cm interval
Floor / Foundation Insulation	EPS 16 kg/m3 EPS 20 kg/m3 EPS 30 kg/m3 EPS 35 kg/m3	3 cm to 20 cm by 1 cm interval
	XPS 25 kg/m3 XPS 30 kg/m3	3 cm to 20 cm by 1 cm interval
Roof Insulation	EPS 16 kg/m3 EPS 20 kg/m3 EPS 30 kg/m3 EPS 35 kg/m3	3 cm to 20 cm by 1 cm interval
	XPS 25 kg/m3 XPS 30 kg/m3	3 cm to 20 cm by 1 cm interval
	Rock wool 50 kg/m_3	6 cm to 25 cm by 1 cm interval
	Glass wool 18 kg/m_3	6 cm to 25 cm by 1 cm interval
	Aerated Concrete	5 cm, 7.5 cm, 8.5 cm, 10 cm, 12.5 cm, 15 cm, 17.5 cm, 20 cm

Table 5.3. Design Alternatives (continued)

Design Type	Design material	Design Alternatives (size, thickness)
Window	Frame	Woodwork, Aluminum Joinery, Aluminum Joinery with Insulation Bridge, Two Hollow Chamber PVC, , Three Hollow Chamber PVC, , Four Hollow Chamber PVC, , Five Hollow Chamber PVC, , Six Hollow Chamber PVC
	Glazing	Single Clear (4 mm),Double Clear Air (3-9-3), Double Clear Air (4-9-4), Double Clear Air (5-9-5), Double Clear Air (6-9-6), Double Clear Air (3-12-3), Double Clear Air (4-12-4), Double Clear Air (5-12-5),Double Clear Air (6-12-6), Double Clear Air (3-16-3), Double Clear Air (4-16-4), Double Clear Air (5-16-5), Double Clear Air (6-16-6), Double Sinergy Air (4-9-4), Double Sinergy Air (4-12-4), Double Sinergy Air (4-16-4), Double Comfort Air (4-9-4), Double Comfort Air (4-12-4), Double Comfort Air (4-16-4),Triple Sinergy Air (4-9-4-9-4), Triple Sinergy Air (4-12-4-12-4), Triple Sinergy Air (4-16-4-16-4) , Triple Comfort Air (4-9-4-9-4), Triple Comfort Air (4-12-4-12-4), Triple Comfort Air (4-16-4-16-4), Double Clear with Argon(3-9-3), Double Clear with Argon(4-9-4), Double Clear with Argon(5-9-5), Double Clear with Argon(6-9-6), Double Clear with Argon(3-12-3), Double Clear with Argon(4-12-4), Double Clear with Argon(5-12-5), Double Clear with Argon(6-12-6), Double Clear with Argon(3-16-3), Double Clear with Argon(4-16-4), Double Clear with Argon(5-16-5), Double Clear with Argon(6-16-6), Double Sinergy with Argon(4-9-4), Double Sinergy with Argon(4-12-4), Double Sinergy with Argon(4-16-4), Double Comfort with Argon(4-9-4), Double Comfort with Argon(4-12-4), Double Comfort with Argon(4-16-4) , Triple Sinergy with Argon(4-9-4-9-4), Triple Sinergy with Argon(4-12-4-12-4), Triple Sinergy with Argon(4-16-4-16-4), Triple Comfort with Argon(4-9-4-9-4), Triple Comfort with Argon(4-12-4-12-4), Triple Comfort with Argon(4-16-4-16-4)

Table 5.4. Location Based Design Variables

Design Type	Design Location/ Direction
Wall Type	Curtain Wall (ventilated or partiating uninsulated ceiling) Exterior Wall Interior Walls (apartment partiating wall, stair, low-temperature surrounding) Soil-contacted Exterior Wall
Wall Insulation	Curtain Wall (ventilated or partiating uninsulated ceiling) Exterior Wall Interior Walls (apartment partiating wall, stair, low-temperature surrounding) Soil-contacted Exterior Wall
Floor / Foundation Insulation	Basement Ceiling Cantilever Floor Floor (partiating apartments or rooms in multi-purpose hall ,bottom up heat flow) Floor (partiating apartments or rooms in multi-purpose hall ,top-down heat flow) Soil-contacted Basement
Roof Insulation	Ceiling (unused garret, under ventilated space) Unventilated roof /ceiling & terrace
Window Frame	East, North, South, West
Window Glazing	East, North, South, West

are collected together and thermal resistance of each building element is calculated without insulation materials. Then, the building element with minimum thermal resistance, in other word, with worst insulation, is accepted as reference building element to eliminate insufficient design alternatives. After that minimum required thermal resistance level is calculated by subtracting thermal resistance of referenced building element from the recommended thermal resistance for that building component by dividing 1 to recommended thermal transmittance value in Table 3.1 according to degree-day region of building location. All design alternatives that have less thermal resistance than the calculated minimum thermal resistance are eliminated before optimization process starts. Similarly, by fixing window frame properties of reference building, all redundant glazing alternatives whose thermal transmittance level are higher than the recommended value are eliminated for each main direction of the building one-by-one. Similar to insulation elimination process, the most critical window system for each direction is referenced.

In building energy based design process, some design alternatives needs to be eliminated due to illogical design. For instance, in building wall insulation design, the use of insulation design combination with higher thermal resistance in interior walls than the one in the exterior wall provides theoretically and practically illogical applications. Therefore, in optimization process, if the thermal resistance of interior walls is higher than the one in exterior and soil contacted exterior walls, then, the design solution is constrained and multiplied by infinitesimally high number to eliminate it from alternative best solutions.

5.2. EnrOpt Graphic User Interface

The details of EnrOpt interface is explained step by step as a user guide as follows:

Step 1: Excel file of the interface is opened and details of wall, roof, floor or foundation (basement) and window is entered into the file as seen in Figure 5.1.-5.4. In excel file, the wall type for wall system and insulation type for wall/roof and basement system are selected among given alternatives whereas the material and thickness details of building layers are selected from given dropdown list obtained from TS 825 material database. The location of the building element (interior, exterior etc.) is also selected from given dropdown list. The excel macro is directly calculates thermal resistance of each layer and whole building element in variation such as thermal resistance of all building elements, thermal resistance without insulation or thermal resistance for only building element layers that are used in Matlab coding. Moreover, area of the material used is entered. The design details for wall system, basement system and roof system are summarized in an excel sheet to follow the details more easily (Figure 5.5).

In window design, the shape of the window system is selected from given dropdown list such as single/double casement, horizontal slider, angular and transom window. Then, frame material and glazing property of window system are selected from the given dropdown list. After that general geometric details of the window system such as window height, window width and window frame thickness are entered. Horizontal and vertical divider and divider thickness with same frame materials are used to better define complex geometry. Finally, by entering the number of windows with same property in the same direction by selecting the window direction from main directions given in dropdown list, frame area and glazing area and glazing perimeter for each window ID are calculated in excel macro and used in the calculations.

Building door design details are also done in excel file. Thermal heat loss values for doors are calculated in excel file and used in Matlab code. Thus, excel based design process is finalized and excel file is saved and closed.

The details of the following steps of Matlab GUI is explained on Figure 5.1 to 5.17.

	Wall System III			
	Material	Thermal Conductivity	Thickness(m)	Thermal Performance
Wall Type	HCB 190 x 190 x 135	0,33	0,19	0,575757576
Insulation Type	4 cm-XPS350 30 kg/m3	0,035	0,04	1,142857143
Layer 1	4.1. Lime mortar , lime - cement mortar	1	0,02	0,02
Layer 2	4.8.2. Plaster mortar made from inorganic based lwgt aggregate- 900 kg/m3	0,35	0,008	0,022857143
Layer 3	Select			
Layer 4	Select			
Layer 5	Select			
Layer 6	Select			
Layer 7	Select			
Wall Location	Interior Walls(apartment partiating wall,stair, low-temperature surrounding)			0,26
Wall Area	28,24	m2		
Only Layers				0,302857143
Wall System without Insulation				0,878614719
All wall system				2,021471861

Figure 5.1. Wall Design Details

	Basement System II			
	Material	Thermal Conductivity	Thickness(m)	Thermal Performance
Insulation Type	4 cm-XPS350 30 kg/m3	0,035	0,04	1,142857143
Layer 1	4.6. Cement mortar screed	1,4	0,02	0,014285714
Layer 2	5.1.1. Plain Concrete (Normal concrete (with TS 500) , made using natural aggregate concrete or gravel)	2,5	0,12	0,048
Layer 3	4.8.2. Plaster mortar made from inorganic based lwgt aggregate- 900 kg/m3	0,35	0,008	0,022857143
Layer 4	8.1.1. Timber derived from coniferous trees	0,13	0,01	0,076923077
Layer 5	Select			
Layer 6	Select			
Layer 7	Select			
Floor Location	Cantilever Floor			0,21
Floor Area	42,15	m2		
Basement System without Insulation				0,372065934
All basement system				1,514923077

Figure 5.2. Floor / Foundation Design Details

Roof System I				
	Material	Thermal Conductivity	Thickness(m)	Thermal Performance
Insulation Type	6 cm-XPS300 25 kg/m3	0,03	0,06	2
Layer 1	5.1.1. Plain Concrete (Normal concrete (with TS 500) , made using natural aggregate concrete or gravel)	2,5	0,12	0,048
Layer 2	4.3. Gypsum mortar, lime plaster mortar	0,7	0,002	0,002857143
Layer 3	4.6. Cement mortar screed	1,4	0,02	0,014285714
Layer 4	1.1.1. Crystalline igneous and metamorphic rocks(mozaic etc) > 2800 kg/m3	3,5	0,01	0,002857143
Layer 5	6.5. Gypsum cardboard boards (suitable to TS EN 520)	0,25	0,008	0,032
Layer 6	Select			
Layer 7	Select			
Roof Type	Unventilated roof /ceiling & terrace			0,17
Roof Area	130,16	m2		
Roof System without Insulation				0,27
All roof system				2,27

Figure 5.3. Roof Design Details

				Window Geometry			Divider				
Window ID	*Window Shape*	*Frame Material*	*Glazing Type*	*Length(m)*	*Width(m)*	*Thickness (m)*	*# of Vertical Divider*	*# of Horizantal Divider*	*Thickness (m)*	*# of Window*	*Window Direction*
1	Single Casement	Millwork	Double Sinergy Air (4-12-4)	5,1	3	0,5				1	North
2	Single Casement	Millwork	Double Sinergy Air (4-12-4)	14,15	5	1				1	South
3	Single Casement	Millwork	Double Sinergy Air (4-12-4)	9,03	5	0,75				1	East
4	Single Casement	Millwork	Double Sinergy Air (4-12-4)	8,4	5	0,75				1	West
5		Select	Select								Select
6		Select	Select								Select
7		Select	Select								Select
8		Select	Select								Select
9		Select	Select								Select
10		Select	Select								Select

Figure 5.4. Window System Design Details

Wall Summary						
Wall System ID	Wall Type	Wall Area(m2)	Insulation Type	Only Layers	Wall System without Insulation	All wall system
Wall System I	HCB 190 x 190 x 135	442,6	4 cm-XPS350 30 kg/m3	0,212857143	0,788614719	1,931471861
Wall System II		305,45	4 cm-XPS350 30 kg/m3	0,312857143		1,455714286
Wall System III	HCB 190 x 190 x 135	28,24	4 cm-XPS350 30 kg/m3	0,302857143	0,878614719	2,021471861
Wall System IV		18,84	4 cm-XPS350 30 kg/m3	0,402857143		1,545714286
Wall System V						
Wall System VI						
Wall System VII						
Wall System VIII						
Wall System IX						
Wall System X						

Basement/Foundation Summary				
Basement System ID	Base Area(m2)	Insulation Type	Basement System without Insulation	All basement system
Basement System I	326,21	4 cm-XPS300 30 kg/m3	0,335084915	1,668418248
Basement System II	42,15	4 cm-XPS350 30 kg/m3	0,372065934	1,514923077
Basement System III				
Basement System IV				
Basement System V				

Roof Summary				
Roof System ID	Roof Area(m2)	Insulation Type	Roof System without Insulation	All roof system
Roof System I				
Roof System II	130,16	6 cm-XPS300 25 kg/m3	0,27	2,27
Roof System III	236,81	8 cm-XPS400 30 kg/m3	0,278	2,278
Roof System IV				

Figure 5.5. Design Summary

Step 2: EnrOpt interface is initialized. The menu in the interface that categorizes the energy optimization model process is explained one by one in followings steps.

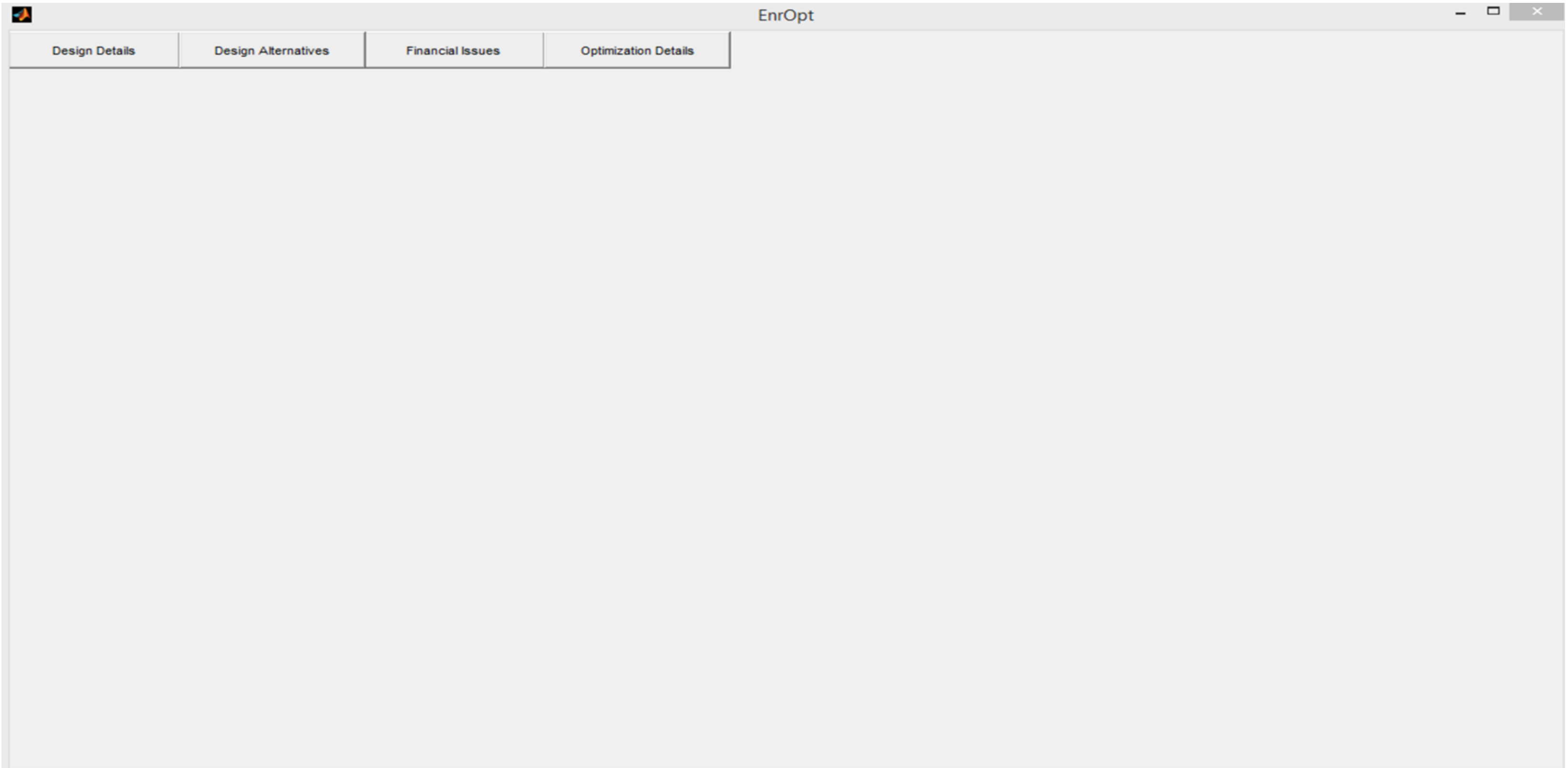


Figure 5.6. EnrOpt Initialization

Step 3: Design details show excel based design of wall, window, roof and floor/ foundation in GUI. The materials in building element layer are explained by its TS 825 material ID.

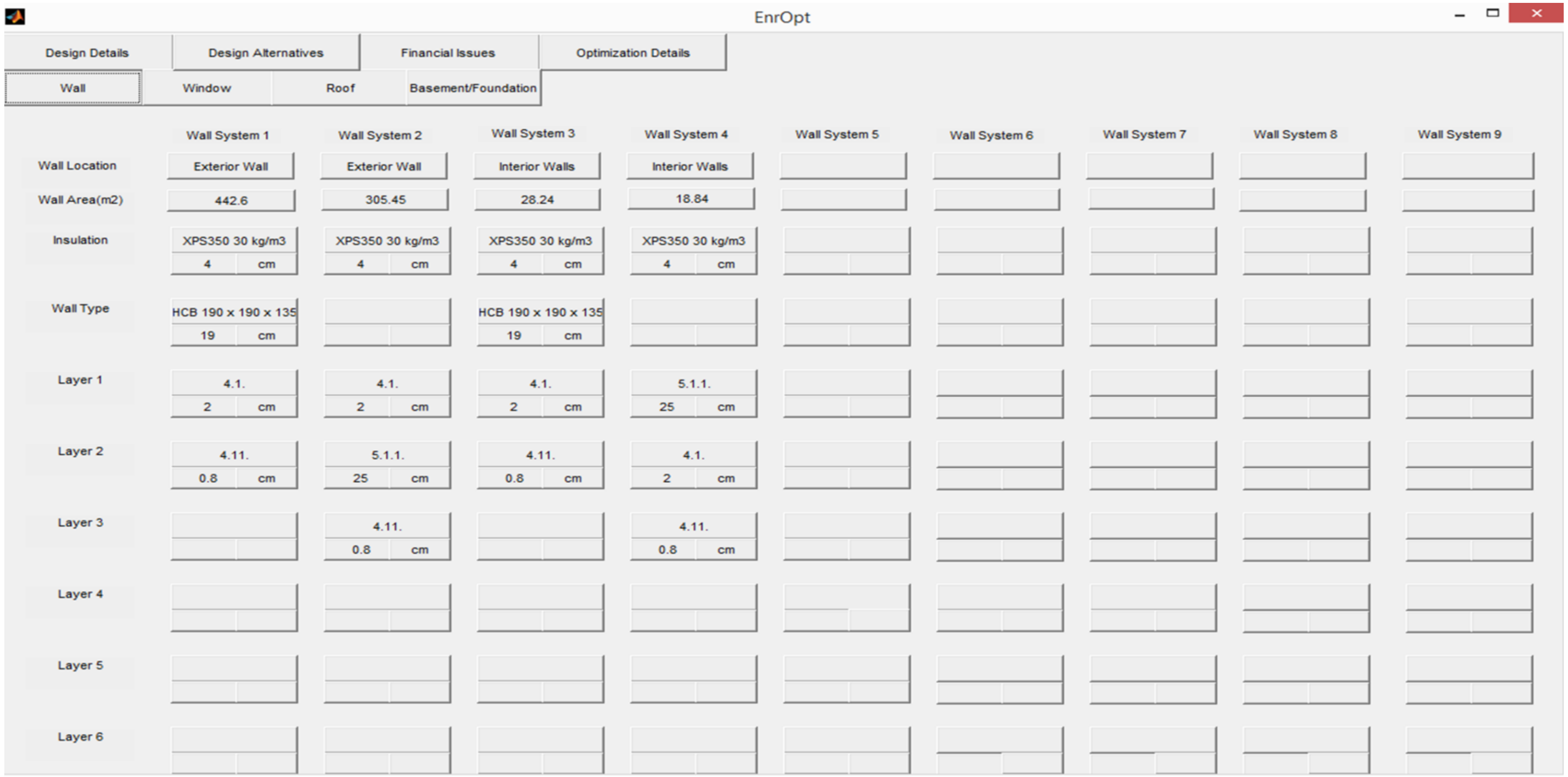


Figure 5.7. Demonstration of Excel based Building Component Design in GUI

Step 4: Design alternatives for wall type and insulation type for different building component and window system are selected and insulation upper thickness limit for each building component are determined to narrow solution space.

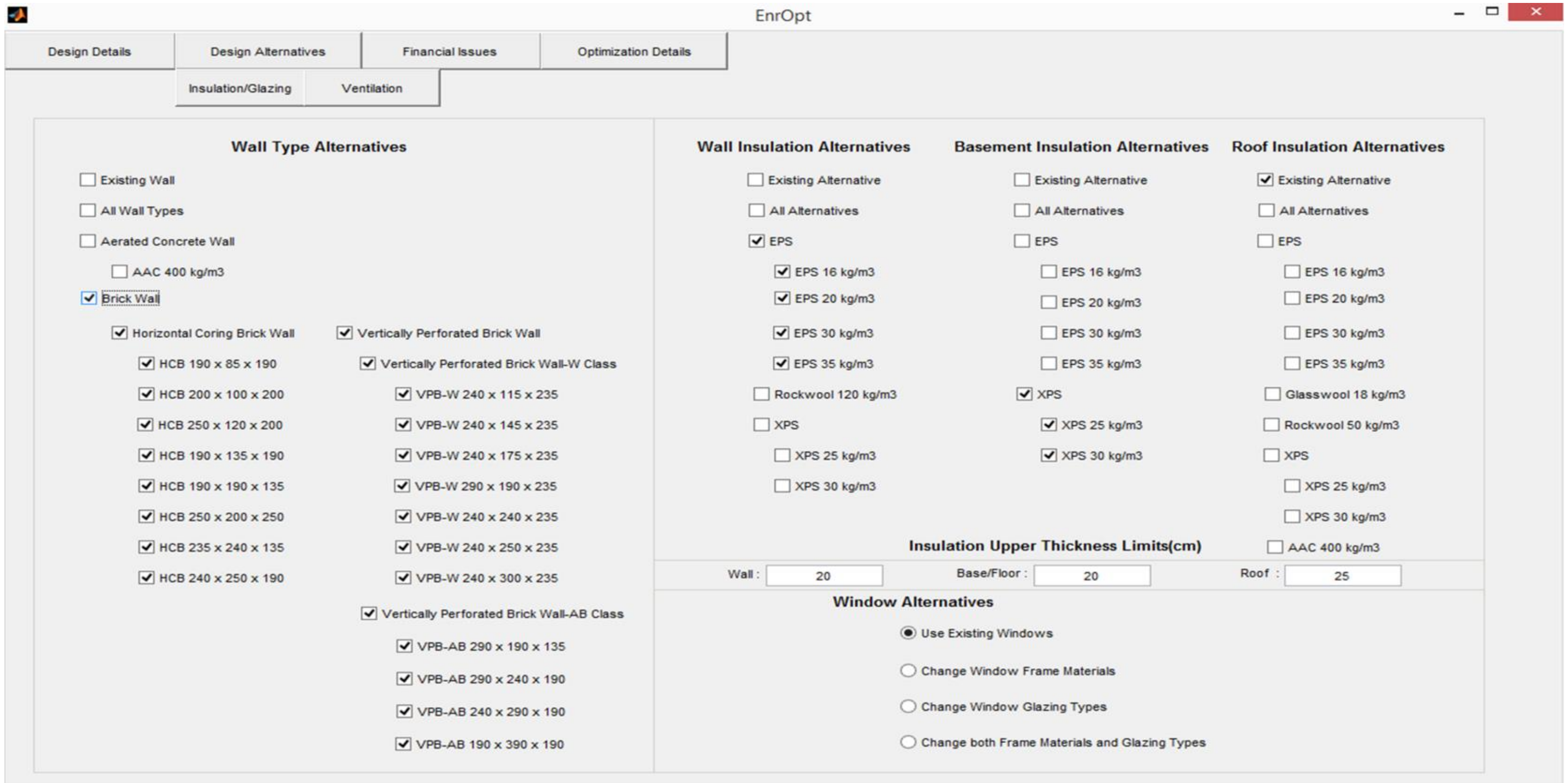


Figure 5.8. Selection of Design Alternatives

Step 5: Ventilation type for building design is selected and ventilation design details are entered in this section.

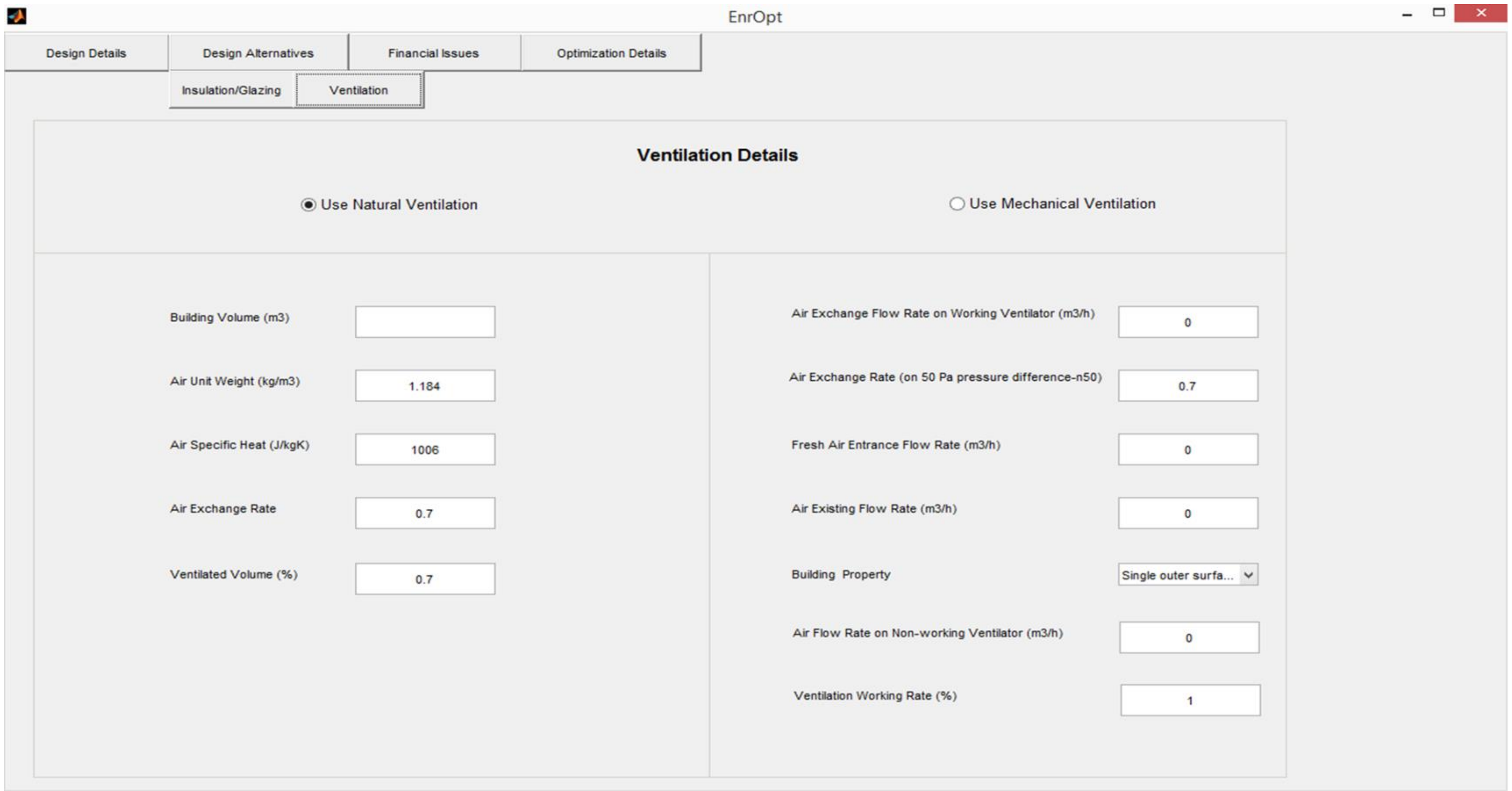


Figure 5.9. Determination of Building Ventilation Details

Step 6: The default interest rate values are determined according to given details in the previous sections. The rates can be changed by the user if it is seen necessary. In energy details part, unit price and energy use weight for the energy resources planned to be used to heat the building are entered. The use weight is normalized for the resources in the code. The resource efficiency for the energy resources can be changed if necessary.

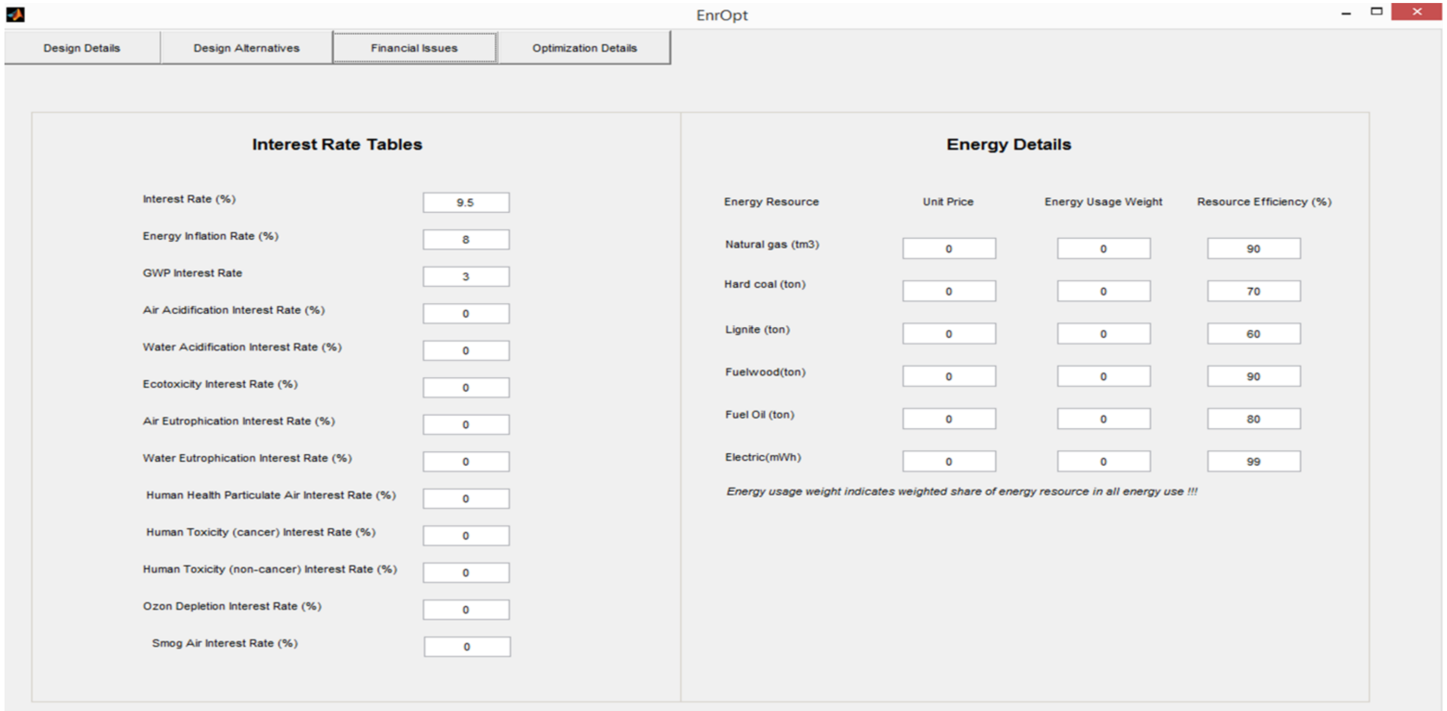


Figure 5.10. Determination of Financial and Energy Detail

Step 7: Optimization details represent the optimization part of the energy optimization model in the interface. In the interface, building type is selected from pop-up menu to obtain building internal balance temperature. The user selects building location to determine thermal and solar effect of climate on the building. From climate data and solar data menu, the user selects which temperature data and solar radiation data are used in the optimization process. The heating schedule of the building is selected from the given alternatives in operational schedule menu.

In optimization process, the meta-heuristic algorithm that generates solutions and directs solution generation process is selected by alternative lists such as Differential Evolution, Particle Swarm Optimizer and Modified Cross Entropy Method. In optimization strategy, the user determines whether to focus more on main objective optimization or generates Pareto optimal solutions by scanning wider space.

In determination of optimization objectives, the user can select the objectives in two ways. In the first one, if the number of objective is less or equal to three, the user can select the objectives from objective dropdown list one by one. The main objective is the key objective that directs all optimization process where the rest is used in the generation of Pareto optimal solutions. In the second approach, the user can enter the objective IDs that are given in dropdown list, by using comma between objective IDs. The objective ID with entered first represents the main objective. When both first and second approaches are used together, the second approach is valid in optimization.

All design details should be checked before optimization process starts. Therefore, checklist for the effective design is given to warn the user not to miss any parts in the design. After all list is checked, the optimization process starts by pushing the button "Run EnrOpt". The model runs in a minute and gives results. When optimization process finishes, "Result", "Graphical Result" and "GWP Results" (if life-cycle GWP savings is in objective lists) are added to menu tabs (Figure 12). Thus, the user can check optimization results within the interface.

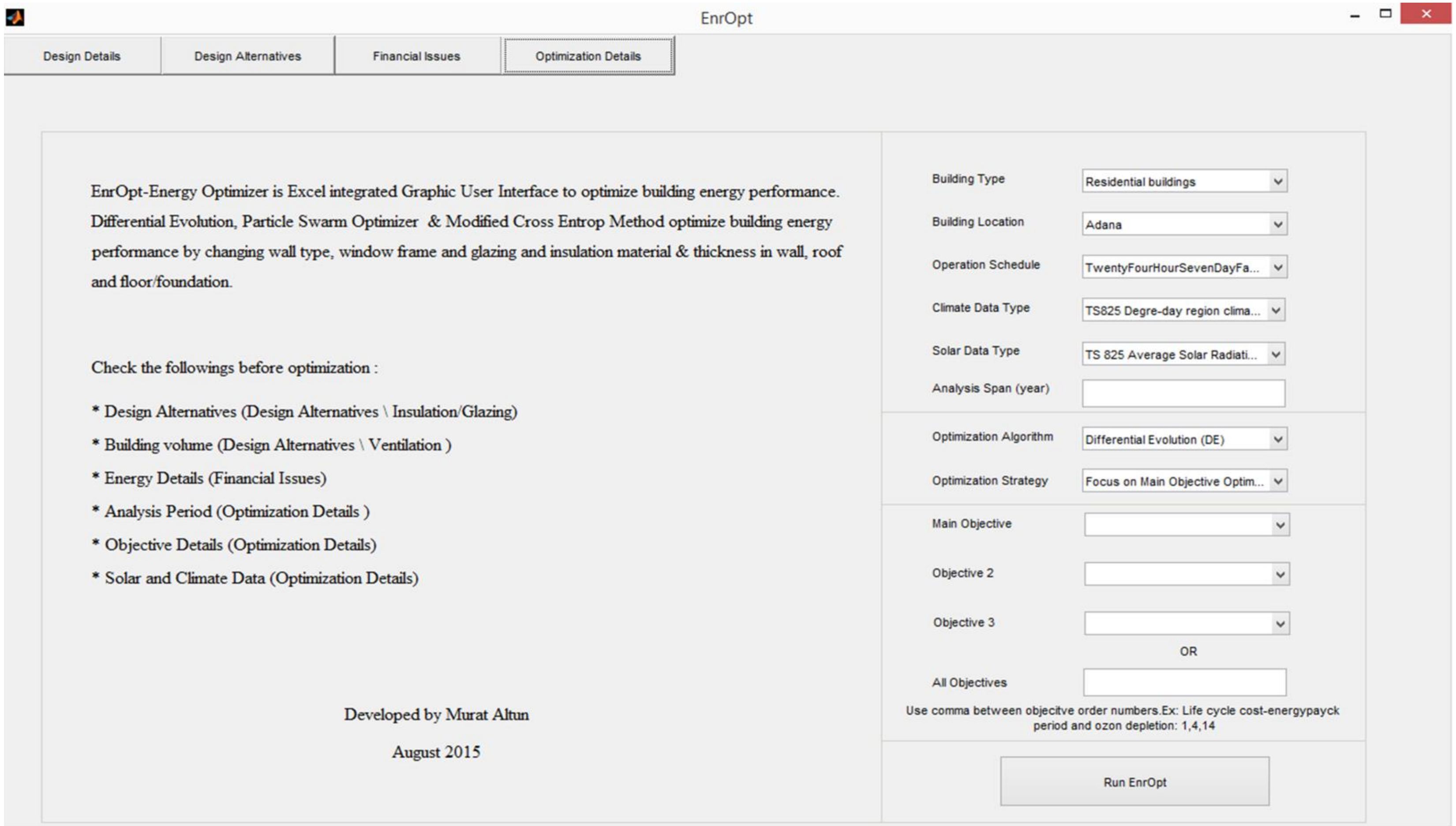


Figure 5.11. Optimization Details (before Optimization starts)

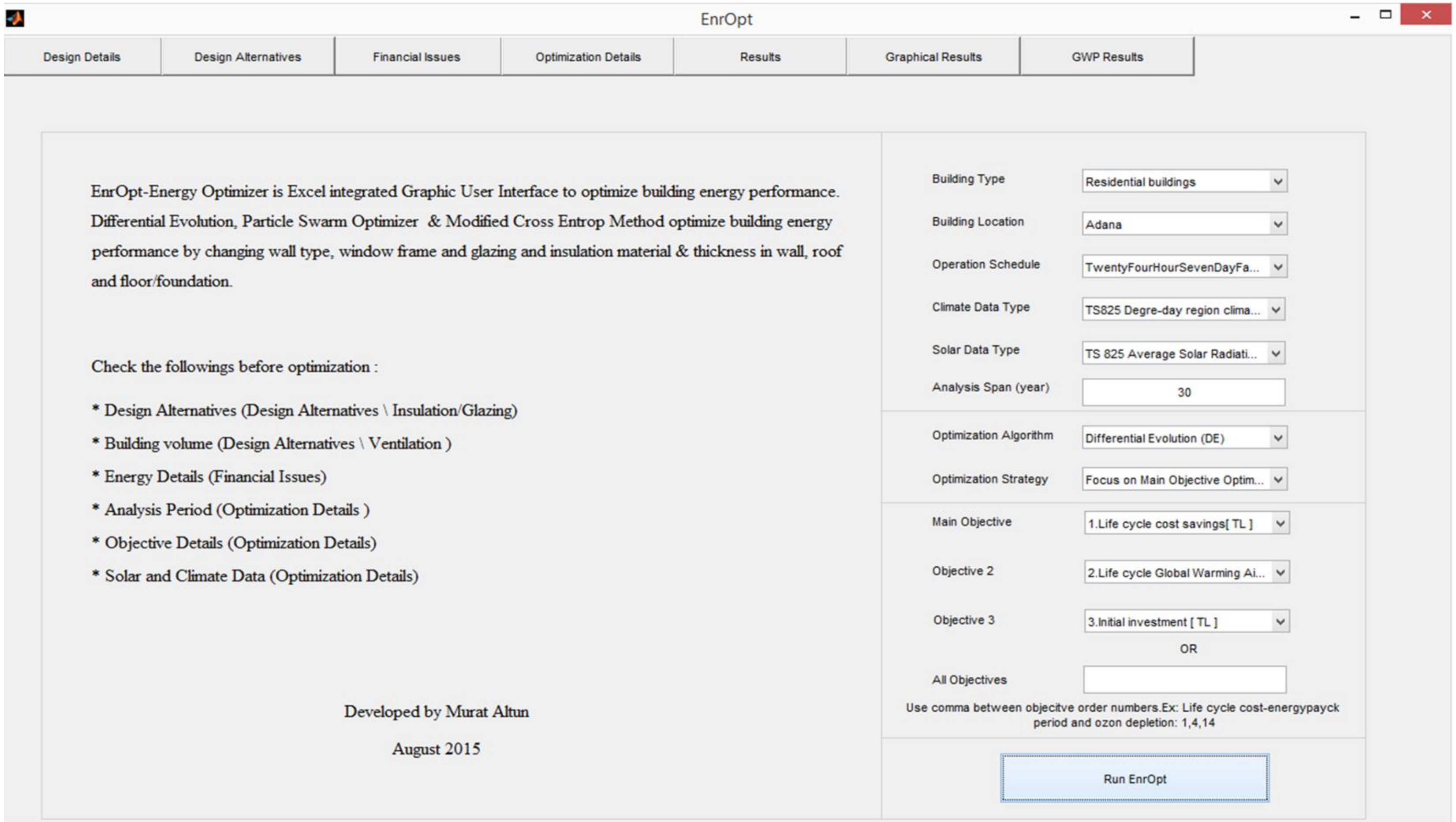


Figure 5.12. Optimization Details (after optimization finishes)

Step 8: The user can control design list and objective values of all Pareto optimal solutions. All Pareto optimal solution are ranked according to main objective performance. Therefore, by changing the rank of the solution from the edit box in the right bottom of the page.

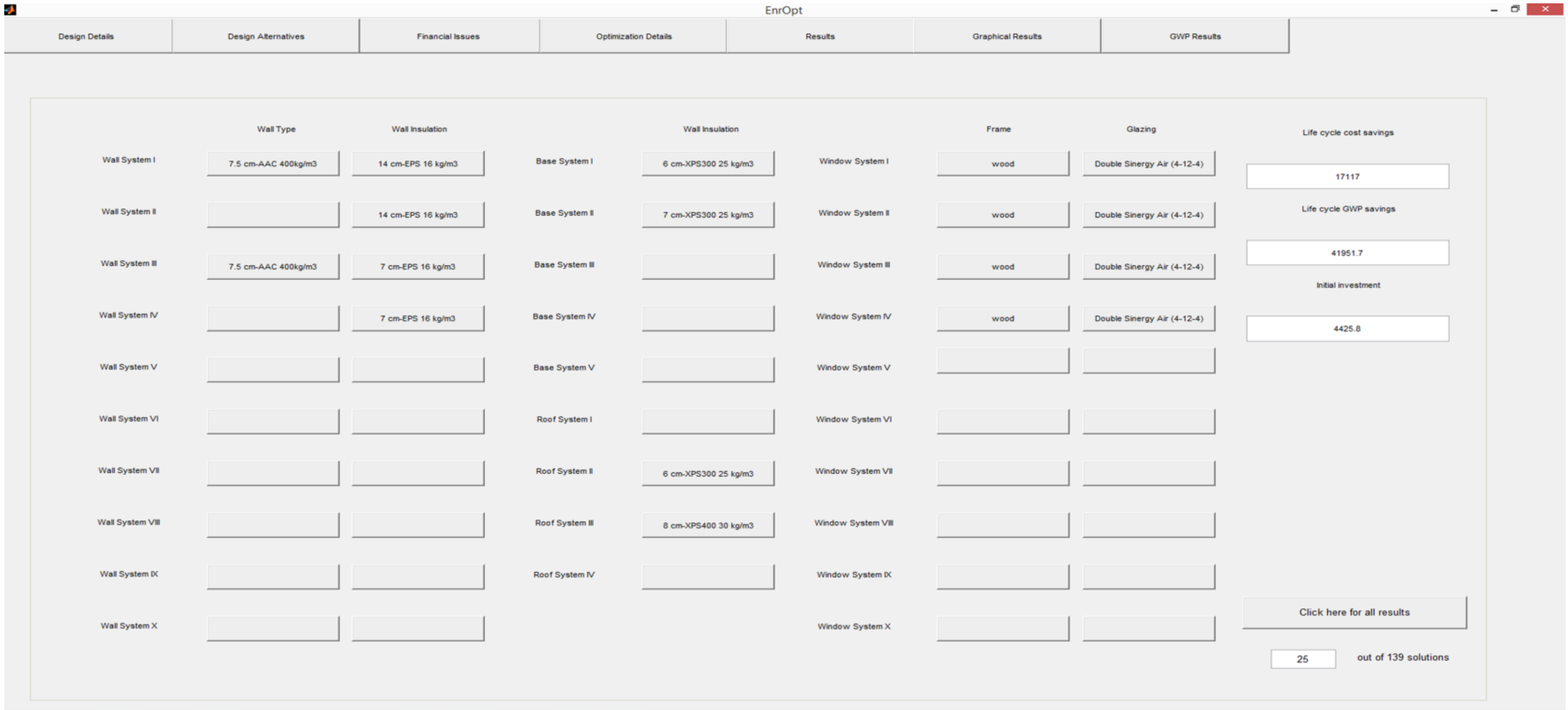
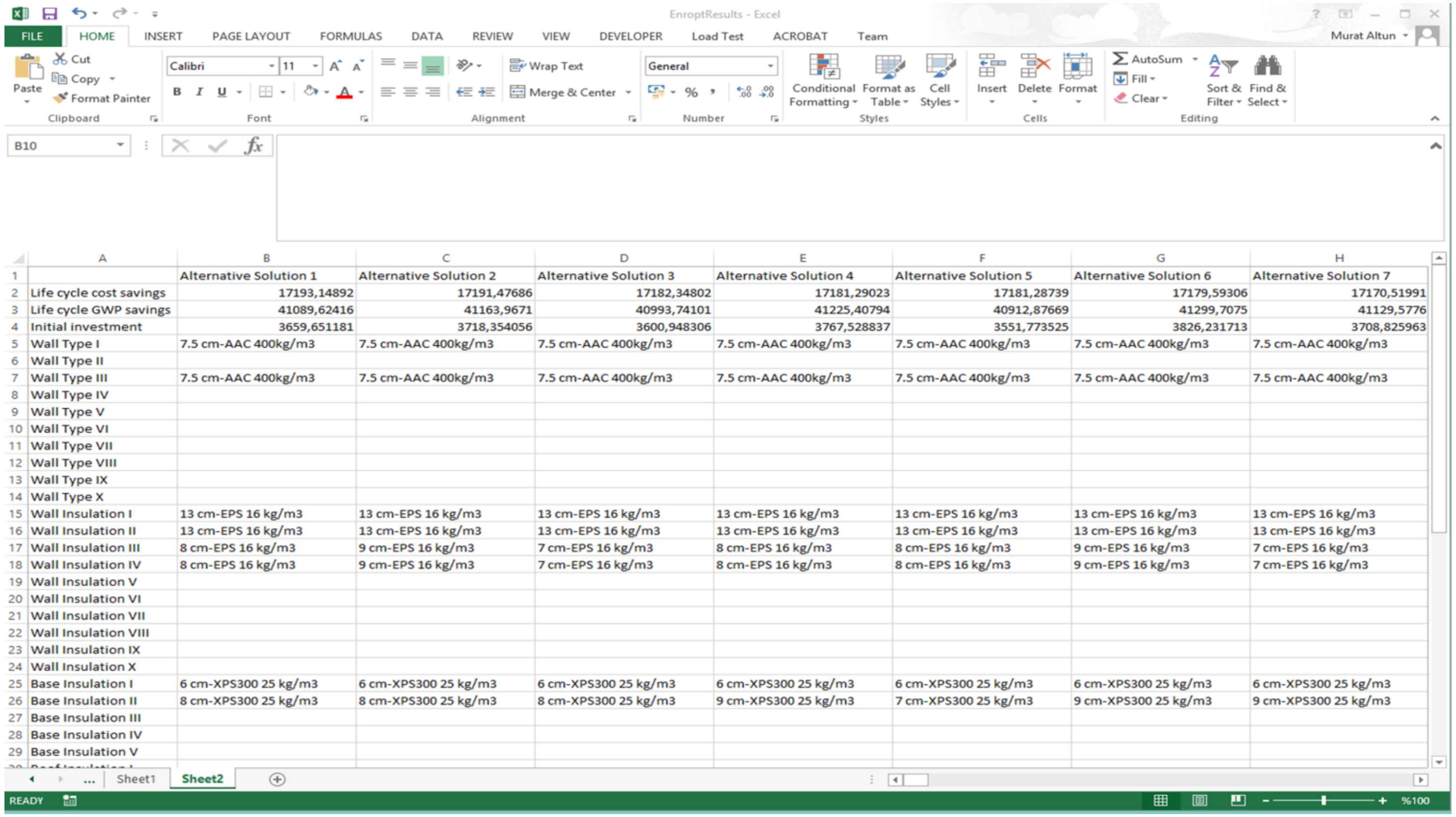


Figure 5.13. Optimization Result one by one

Step 9: All Pareto optimal solutions with design details in excel sheet can be checked by clicking “Click here for all results” button.



	A	B	C	D	E	F	G	H
1		Alternative Solution 1	Alternative Solution 2	Alternative Solution 3	Alternative Solution 4	Alternative Solution 5	Alternative Solution 6	Alternative Solution 7
2	Life cycle cost savings	17193,14892	17191,47686	17182,34802	17181,29023	17181,28739	17179,59306	17170,51991
3	Life cycle GWP savings	41089,62416	41163,9671	40993,74101	41225,40794	40912,87669	41299,7075	41129,5776
4	Initial investment	3659,651181	3718,354056	3600,948306	3767,528837	3551,773525	3826,231713	3708,825963
5	Wall Type I	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3
6	Wall Type II							
7	Wall Type III	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3	7.5 cm-AAC 400kg/m3
8	Wall Type IV							
9	Wall Type V							
10	Wall Type VI							
11	Wall Type VII							
12	Wall Type VIII							
13	Wall Type IX							
14	Wall Type X							
15	Wall Insulation I	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3
16	Wall Insulation II	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3	13 cm-EPS 16 kg/m3
17	Wall Insulation III	8 cm-EPS 16 kg/m3	9 cm-EPS 16 kg/m3	7 cm-EPS 16 kg/m3	8 cm-EPS 16 kg/m3	8 cm-EPS 16 kg/m3	9 cm-EPS 16 kg/m3	7 cm-EPS 16 kg/m3
18	Wall Insulation IV	8 cm-EPS 16 kg/m3	9 cm-EPS 16 kg/m3	7 cm-EPS 16 kg/m3	8 cm-EPS 16 kg/m3	8 cm-EPS 16 kg/m3	9 cm-EPS 16 kg/m3	7 cm-EPS 16 kg/m3
19	Wall Insulation V							
20	Wall Insulation VI							
21	Wall Insulation VII							
22	Wall Insulation VIII							
23	Wall Insulation IX							
24	Wall Insulation X							
25	Base Insulation I	6 cm-XPS300 25 kg/m3	6 cm-XPS300 25 kg/m3	6 cm-XPS300 25 kg/m3	6 cm-XPS300 25 kg/m3	6 cm-XPS300 25 kg/m3	6 cm-XPS300 25 kg/m3	6 cm-XPS300 25 kg/m3
26	Base Insulation II	8 cm-XPS300 25 kg/m3	8 cm-XPS300 25 kg/m3	8 cm-XPS300 25 kg/m3	9 cm-XPS300 25 kg/m3	7 cm-XPS300 25 kg/m3	9 cm-XPS300 25 kg/m3	9 cm-XPS300 25 kg/m3
27	Base Insulation III							
28	Base Insulation IV							
29	Base Insulation V							

Figure 5.14. All Pareto Optimal Solutions

Step 8: If the number of objectives are two or three, both Pareto optimal solutions and all generated solution are plotted in 2D (Figure 5.15) or 3D (Figure 5.16) format.

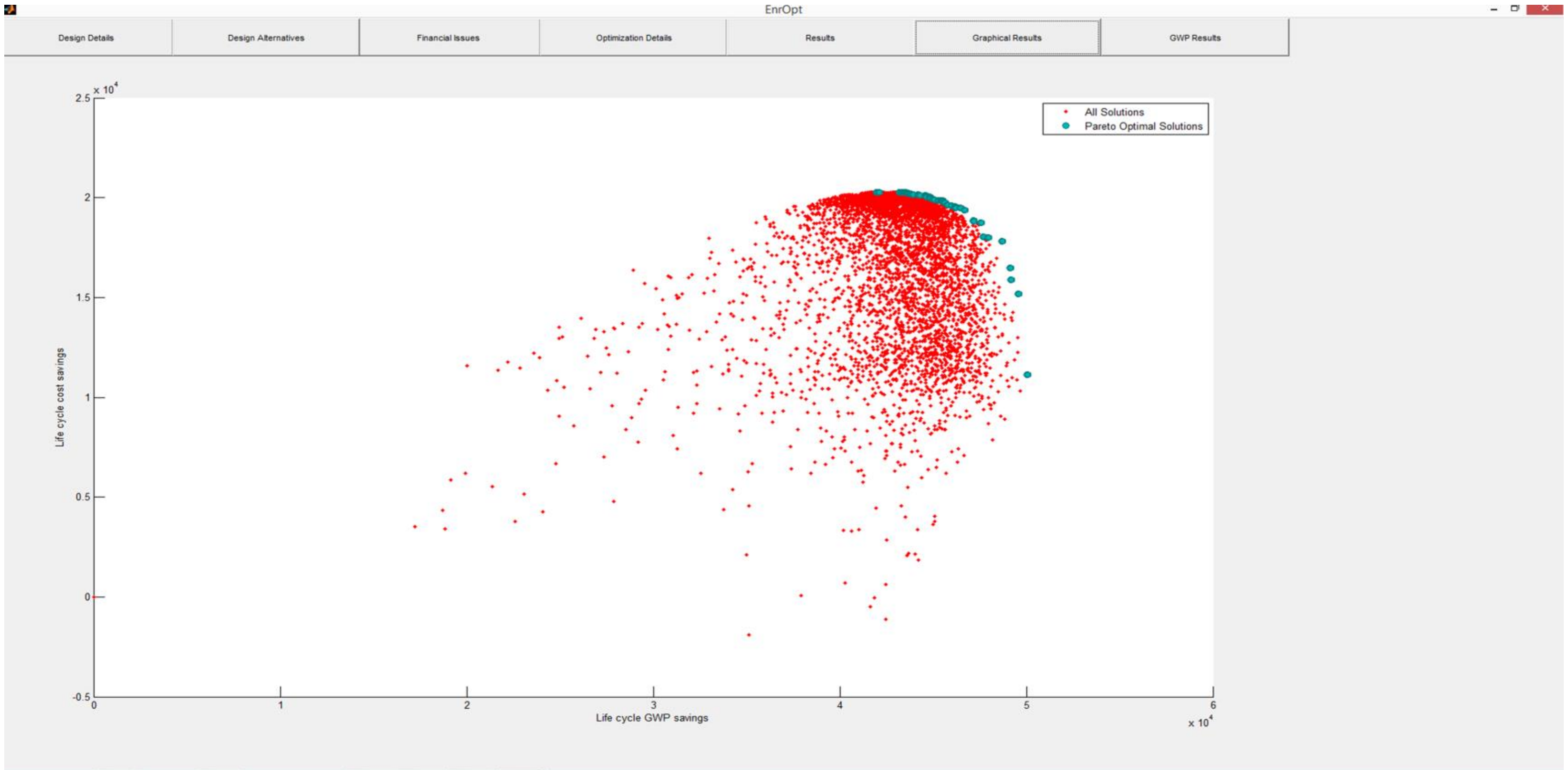


Figure 5.15. Bi-objective Graphical Results

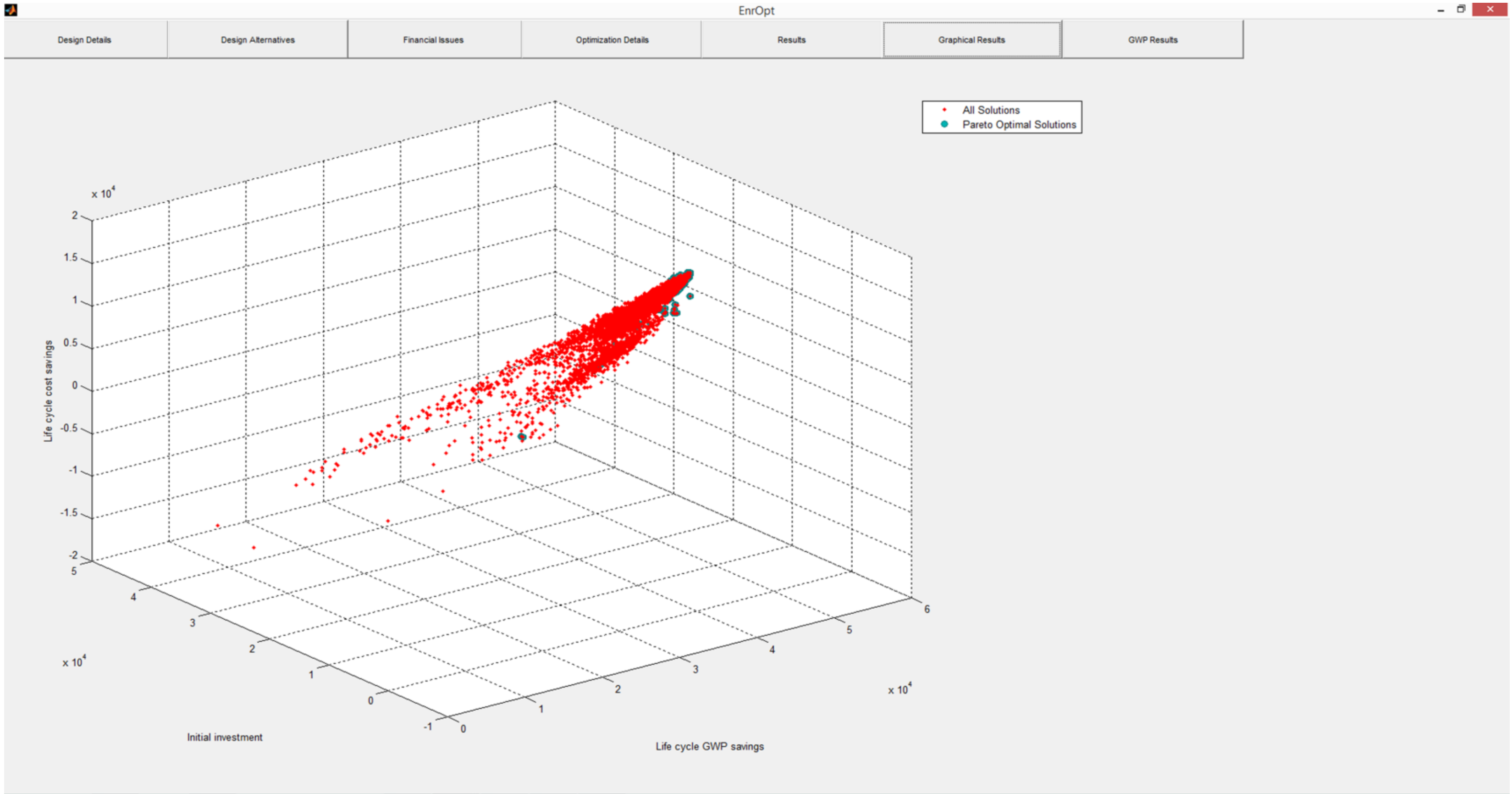


Figure 5.16. Three-objective Graphical Results

Step 10: GWP Results represents effects of global warming savings in terms of number of trees thanks to better design. It shows how many number of trees can reduce the global warming potential in that amount if the trees are planted in the early design stage and reduce GWP until the end of analysis period. The solutions in GWP Results are also ranked according to main objective and the performance results belongs to solution alternative in a rank of the number in edit box in the right bottom.

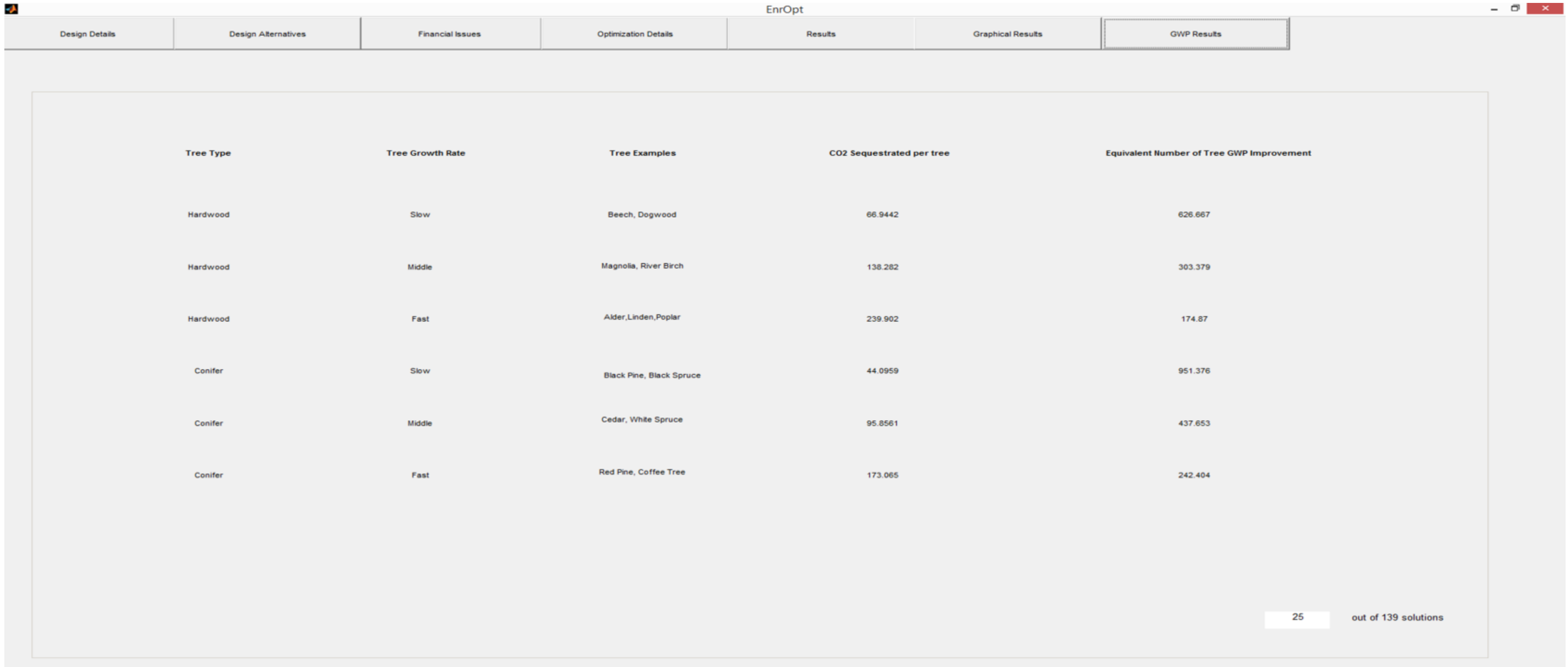


Figure 5.17. GWP Performance

5.3. Case Study I: Typical TOKI Building Energy Performance Optimization

In Turkey, instead of renovation and retrofit projects, construction of new buildings is more common. Turkish housing sale statistics (2013) support this idea that 46% of the dwellings sold are brand new. 44% of total first sales belongs to five major Turkish cities (Istanbul, Ankara, Izmir, Bursa, and Antalya). Urbanization factor plays dominant role in the first sale distribution in Turkey (Figure 5.18). Moreover, shanties and old buildings with high damage risk due to earthquake are planned to be demolished and new buildings are constructed via urban renewal projects. According to Ministry of Environment and Urbanism, 6.5 million dwellings of nearly 20 million dwelling stocks in Turkey are planned to be reconstructed in 20 year-period (Deloitte Turkey 2014). Housing Development Administration of Turkey (TOKI), established in 1984 to find solutions for distorted urbanization and housing problems, is the main player of the residential sector with a share of 9.1% of total sector for the years from 2002 to 2012 (Emlak Konut Gyo 2014) and completion of 644,079 housing units till February,2015 (Housing Development Administration of Turkey 2015). Currently, approximately 2.5 million people reside in TOKI houses. The main customers of TOKI projects are medium low income groups and the poor with nearly 410243(506387) housing units (Housing Development Administration of Turkey 2015). In the upcoming urban renewal projects TOKI is tasked with management of urban renewal projects by Law 6306 (2012).Therefore, in the next years, TOKI is expected to sustain its share and reinforce its power in the housing market.

In this case study, a typical 10-story TOKI building with 44 dwelling housing units whose gross are is 85 m^2 is re-designed according to given alternatives in technical specifications in early design stage by EnrOpt graphical user interface to maximize its energy efficiency. All design alternatives in building design are tabulated in Table 5.5.

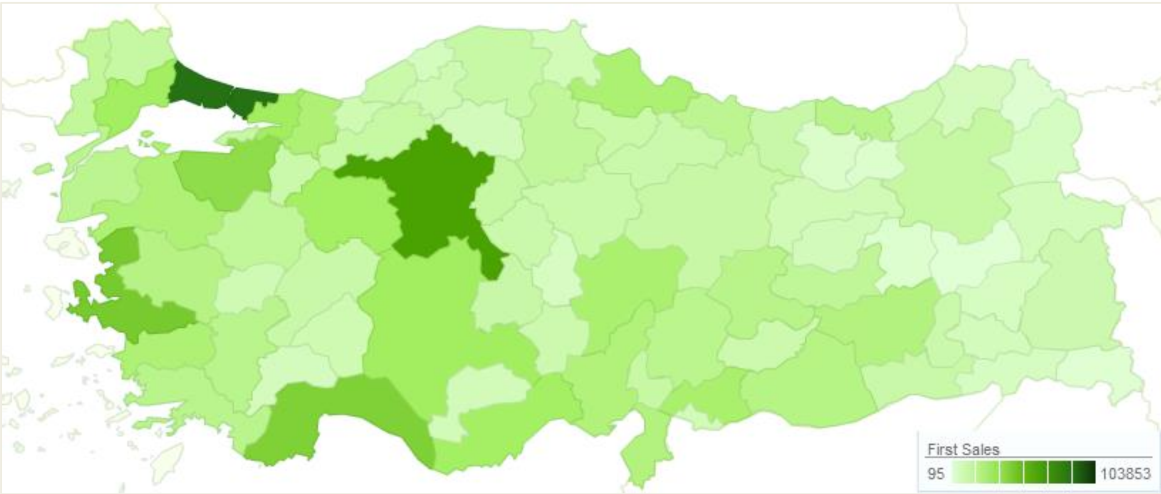


Figure 5.18. The Sales of First-hand Residential Properties for Cities in Turkey

Table 5.5. All Design Alternatives

Design Type	Design Alternatives
All Infilled Walls	All Wall Types in Table 5.3
Wall Insulation	EPS with minimum 22 kg/m^3 XPS Rockwool
Foundation	XPS
Floor	EPS with minimum 22 kg/m^3 XPS
Roof	Glass wool Rockwool EPS with minimum 22 kg/m3 XPS
Window Frame	PVC with 3 hollow chambers
Window Glazing	All glazing types

TOKI building is initially designed in Microsoft Excel according to given conditions in Project Drawings and TS 825 standard whose details are given in Appendix A. Then, Excel file is exported to EnrOpt to optimize the process. In optimization procedure, performance of TOKI buildings is evaluated in different perspectives explained below.

Energy performance of TOKI buildings in different degree-day regions are tested by selected cities with top housing sales from each degree-day region such as İzmir, İstanbul, Ankara, Kayseri and Erzurum. For each city, insulation design of TOKI building is re-designed and adjusted according to TS 825 standard. Recent degree-day data, corrected solar radiation data with Isıcam daylight transmittance factors and natural gas as energy resource are used in the optimization process.

Performance of all three algorithms is tested by buildings located in Ankara with efficient optimization strategy depending on results by optimizing LCC savings, LCGWP savings and initial investment of the buildings according to given design alternatives. The most efficient algorithm with suitable optimization strategy is selected to be used in the rest of the optimization analysis according to optimization results.

In the rest of the case studies, Ankara is considered as reference city in energy optimization process. Performance of TOKI buildings located in Ankara is tested by multiple multi-objective energy optimization with alternative objective sets to prepare detailed reports for decision maker to take right decision with enriched data in early design stage.

The multiple multi-objective energy optimization objectives can be listed below:

- ✓ LCC savings vs LCGWP savings vs Initial Investment
- ✓ LCC savings vs Initial Investment vs Energy Cost Payback Period
- ✓ LCGWP savings vs Initial Investment vs Energy Emission Payback Period
- ✓ LCC savings vs Initial Investment
- ✓ LCC savings vs LCGWP savings

- ✓ LCC savings vs Energy Cost Payback Period
- ✓ LCC vs Other Environmental Factors
- ✓ LCGWP savings vs Initial Investment
- ✓ LCGWP savings vs Energy Emission Payback Period

Results of some of the above optimization scenarios are presented in Chapter 6.

In the following analyses, building energy performance is optimized according to different scenarios such as different analysis period, initial investment limitations and different energy resources and limitations in design alternatives. Life cycle performance of the building is optimized according to LCC savings and LCGWEP savings whereas LCC savings objective is assigned as main objective to generate life cycle cost savings designs.

Performance of the building is also tested by changing analysis period horizon from 5 years to 40 years to evaluate change in design parameters.
Initial investment limits are determined according to investment value on life cycle cost savings maximization design scenario.
Energy resources are one of the determinant parameters in this optimization problems where their performance, costs and environmental impacts consider trade-offs with each other. Therefore, building life cycle performance for different energy resources such natural gas, hard coal, lignite and fuel oil are optimized.

Reaction of EnrOpt on changes in insulation materials or their upper thickness limits where the market conditions limits insulation thickness are tested and compared with unlimited case for this case study.

Parametric analysis is done to check how the change in design parameters in energy model changes reference building performance and optimization results. Modification parameters in the energy model are compared with existing parameters in TS 825 standard. The details of parametric analysis in energy model is explained below:

- ✓ Performance of TOKI building in 3rd degree-day region in TS 825 standard is compared with performance of the same building in different cities of 3rd degree-day region according city specific long-term average temperature data and recent heating degree-day data instead of given temperature data in TS 825.

- ✓ TOKI building energy optimization results are compared according to existing solar radiation data in TS 825 standard and coefficient corrected solar radiation data. Moreover, daylight transmittance of glazing alternatives are calculated according to both TS 825 standard and Isıcam data set and compared.

- ✓ Importance of time schedule is underlined by assigning different operating schedules.

Performance of the optimization algorithm is compared with each other according to same number of function evaluation. Moreover, parametric analysis is done for optimization algorithms by changing population size and algorithm specific parameters.

5.4. BIM Integrated Dynamo based Meta-heuristic Framework

Computational Design refers to the ability to provide linkage between problem solving approaches with computational algorithms for automation, simulation and design solution generation (BIM-SIM 2014). In practice, it provides innovation solutions with huge impact in design; however, the framework that is easy to use for the designers to generate multiple design and evaluate them according to their purpose is needed to be constructed for effective computational design.

“Visual Programming Language “concept provides easy and flexible solutions for designers to construct their design by programming via graphical user interface. The users can construct and automate their design by custom relationship with pre-packaged nodes. The design construction with nodes provides easy use for the non-programmers without advanced coding.

Dynamo is a visual programming tool that provides flexibility for users to both code via Python language in the tool and use built-in functions graphically without any coding which makes the tool easier to use and understand for non-programmers (Kron 2013). It allows designers to customize computational design and automate whole process via its node-based visual programming interface. Dynamo can interact with BIM tools such as Autodesk Vasari and Revit by its Add-in to change geometric properties of BIM elements automatically and manipulate BIM data. Therefore, automated geometric control and data manipulation incent Dynamo use for different purposes. For instance, by changing BIM element geometric and material properties, the performance of the building for different purposes such as aesthetics, cost-effectiveness and energy efficient solutions can be optimized according to pre-determined fitness functions in the early design stage of the building.

In this study, geometric and material properties of the building elements are manipulated to optimize life-cycle energy performance of the structure. Dynamo based BIM integrated optimization framework is constructed by using both built-in functions and Python coding to optimize multi-objective functions and talk with BIM tool to change building elements and run energy simulation. Each phase of the framework is explained step by step as follows:

Step 1: Dynamo interacts with BIM tools via built-in functions and Python scripts to change building element property. For instance, Dynamo code in Figure 5.20 is written to change family type and glazing property of the selected windows. The family types in the window are pre-defined with different shape and height and width values whereas glazing properties are selected from Revit add-in property. The code explains that all window family types are listed and one with defined family type ID is selected to be assigned to the chosen building element(s). Similarly, glazing property for the selected building element is assigned from glazing type list via defined glazing ID. Figure 5.19 demonstrates different family and glazing type assignment on the same window system.

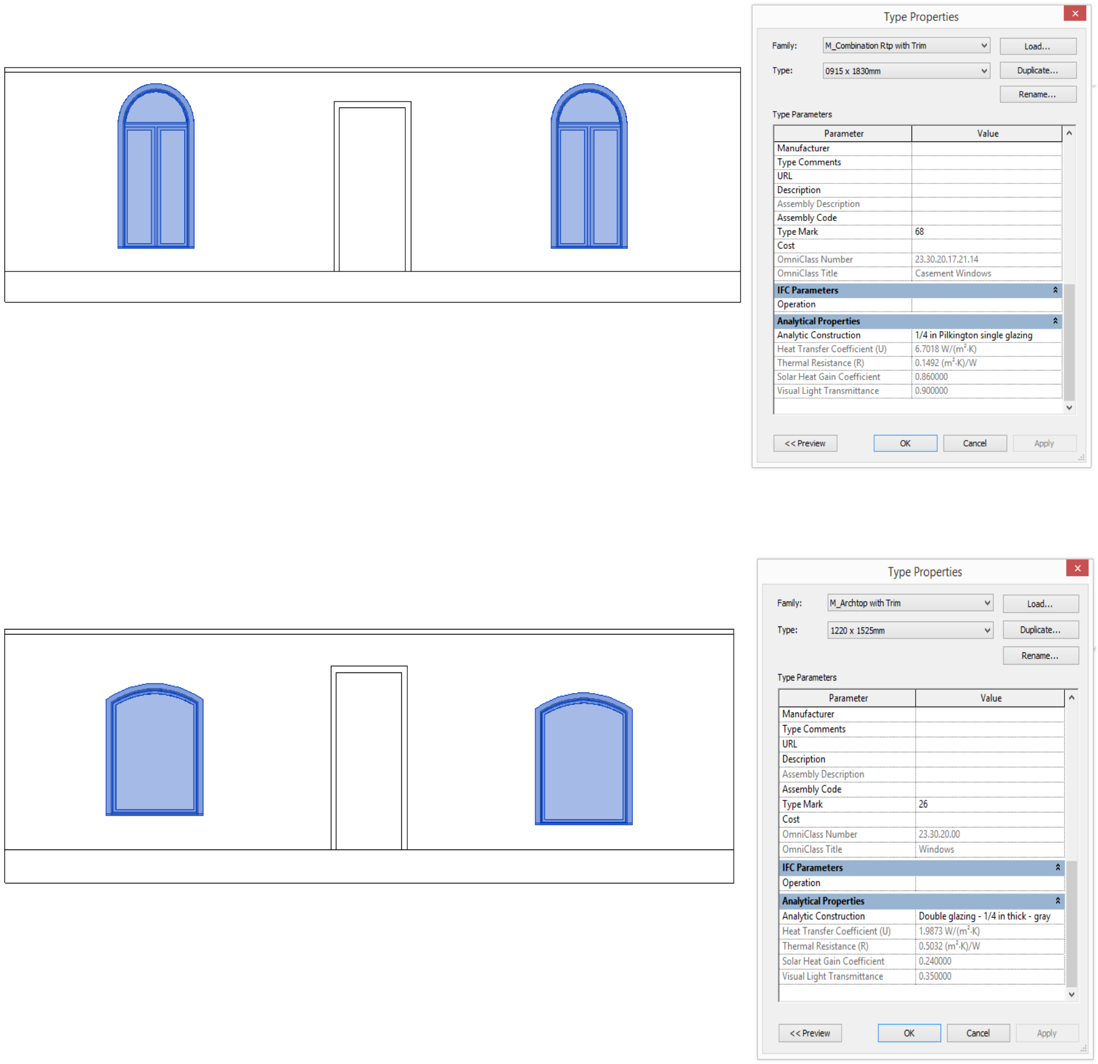


Figure 5.19. Window Property Change in BIM via Dynamo

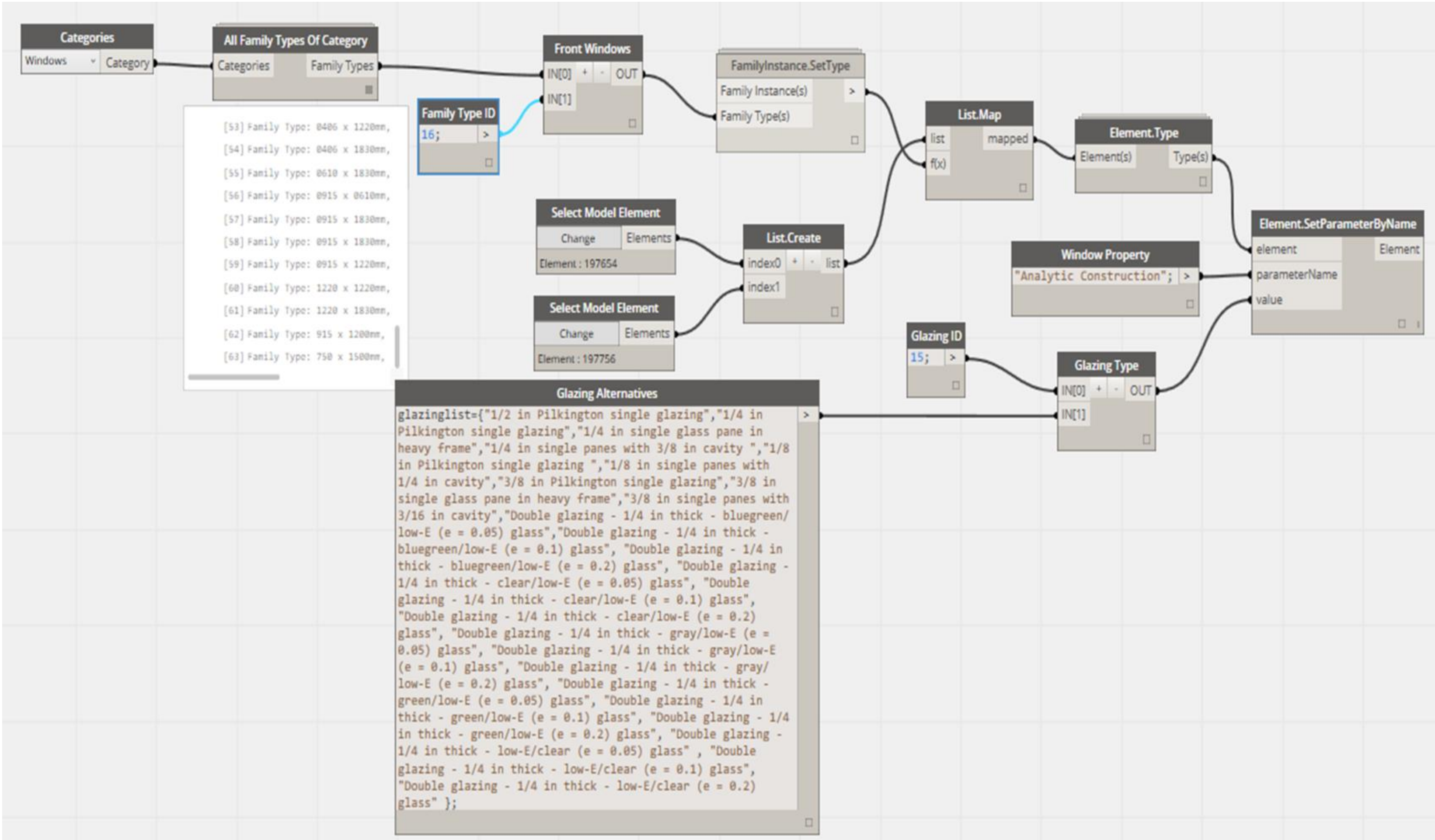


Figure 5.20. Dynamo Programming for Window Property Change

Step 2: Energy performance of selected building design is calculated using GBS in Revit. In Dynamo programming, firstly, Dynamo interacts with BIM tool to change design properties and then, connects to GBS to run the energy performance of the design solution. In Dynamo, Project ID is determined by connecting to GBS and a gbXML file is created to convert BIM model into the energy model. After that gbXML file is uploaded to GBS to run building energy model. The results include annual and life cycle energy and energy cost, and annual carbon footprints of the selected energy model. The results can be used directly or manipulated to be used with different parameters in optimization process as fitness function.

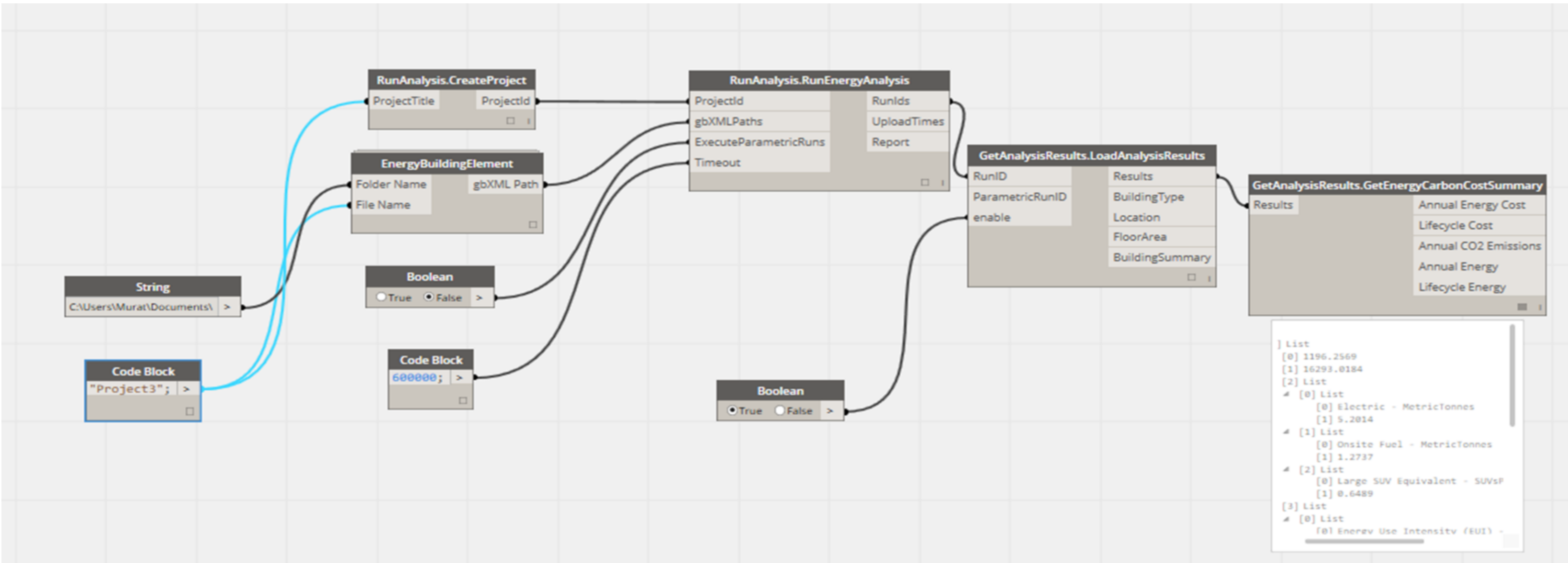


Figure 5.21. GBS Energy Analysis in Dynamo

Step 3: Meta-heuristic optimization section is the brain of the integrated model. In this section, as seen in Figure 5.22, optimization model interacts with all stakeholders of the model. Initially, the optimization model interacts with BIM tools to assign initial design solution into model to test its energy performance and environmental performance of alternative materials are obtained from life cycle assessment database and transferred into fitness function via optimization model. Then, energy performance of the design solutions are calculated by GBS model and written into Dynamo fitness function. The loop shown in Figure continues until termination criteria are met. The details of the meta-heuristic optimization model, Multi-objective Differential Evolution are explained below.

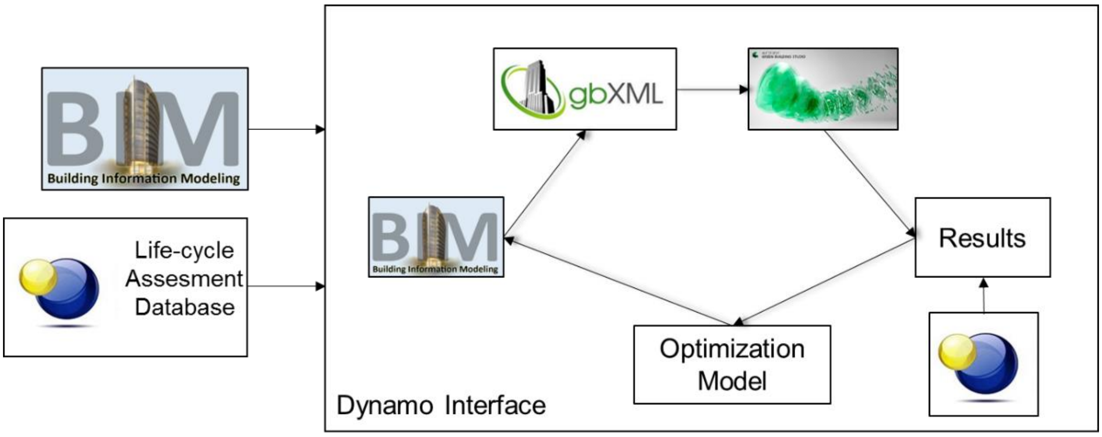


Figure 5.22. General Description of Dynamo based BIM Integrated Optimization Framework

In Dynamo interface, MODE is constructed as presented in Figure 5.22. The model starts with input parameters such as number of agents and crossover rate and boundary limits for each design variables. The initial design variables are created randomly in initialization custom node. The performance of each solution is evaluated by integrated design variables and fitness functions nodes. Fitness values of the main objective function (first fitness function) and initialized design variables for each agent are assigned as local best fitness and local best position. Then, all fitness functions of agents are compared with each other to create initial non-dominated solution sets. The model performance evolves in the main loop by giving all necessary constructed and initialized parameters as inputs to generate new design variables and evaluate its performance with respect to others to construct Pareto optimal non-dominated solution sets while the termination criterion is met.

The main structure of MODE model in Dynamo is shown in Figure 5.23. The details of sub-sections of the model and Python codes in the model is explained and presented in Appendix C.

5.5. Case Study II: Simple Cottage Energy Performance Optimization

In this case study, a simple cottage is modelled in Revit software to optimize its energy performance. The cottage has 47 m^2 usable area enclosed by 8.5 inch concrete wall and covered by compounded ceiling with 0.45 U-value. The cottage is located in Middle East Technical University. It has two symmetric windows in north-south direction and two symmetric windows according to entrance door in west direction.

In this case study, it has been planned to optimize life cycle performance of the cottage; however, in optimization process, the main energy analysis framework in Dynamo called Energy Analysis for Dynamo gave uncontrollable error in some of the multiple runs of the same input file that is accepted by the framework developers, Thorthon Tomasetti research group with Autodesk Building Performance Analysis research group. Therefore, additional Python code was implemented to eliminate the interruption in automated energy optimization process due to encountered error. In optimization process, 10 agents in DE are iterated 3 times but, the system was able to reach an energy performance results in only 45% of the constructed design alternatives in an hour. On the other hand, a single run of energy analysis in the system just takes 10 to 20 seconds whereas this run time is extended up to 5 minutes in error encountered analysis. Therefore, in this case study, 500 function evaluations based model is

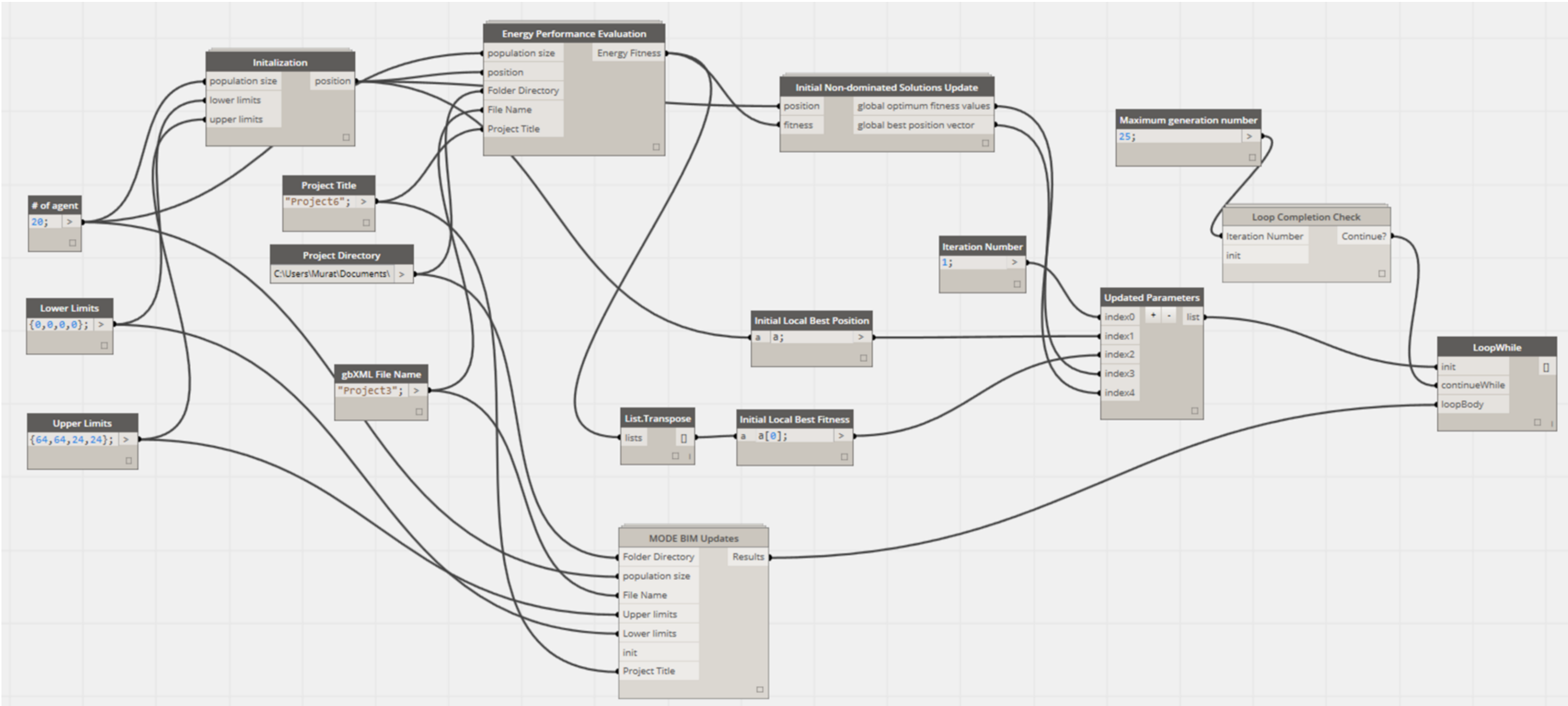


Figure 5.23. Multi-objective Differential Evolution Applied on Building Energy Performance Optimization in Dynamo

expected to be finished in at least 15 hours whereas this run time is expected to be improved down to 2 hours. Moreover, more than half of the runs do not give results in the automated process and efficient design solution may be missed due to internal errors in the model. Therefore, a new framework structure communicating with excel files are constructed to update parameters and fitness solutions in each algorithm step. If energy model does not give results at once, the model re-runs to obtain the results. Therefore, all solutions are controlled and used in optimization process.

In optimization process, initial cost and emission data of design alternatives are planned to be exported from excel file to optimization model; however, due to the internal error, life cycle performance analysis is postponed. Instead of life cycle analysis, annual energy consumption is taken into consideration. The simple cottage model is optimized by Differential Evolution to improve building annual energy cost and annual carbon footprints and to find non-dominated solution for decision maker. Moreover, if annual energy cost and carbon footprints values are multiplied by a single discounted coefficient, the results give life cycle operational energy cost and carbon footprints.

In optimization process, energy cost comes from electricity use and heating and cooling process of the cottage. Therefore, different design solutions provides trade-off between electricity use and direct energy resource consumption. Hence, this also provides trade-off in carbon footprints due to different emission rates of energy resources.

In energy analysis process, first energy settings of the model are set. In this case study, location of cottage and building type are entered as METU and office (Figure 5.24). The model use rooms to export building geometry to gbXML file and the most detailed shading analysis that gives most accurate results among alternatives are used. The model first analyzed in Revit add-in analysis tool by communicating with GBS to create project file in GBS. Then, energy optimization model starts to generate solutions to optimize building performance.

In this case study, 64 different window family types with different geometric details and 24 glazing types are used to generate four different design variables. The first design variable is family type of side windows and the second one is family type of front windows in the model. Third and fourth design variables are glazing properties of these windows. Multi-objective Differential Evolution aims at reducing annual energy cost and carbon footprints by changing design variables in 500 function evaluation using 20 agents in 25 runs. The number of function evaluations is limited due to manual update procedure in the model.

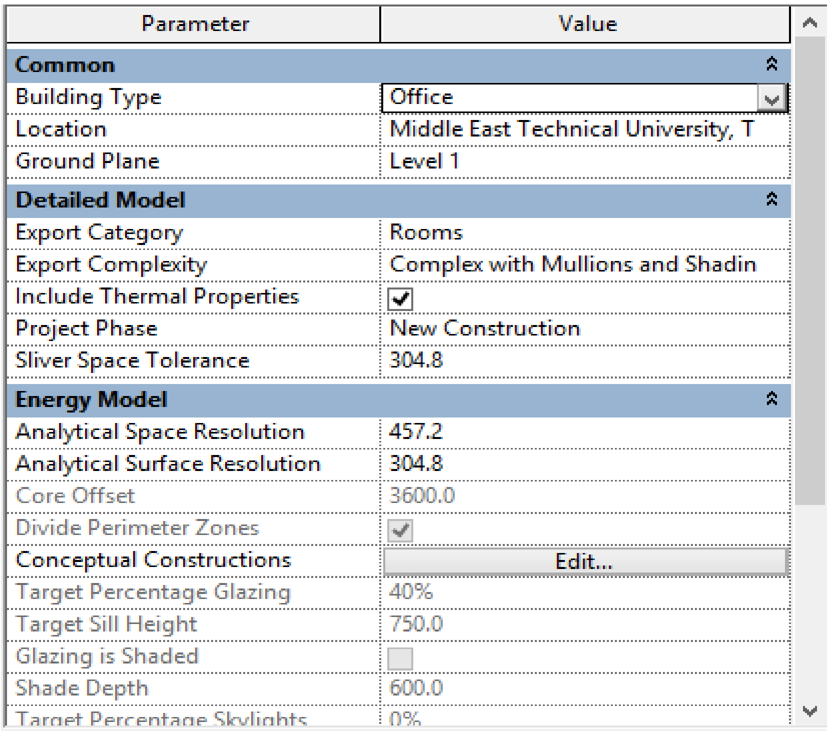


Figure 5.24. Energy Settings in Revit

The optimization model initially starts with random distribution and the position matrix are written in excel file with sheet name of ‘position’. Then, performance of each agent is simulated in GBS model one by one by exporting position matrix into Dynamo model and the fitness results are written in excel file. After fitness values of all agents are obtained, all position and fitness values of agents are assigned as local best position and fitness in a new excel files. After that, non-dominated solutions are generated by comparing initial fitness results in Dynamo file and non-dominated solutions are written in excel file in global best position and fitness files. Thus, first iteration of energy optimization model ends. In the next iteration, all necessary local and global best position matrix are exported into Dynamo node and new position vector is generated according to DE position update strategy. In the next step, performance of each agent’s position is evaluated by GBS run one by one and overwritten on previous position and fitness results. Next, local best and fitness values are updated by comparing new fitness results with existing local best fitness values and non-dominated solutions are checked with new fitness results to re-generate all non-dominated solutions. All updated results are overwritten on their existing values. The optimization process goes on until function evolution termination criterion is satisfied.

CHAPTER 6

RESULTS

In Chapter 5, case studies are prepared to test performance of constructed energy optimization models. In this chapter, optimization results in case studies are presented. Performance of meta-heuristics are compared. Parametric analysis of optimization algorithms and energy model in EnrOpt and sensitivity analysis of Dynamo based BIM integrated energy optimization model are presented and discussed.

The performance of constructed energy optimization model frameworks on case studies in Section 5.3 and 5.5 is tested with detailed parametric or sensitivity analysis to explain research findings efficiently. In this chapter, Section 6.1 presents and discusses performance of TOKI buildings applied by EnrOpt energy optimization interface. In the following parts, performance of optimization techniques, DE, MCEM and PSO is compared with each other with respect to two different optimization strategies. In next parts, performance of TOKI buildings in different degree-days regions is optimized and compared with each other according to design details. In the last part of this section, parametric analysis of energy model and selected optimization model is done to show how the change in parameters influences optimization process and building performance. In Section 6.2, performance of simple cottage is improved by changing geometric and material properties of window systems. In the next part, sensitivity analysis in Dynamo based model is presented and discussed.

6.1. Performance Optimization of TOKI Buildings Case Study

Performance of TOKI buildings is tested by different objective combinations. Bi-objective and triple-objective models are graphed in Figure 6.1 and 6.2. Number of non-dominated solutions generated in optimization procedures varies depending on number of objectives, optimization strategy and main objectives. For instance, in bi-objective problems figured in 6.2.a and 6.2.b, optimization algorithms try to generate non-dominated design solutions to optimize life cycle cost savings and life cycle global warming savings. While global warming potential reduction is selected as main objective, the optimization procedure generates 89 non-dominated solutions whereas this number decreases to 65 when life cycle cost savings is assigned as main objective. Moreover, while initial investment is added to objectives, number of non-dominated solutions increases up to 248.

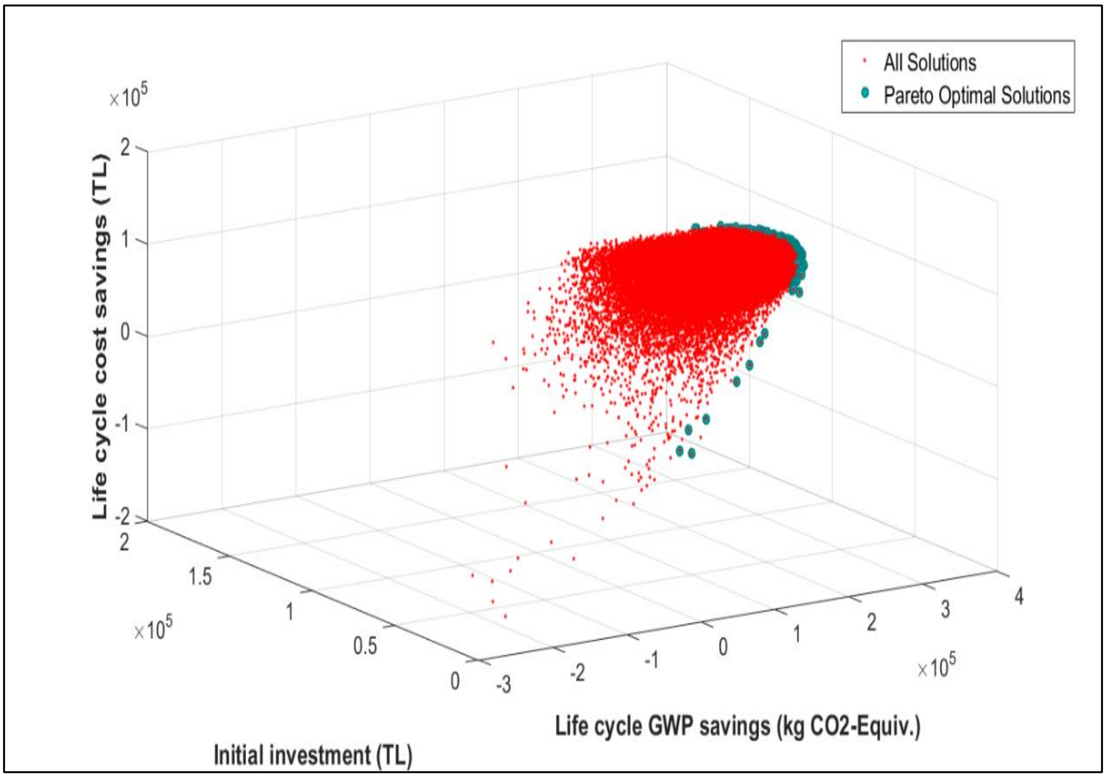
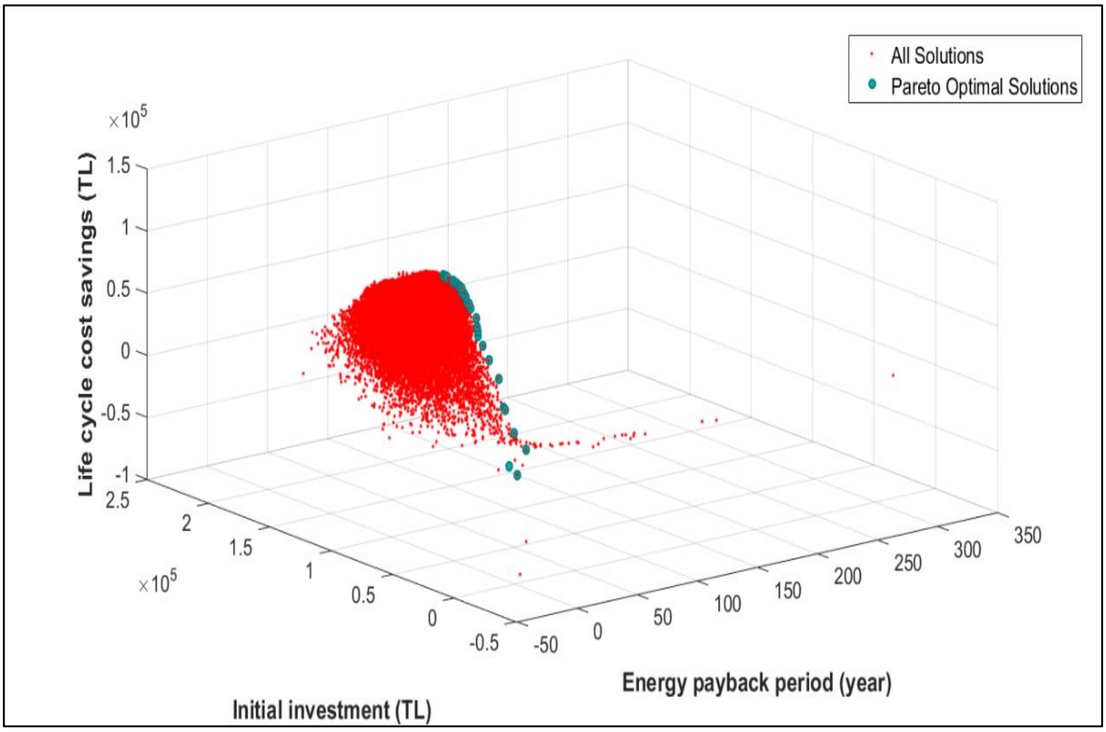


Figure 6.1. EnrOpt 3D Graph Outputs



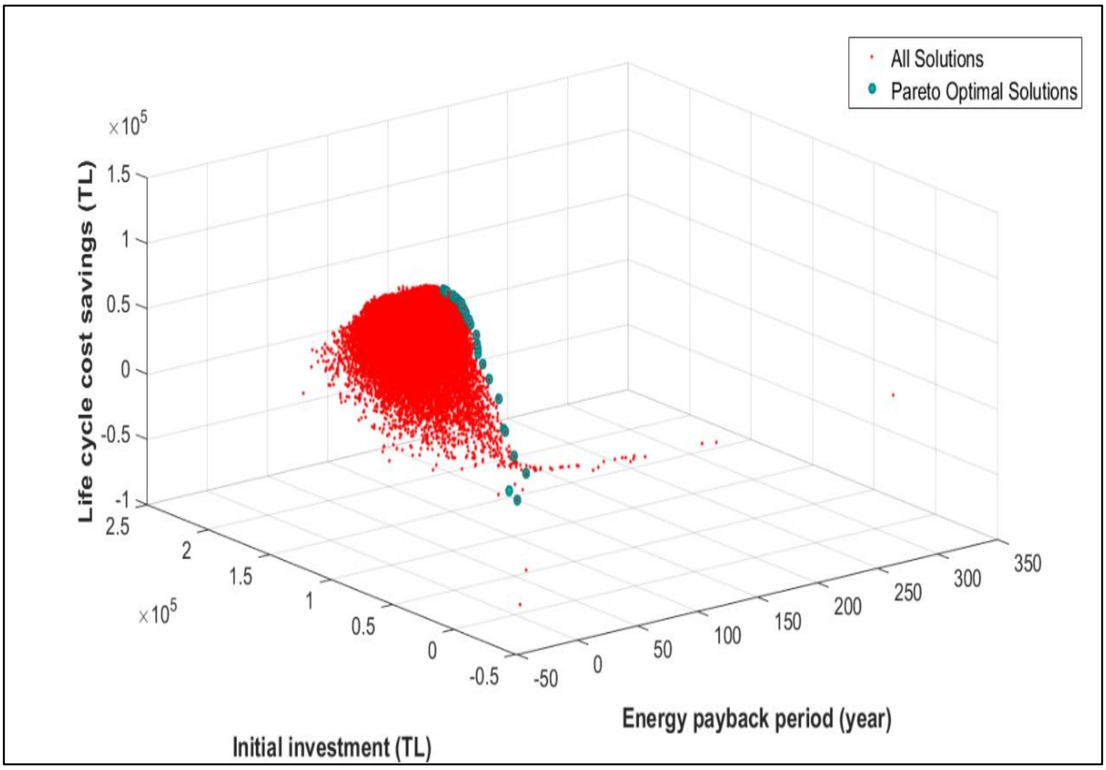
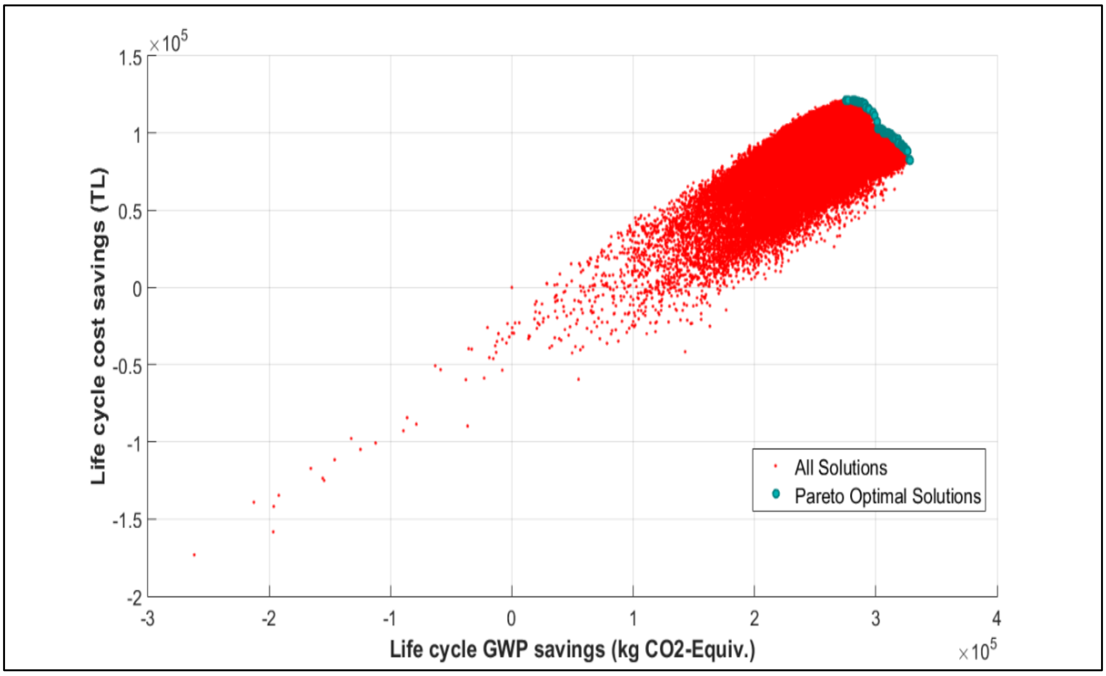


Figure 6.1. EnrOpt 3D Graph Outputs (continued)



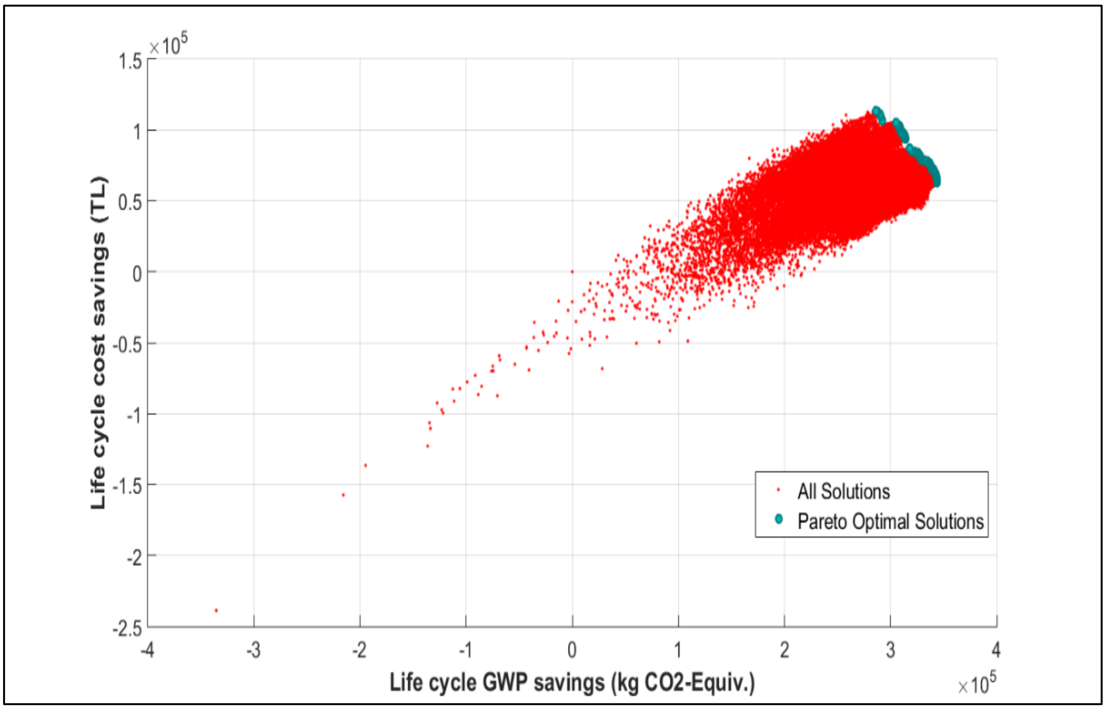


Figure 6.2. EnrOpt 2D Graph Outputs

In extreme case, while all 15 objectives are evaluated in the same optimization procedure, 7418 non-dominated solutions are generated in 200000 function evaluations. In Pareto optimal solution generation, vast number of alternative solutions would be valuable to show alternatives in literature studies; however, in real life, excessive number of alternative solutions reduces the efficiency of post-decision making process. Therefore, the decision maker needs to generate alternative solution strategy or decrease number of objectives. In main objective optimization based strategy, optimization algorithm more focuses on optimizing the main objectives while generating non-dominated solutions. As understood from projections of Figure 6.2.a and 6.2.b, in main objective problems, optimization curve slips on main objective optimum points. As seen in Figure 6.2.a, non-dominated solutions collected near highest life cycle cost savings values whereas this focus changes into maximum points of life cycle GWP savings values. When, these non-dominated solution sets are combined in Figure 6.3, it is seen that Pareto optimal solutions in extreme points are generated easily in the combined graph; however, in Pareto curves in Figure 6.3, performance of optimization algorithm is questionable whenever non-dominated solutions moves away from extreme points. Similarly, in triple objective problem as figured out in Figure 6.1, 698 non-dominated solution sets are generated in three runs by assigning each objective as main objective once. After comparison of all alternatives, all dominated solutions are eliminated and 562 non-dominated solutions are kept. The results shows that nearly eight percent of solutions focuses on dominant objective purpose. In initial investment dominant case, generated solutions tries to reduce investment by decreasing thermal performance of the building to minimize initial investment or maximize money on hand initially while in life cycle GWP savings, thermal performance of the building is maximized to improve building performance to reduce energy resource based emission. In life cycle cost savings, optimization algorithm makes trade-off between initial investment and building thermal performance to find optimum solutions. Therefore, in 3 cases, different solution alternatives are generated. Focusing on one single objective and generating alternative non-dominated solution increase post-decision making process.

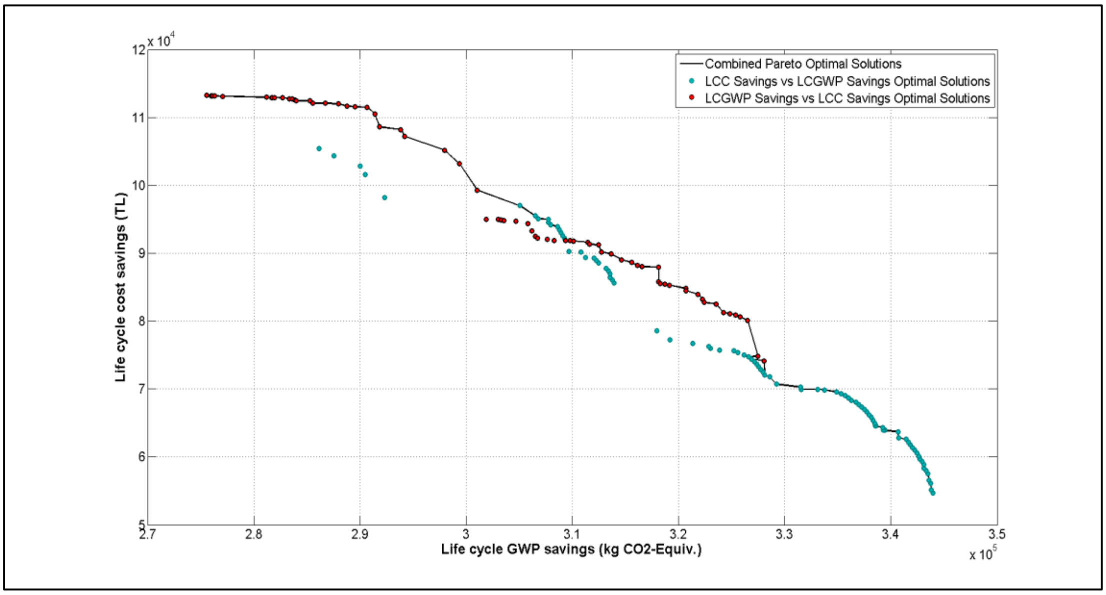


Figure 6.3. Combined Pareto Optimal Curve

In main objective based optimization process, performance of optimization algorithm is first tested by bi-objective problem drawn in Figure 6.2.a. For each algorithm, commonly used optimization parameters in literature are assigned. In Differential Evolution algorithm, crossover rate is assigned as 1 to reduce evaluation time. In PSO, initial inertia weight and constant parameters are assigned as 0.5 and 2, respectively whereas in MCEM, elite sample percentages for mean and standard deviation are assigned as 0.05 and 0.5 respectively. In optimization process, each algorithm is tested by 200000 function evaluations with different population sizes if it is seen necessary by 20 runs. The results shows that DE generates 63 solutions by reaching optimum fitness value of main objective with 100% success whereas PSO find optimal solution with 50% success and MCEM just finds optimal solutions in 2 runs. Inertia weight parameter in PSO is changed to improve algorithm performance. While it is increased up to 0.7 the performance results get worse. Therefore, inertia weight is decreased down to 0.1. In this case, PSO is able to reach optimal solution with 80% success and generates 57 non-dominated solutions. On the other hand, although the performance of MCEM is improved by changing elite percentage parameters and population size, it does not give similar performance improvement as seen in PSO. In this case study problem, performance and cost parameters of design alternatives are near to each other. Therefore, multiple local optimum points are generated in the problems. According to observations in optimization process, MCEM gets trapped in one of the local optimum design alternative. Moreover, nature of distribution algorithm guides next solution with collective performance of the algorithm whereas memory of any population member is not considered. On the other hand, in PSO and DE, memory of population member guides position update procedure. In a similar way, performance of MCEM on problem 8 in Gravitational Search Algorithm (2009) introduction paper shows similar behavior.

In Pareto optimal solution finding strategy, contrast to main objectives, non-dominated solutions guides position update procedure of optimization algorithm. In main objective based optimization strategy, algorithm find more non-dominate solution near optimal fitness value of main objective whereas in Pareto optimal solution finding strategy, algorithms scan nearly all solution space to improve the performance of existing building. The performance of optimization algorithms figured out in Figure 6.4. shows that MCEM generates more and effective non-dominated solution compared to other two algorithms. The reason behind this performance is that new position value of next generation is updated according to randomly selected non-dominated solution and population based deviation. Therefore, it improves local search ability of the algorithm around non-dominated solutions. On the other hand, PSO and DE needs to follow a path to improve the solution; however, in each iteration, the change in best position value which is selected randomly from non-dominated solutions disconcert optimization procedure of the algorithms. Therefore, compared to MCEM, DE and PSO fail.

Performance of MCEM algorithm is compared with Differential Evolution with main objective optimization strategies by 1000000 function evaluations. The results are figured out in Figure 6.4 compared with performance of MCEM. The graph readings

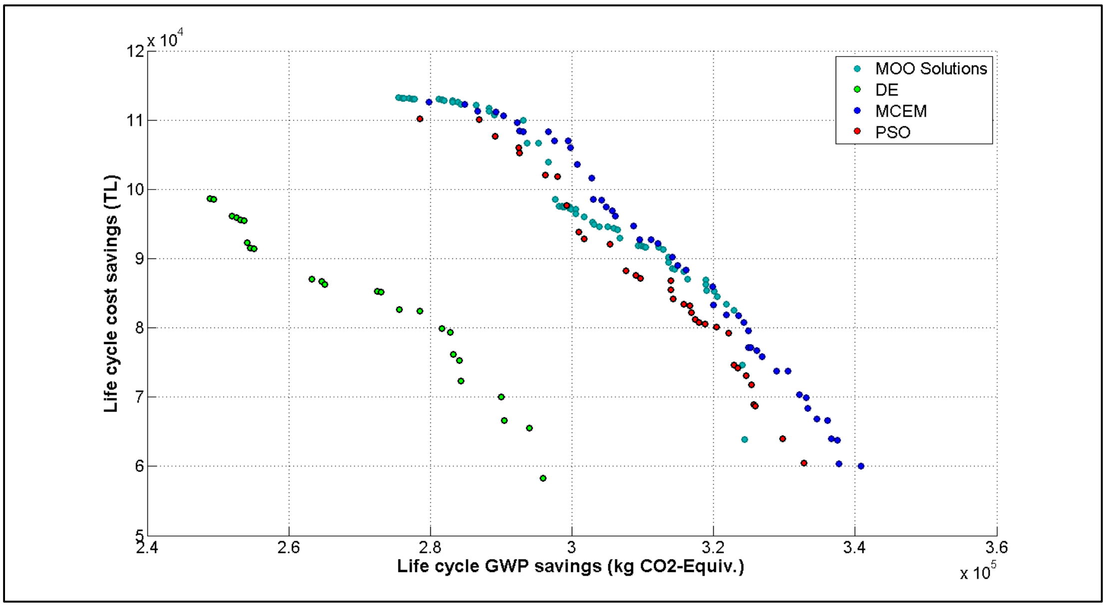


Figure 6.4. Performance Comparison of Optimization Algorithms with Pareto Optimal Solution Finding Strategy

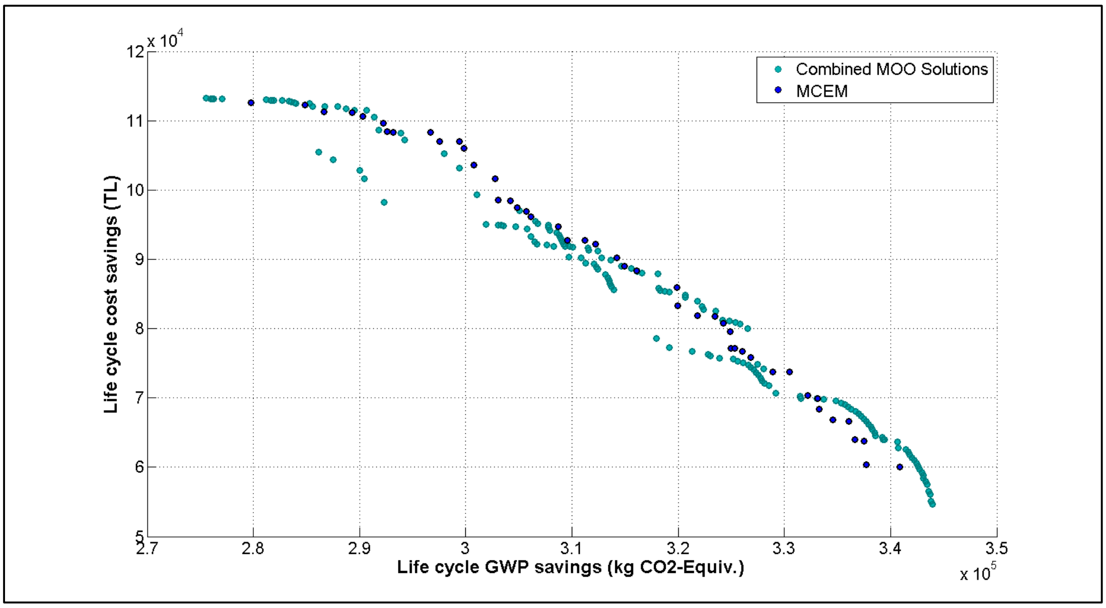


Figure 6.5. MCEM Comparison with Combined Pareto Solutions

explain that Modified Cross Entropy Method generates effective non-dominated solution to generate more improved non-dominated solution sets in the case where design alternative solution is away from extreme points in MOO solutions. Similarly, in Figure 6.3, performance of combined non-dominated solution needs to be improved to generate more improved non-dominated solutions. Figure 6.5 underlines that MCEM with Pareto optimal solution finding strategy can strengthen the performance of combined non-dominated solution.

In the rest of optimization analyses, non-dominate solutions are generated by main objective based optimization strategy to more focus around optimum value of main objective solution. Therefore, Differential Evolution algorithm is preferred thank to its performance on main objective based optimization process.

6.1.1. Optimum Design of TOKI Building in Cities in Different Degree-Day Regions

Reference TOKI building is designed according to TS 825 standard limits tabulated in Table 3.1. In initial case, Ankara is selected as reference city to optimize building performance according to all objectives by taking LCC savings as main objective. Out of 7418 non-dominated solutions, performance of main objective based optimum solution is tabulated in Table 6.1. Design details of optimum solution is also tabulated in Table 6.2.

Performance analysis of optimum design indicates that discounted life cycle cost of TOKI building can reduced up to 113225.36 ₺ while nearly 275 CO_2 equivalent metric ton- life cycle GWP is saved in 30-year life cycle of the building. The equivalent amount of GWP savings by carbon sequestration of different tree types are tabulated to show prominence improvement in energy based emission reduction in Table 6.3. More than half of cost savings are required to be invested initially to improve building thermal performance. Moreover, nearly ten year period is required to recover initial investment on building design whereas energy reduction recovers extra emission of selected design alternatives in one-year period. Therefore, one-year recovery shows that GWP reduction based optimization process is positively and highly correlated with energy reduction. Nearly ₺1700 initial investment per dwelling is required to provide ₺175 annual improvement in each dwelling by 28.57% improvement in building heating. Moreover, except europhication and ozon depletion , the rest of environmental impacts in the building are reduced.

Table 6.1. Performance Details of Main Objective Based Optimum Design in Ankara

Objectives	**Performance Results**
Life Cycle Cost Savings (TL)	113225.36
Life Cycle Global Warming Potential Savings (kg CO2-Equiv.)	274904.73
Initial Investment (TL)	75066.90
Energy Payback Period (year)	10.52
Emission payback period (year)	0.99
Life Cycle Acidification Air Savings (kg SO2-Equiv.)	403.12
Life Cycle Acidification Water Savings (kg SO2-Equiv.)	0.03
Life Cycle Ecotoxicity Savings (CTUeco)	42.44
Life Cycle Eutrophication Air Savings (kg N-Equiv.)	-10.53
Life Cycle Eutrophication Water Savings (kg N-Equiv.)	-1.22
Life Cycle Human Health Particulate Air Savings (kg PM2.5-Equiv.)	33.99
Life Cycle Human Toxicity, Cancer Savings (CTUh)	2.83E-05
Life Cycle Human Toxicity, Non-cancer Savings (CTUh)	3.16E-07
Life Cycle Ozone Depletion Air Savings (kg CFC 11-Equiv.)	-8.80E-04
Smog Air Savings (kg O3-Equiv.)	6930.09
Reference Building Energy Consumption (MWh/year)	194.31
Optimized Energy Consumption (MWh/year)	138.78
Energy Efficiency (MWh/year)	55.52

In optimized procedure, optimization algorithm considers trade-off between design alternatives based on their cost effectiveness and thermal efficiency. Moreover, the metric requirements of design variables also direct optimization procedures; because, smaller change in design variable would cause significant change in objective fitness values if its requirement is much more than other design alternatives. In this case study, wall insulation design and wall type are main drivers of optimization procedure. In optimized design in Table 6.2, thermal performance of window glazing systems are maximized with their maximum initial investment level that means improvement in thermal performance of glazing system recovers its investment efficiently. Similarly, in roof system, glass wool that is the cheapest material among alternatives is selected with its upper thickness limits. On the other hand, in foundation, the smallest thickness value of XPS is selected with possible highest thermal performance. Therefore, in

Table 6.2. Design Details of Main Objective Based Optimum Design in Ankara

Design Variables	**Selected Design Alternative**
Wall Type I	HCB 190 x 85 x 190
Wall Insulation I	16 cm-EPS 30 kg/m^3
Wall Insulation II	11 cm-EPS 30 kg/m^3
Wall Insulation III	16 cm-EPS 30 kg/m^3
Wall Insulation IV	16 cm-EPS 30 kg/m^3
Base Insulation I	11 cm-EPS 35 kg/m^3
Base Insulation II	11 cm-EPS 35 kg/m^3
Base Insulation III	11 cm-EPS 35 kg/m^3
Base Insulation IV	3 cm-XPS300 25 kg/m^3
Roof Insulation I	25 cm-Glass wool 18 kg/m^3
Roof Insulation II	25 cm-Glass wool 18 kg/m^3
Window Frames	PVC (3 chambers)
Window Glazing I	Triple Synergy with Argon (4-16-4-16-4)
Window Glazing II	Triple Synergy with Argon (4-16-4-16-4)
Window Glazing III	Triple Synergy with Argon (4-16-4-16-4)
Window Glazing IV	Triple Synergy with Argon (4-16-4-16-4)
Window Glazing V	Triple Synergy with Argon (4-16-4-16-4)
Window Glazing VI	Triple Synergy with Argon (4-16-4-16-4)
Window Glazing V	Triple Synergy with Argon (4-16-4-16-4)
Window Glazing VI	Triple Synergy with Argon (4-16-4-16-4)

selection procedure, optimization algorithm directs design selection according to effectiveness of cost-thermal performance ratio of design alternatives among smallest thickness XPS materials. In wall design procedure, cost effectiveness of wall type is considered in optimization procedure where thermal performance of the wall is improved significantly by wall insulation design. In wall insulation design, EPS materials are preferred by optimization algorithm to maximize cost-effectiveness of design alternative in material selection and balance between thermal performance improvement and cost increment is regarded in thickness determination. Similar behavior is also observed in basement ceiling insulation design. The optimization algorithm selects design alternatives according to their thermal improvement in the building and its cost. Whenever non-dominated solutions in life-cycle cost savings vs life cycle global warming optimization problem, it is seen that marginal changes in thickness and material selection in basement ceiling insulation determines the order of non-dominated solutions. Moreover, smaller changes in wall insulation design follows this and one or two cm changes in glass wool thickness in roof insulation design is observed among optimal alternatives. On the other hand, changes in window glazing types and wall types are rare in cost optimal designs.

After optimizing building energy performance of TOKI building, four new input excel files are generated separately for the same buildings in İzmir, İstanbul, Kayseri and Erzurum. Thus, TOKI buildings in five different degree-day regions are generated and optimized. The performance of the buildings are tested by life cycle cost and GWP savings and initial investments. The energy performance of optimized buildings in different cities are presented in Table 6.3.

Table 6.3 shows that building energy heating consumption is increasing as climate conditions get harsh. Therefore, in each building, different insulation alternatives, generally different thickness values of same material, are selected in initial design. Moreover, natural gas price values are adjusted according to prices of local energy distributors for each design in the optimization procedure. The optimization results indicates that energy prices and climate conditions play important role in the selection of non-dominated solutions. The general view of optimum design values for different cities tabulated in Table 6.4 demonstrates that thermal performance of optimum design variables increases as climate conditions gets harsh whereas performance of objective functions depending on trade-off between energy prices and climate conditions. In Ankara and Istanbul, natural gas price is higher than the rests. Therefore, this effect is reflected on objective fitness value.

Table 6.3. City based Performance Results

Objectives	**İzmir**	**İstanbul**	**Ankara**	**Kayseri**	**Erzurum**
LCC Savings (TL)	34497.49	90270.01	113225.36	83220.15	177477.35
LCC GWP Savings (kg CO2-Equiv.)	108578.98	223772.57	274904.73	227704.01	422342.61
Initial Investment (TL)	29002.58	59406.34	75066.90	67015.31	87659.26
Reference Building Energy Consumption (MWh/year)	71.19	136.44	194.31	212.01	382.24
Optimized Energy Consumption (MWh/year)	50.95	91.75	138.78	166.26	297.49
Energy Efficiency (MWh/year)	20.24	44.69	55.52	45.75	84.75

6.1.2. Scenario based Optimization Analysis of TOKI Buildings

In this section, performance of TOKI building is optimized with respect to different scenarios that are free from energy and optimization model. TOKI building in Ankara is selected as reference building to optimize building life cycle energy performance with respect to life cycle cost and GWP savings and initial investment. In each scenario, objective fitness values and energy consumption details of main objective based optimum design are tabulated and non-dominated optimal solutions are graphed

Table 6.4. Design Details of Optimum Design in City based Analysis

Design Parameters	İzmir	İstanbul	Kayseri	Erzurum
Wall Type I	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190
Wall Insulation I-III-IV	9 cm-EPS30	13 cm-EPS30	17 cm-EPS30	20 cm-EPS30
Wall Insulation II	6 cm-EPS30	9 cm-EPS30	12 cm-EPS30	15 cm-EPS30
Base Insulation I-II-III	5 cm-EPS35	8 cm-EPS35	12 cm-EPS35	16 cm-EPS35
Base Insulation IV	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25
Roof Insulation	17 cm-GW18	25 cm-GW18	25 cm-GW18	25 cm-GW18
Window Frames	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)
Window Glazing I-II	Double S-Argon (4-16-4)	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing III	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing IV	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing V	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VI	Double S-Argon (4-16-4)	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VII	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VIII	Double S-Argon (4-16-4)	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)

if it is seen efficient. Moreover, details of optimum design is tabulated in Appendix and compared and contrasted with other designs in following parts.

Analysis period: In this case study, performance of the building is optimized with respect to 30-year period; however, the analysis period varies depending on quality of insulation works and materials. Therefore, five different periods are analyzed to compare change in optimum design details and energy consumption in the building.

Table 6.5. Building Optimized Energy Performance for Different Analysis Period

Objectives	**5-year Analysis**	**10-year Analysis**	**20-year Analysis**	**30-year Analysis**	**40-year Analysis**
LCC Savings (TL)	7404.54	18665.24	62046.42	113225.36	162346.66
LCC GWP Savings (kg CO2-Equiv.)	25838.66	74201.60	180912.07	274904.73	342461.33
Optimized Energy Consumption (MWh/year)	187.79	164.95	147.47	138.78	135.24
Energy Efficiency (MWh/year)	6.52	29.36	46.84	55.52	59.06

5-year period analysis underlines the role of initial investment in optimum design by decreasing insulation thicknesses of original case study whereas thermal performance of glazing system is improved and cost-effective wall type is selected. In 20-year analysis, thickness values in each wall and base insulation design are increased and, thickness values of roof glass wool is maximized whereas thermal performance of glazing system is improved. Energy consumption in each optimized building is improved as the length of analysis period increases. Figure 6.6 shows that in each time step increases, better non-dominated solutions are generated with evolution in the shape of non-dominated solution curve.

Energy Resource: In case study, building optimized performance is analyzed with respect to natural gas use. In this scenario, different energy resources are used to meet building heating energy requirement. Hard coal, lignite and fuel oil are assigned as alternative energy resources into energy optimization model. The price of each energy resource, their unit calorie value and efficiency rate are tabulated in Appendix with respect to first week of August, 2015. Among energy resources, fuel oil is the one with highest price-calorie ratio and natural gas is cleaner resource compared to other alternatives. The optimization results tabulated in Table 6.6 explain that performance of fuel oil used building can be reduced more than other alternatives by using insulation thicknesses to improve building thermal performance. Therefore, energy payback period in fuel oil is expected to be less than all other alternatives due to its highest price-calorie ratio by decreasing one-third of energy consumption in initial design. This result also underlines the inefficiency of fuel oil compared to other alternatives. On the other hand, hard coal or lignite improves building performance less than natural gas; however, improvement in emissions in hard coal is much more than the one in natural gas. The results show that hard coal is cheaper than natural gas whereas it releases more greenhouse gases compared to natural gas.

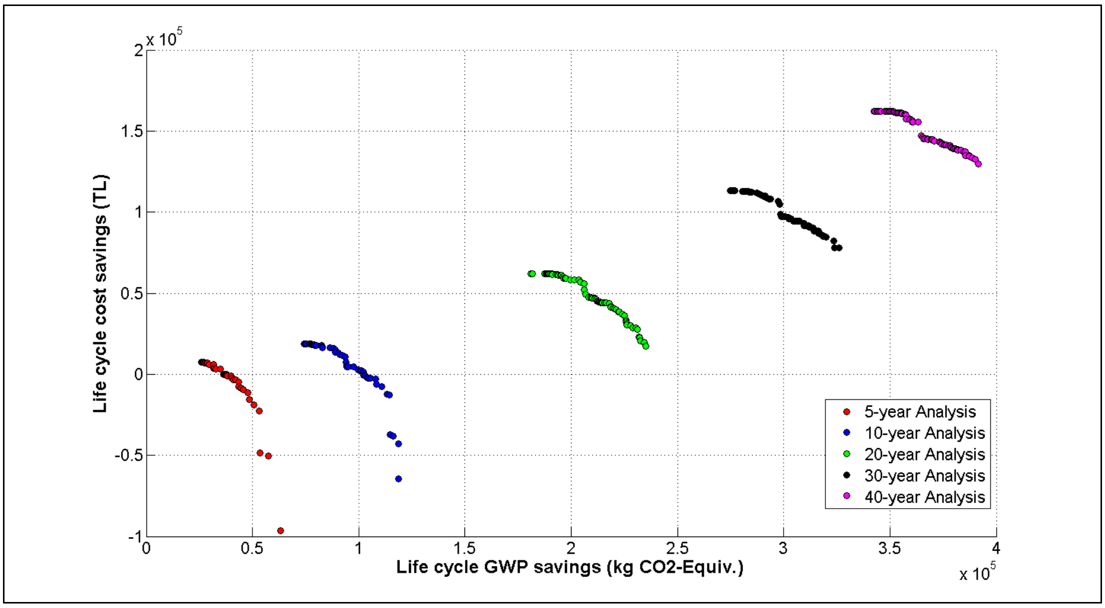


Figure 6.6. Non-dominated Solutions in Different Analysis Period

Table 6.6. Building Optimized Energy Performance for Different Energy Resources

Objectives	Natural Gas	Hard Coal	Lignite	Fuel Oil
LCC Savings (TL)	113225.36	56424.54	68869.13	249272.32
LCC GWP Savings (kg CO2-Equiv.)	274904.73	477215.39	247529.53	446388.68
Optimized Energy Consumption (MWh/year)	138.78	148.47	144.92	131.81
Energy Efficiency (MWh/year)	55.52	45.84	49.38	62.48

Material Selection and Limitation: This scenario is generated to see how change in material selection changes building performance. Wall insulation design is taken into consideration and performance of each alternative insulation material, EPS, XPS and rock wool is tested. The results are tabulated in Table 6.7 and graphed in Figure 6.7. The results indicates that rock wool is cost-inefficient material compared to XPS and EPS although its emission performance is better than organic foams. Similarly, XPS costs higher than EPS although energy efficiency level in each design scenarios are nearly same. Therefore, EPS should be preferred in wall insulation design if different insulation materials are not required for specific purpose(s) in wall insulation applications. The graph results confirm that EPS is selected in most of the non-dominated solutions.

Table 6.7. Building Optimized Energy Performance for Different Design Materials

Objectives	EPS	Rockwool	XPS
LCC Savings (TL)	113225.36	57411.62	99727.38
LCC GWP Savings (kg CO2-Equiv.)	274904.73	227919.23	278196.85
Optimized Energy Consumption (MWh/year)	138.78	141.21	140.19
Energy Efficiency (MWh/year)	55.52	53.10	54.11

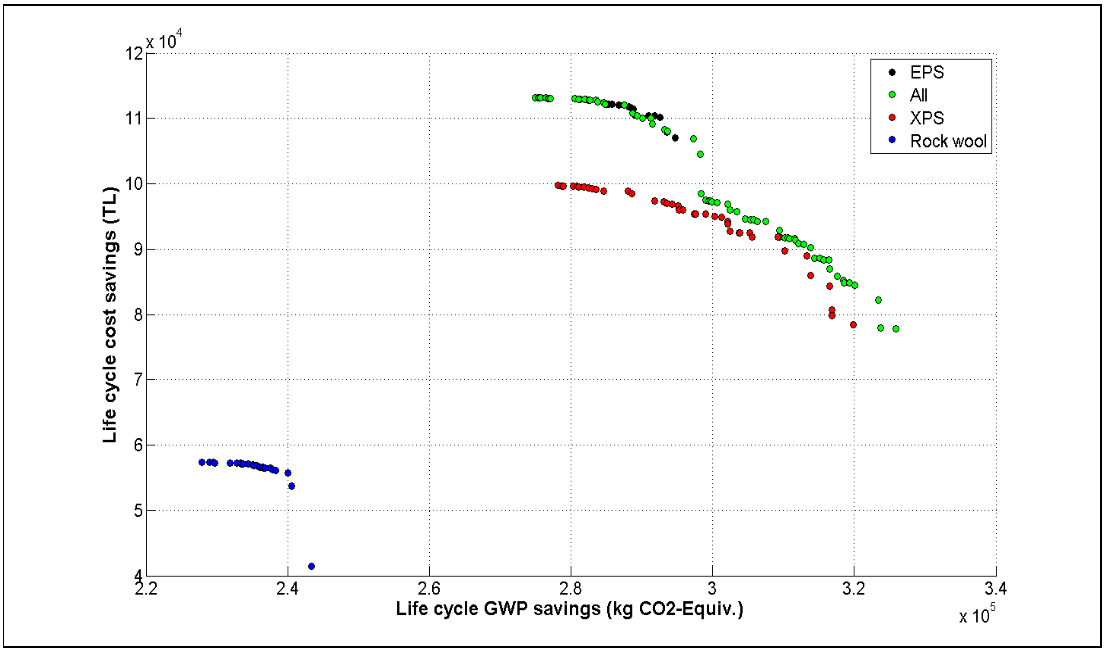


Figure 6.7. Non-dominated Solutions for Different Design Materials

Insulation Thickness Limitation: In this case study, some of insulation thickness data are generated by extrapolation to evaluate more design alternatives. In this scenario, insulation thickness values in wall, base /floor and roof is limited as 10 cm, 10 cm and 15 cm, respectively. The optimization performance of the building is calculated according to this limitation. The results show that in optimal design, all design variables higher than assigned limits decreased to maximum design limits whereas in wall design , EPS with better thermal performance and aerated autoclaved concrete that belongs to better thermal performance compared to brick wall are selected by optimization algorithm. Table 6.8 shows that the limitation in insulation thickness decrease the efficiency level of the building in 15 MWh annually. Moreover, limitations decrease number of non-dominated solution alternatives for decision makers (Figure 6.8).

Table 6.8. Building Optimized Energy Performance for Insulation Thickness Limitation Case

Objectives	**Unconstrained**	**Constrained**
LCC Savings (TL)	113225.36	93866.16
LCC GWP Savings (kg CO2-Equiv.)	274904.73	209640.37
Optimized Energy Consumption (MWh/year)	138.78	153.60
Energy Efficiency (MWh/year)	55.52	40.71

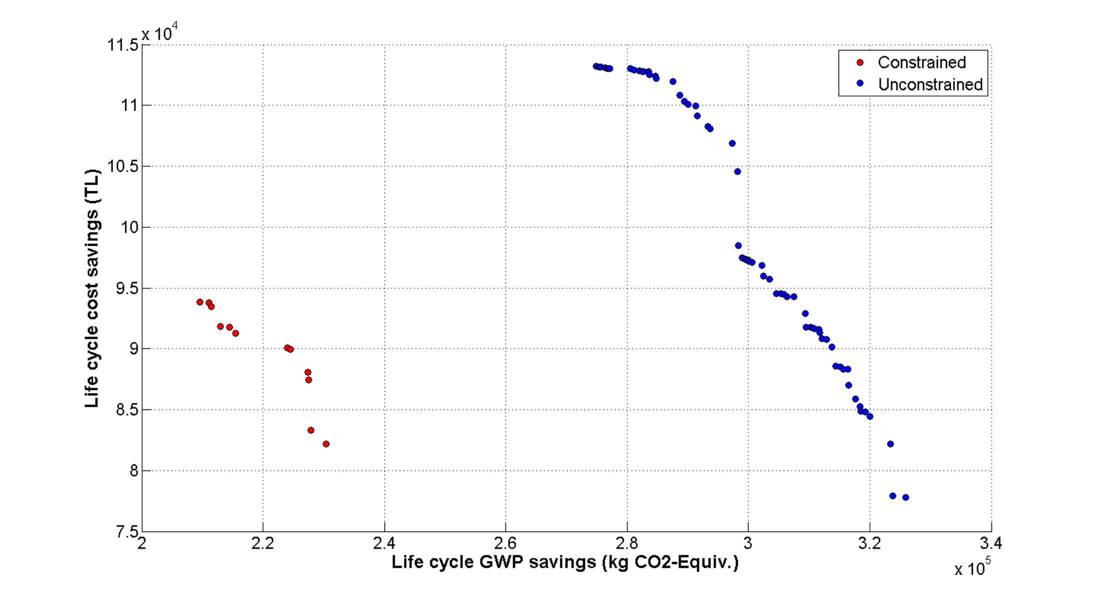


Figure 6.8. Non-dominated Solutions for Insulation Thickness Limitation Case

6.1.3. Parametric Analysis of Energy Model

In this section, the effects of modifications in TS 825 are observed in optimization process by comparing performance of modified parts of energy model with existing TS 825 standard based energy model. Climate effect, solar radiation on window system and alternative detailed shading data on window glazing system and operational heating schedule parameters are analyzed to interpret how the change in energy model input changes energy optimization model output.

Climate Temperature Data: In TS 825 standard, each degree-day region use single monthly average temperature data to calculate annual heating energy requirement. On the other hand, in reality, climate conditions of cities in the same degree-day regions shows variety. Therefore, two different types of city specific temperature data are used in optimization analyses. TOKI building in 3rd degree-day region is assigned as reference and four different cities such as such as Ankara, Artvin, Isparta and Malatya from different geographic regions but in same degree-day region are selected. Performance of TOKI buildings are optimized according to TS 825 temperature data, long-term average temperature data, and recent heating degree-day temperature data. The results of main objective based optimization solutions are tabulated in Table 6.9 and 6.10 and graphed in Figure 6.9 and 6.10. Tabulated results claims that in both comparison, TS 825 standard calculates higher energy requirement than the one calculated for each city. Moreover, less amount of energy is required in long-term average data compared to recent heating degree-day data. The main reason behind this result is that in long-term average data, monthly average value of temperature data is calculated whereas higher temperature value than 15'C eliminates lower temperature ones. Therefore, less heating degree-day values are calculated in design stage. In reference building heating energy consumption, energy use is reduced in a range from 12% to 23% by changing heating degree-day data. In optimization process, therefore, change in degree-day calculations directly change optimization results. The optimum design results indicate that more insulation design is required to improve building performance in TS 825 standard whereas optimum design thickness values decreases as energy consumption of reference buildings in different cities decreases in both data type. Compared to long-term temperature data type, recent heating degree-day data gives more incentive to insulation to increase life cycle cost.

Table 6.9. Building Optimized Energy Performance according to Long-term Average Temperature Data

Objectives	**Ankara**	**Artvin**	**Isparta**	**Malatya**	**TS 825 3rd DDR**
LCC Savings (TL)	109063.3354	84925.52	100375.32	94710.55	139911.82
LCC GWP Savings (kg CO2-Equiv.)	267850.54	222339.74	252883.36	238181.88	324175.54
Reference Building Energy Consumption (MWh/year)	189.18	160.50	178.41	175.49	222.53
Optimized Energy Consumption (MWh/year)	135.07	115.79	127.29	127.69	156.83
Energy Efficiency (MWh/year)	54.11	44.71	51.11	47.80	65.70

Table 6.10. Building Optimized Energy Performance according to Recent Heating Degree-day Data

Objectives	**Ankara**	**Artvin**	**Isparta**	**Malatya**	**TS 825 3rd DDR**
LCC Savings (TL)	113225.36	102353.14	113654.32	101549.95	139911.82
LCC GWP Savings (kg CO2-Equiv.)	274904.73	238154.01	275563.42	256313.36	324175.54
Reference Building Energy Consumption (MWh/year)	194.31	171.76	193.56	183.59	222.53
Optimized Energy Consumption (MWh/year)	138.78	124.02	137.91	131.69	156.83
Energy Efficiency (MWh/year)	55.52	47.68	55.65	51.90	65.70

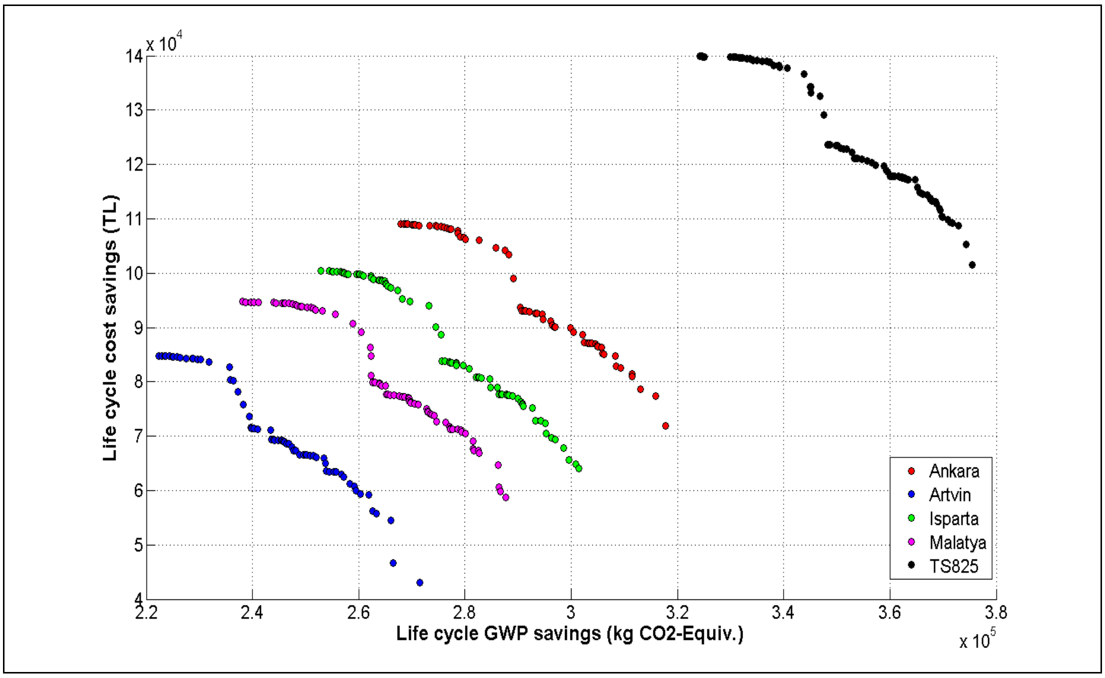


Figure 6.9. Non-dominated Solutions in Long-term Average Temperature Database

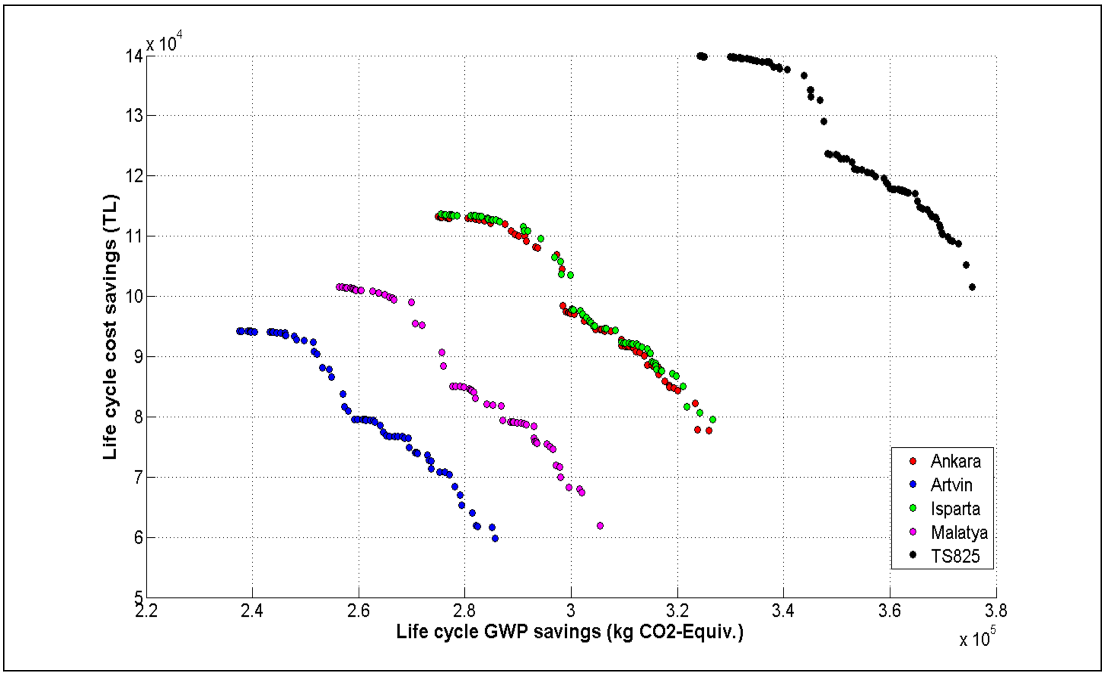


Figure 6.10. Non-dominated Solutions in Recent Heating Degree-day Database

Solar Radiation Data: In TS 825 standard, single solar radiation data are used in solar gain calculations for all country. In this case, a solar radiation normalization coefficient is proposed by dividing city based annual cumulative solar radiation value per meter square to same value from country average. Thus, the solar radiation difference between different latitudes are clearly explained. The effect of solar radiation in optimization results presented in Table 6.11 shows that solar radiation coefficient changes performance of TOKI building in Ankara slightly.

Glazing Property Data: In TS 825 standard, shading factors of window glazing system are categorized into groups. On the other hand, in Isıcam database, shading factors are differentiated in detail according to window glazing properties. Thus, more detailed data give more accurate results. Optimization results support this idea that differentiated data changes life cycle performance of TOKI building in an observable value. Moreover, design details of main objective based optimum results indicate that alteration of the glazing database changes glazing design details in optimum design of the buildings. In this case, the optimization algorithm offers triple comfort glazing system with argon gas for the gaps instead of triple synergy glazing with argon.

Table 6.11. Building Performance according to Solar Radiation and Glazing Property Database

Objectives	**TS 825 SR & DTGD**	**Isıcam SR & DTGD**	**TS 825 SR & Isıcam DTGD**	**Isıcam SR & TS 825 DTGD**
LCC Savings (TL)	119598.05	113225.36	112723.32	119908.29
LCC GWP Savings (kg CO2-Equiv.)	283847.70	274904.73	274133.82	284324.09
Reference Building Energy Consumption (MWh/year)	195.16	194.31	193.76	195.66
Optimized Energy Consumption (MWh/year)	137.92	138.78	138.38	138.33
Energy Efficiency (MWh/year)	57.24	55.52	55.38	57.33

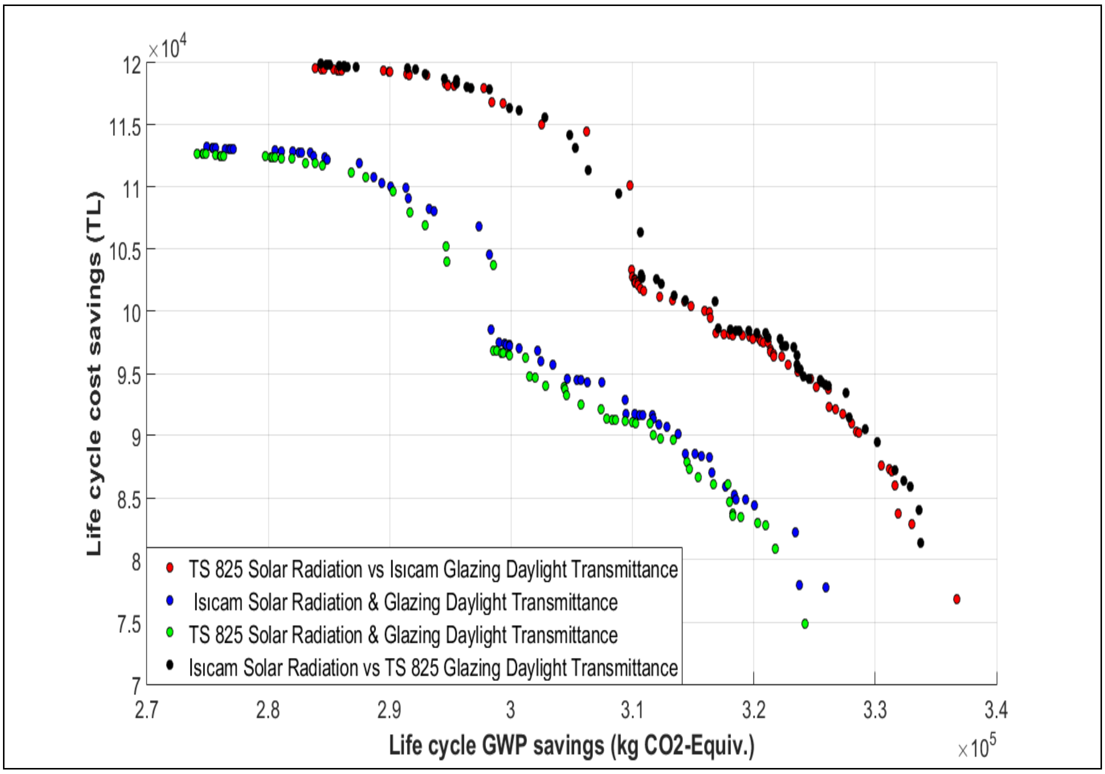


Figure 6.11. Non-dominated Solutions in Solar Radiation and Glazing Property Database

Operational Schedule: TS 825 is constructed based on constant continuous heating during all month; however, occupancy conditions determine heating schedule. In case, 3 different heating schedules such 7/24 facility, 7/16 facility and 5/12 facility (that means working five days and twelve hours a day) are constructed to compare effects of heating schedule on energy consumption of the reference building and its optimization process. The optimization results prove that decrease in occupancy in a building reduces annual energy consumption in the building (Table 6.12). Moreover, insulation thickness values in basement ceiling and walls increases while more energy is consumed in the building. Furthermore, Figure 6.12 shows that building shows similar behavior in non-dominated solution generation whereas only values change.

Table 6.12. Building Optimized Energy Performance according to Heating Schedule

Objectives	7/24 Facility	7/16 Facility	5/12 Facility
LCC Cost Savings (TL)	113225.36	96940.06	73266.67
LCC GWP Savings (kg CO2-Equiv.)	274904.73	241605.39	193200.04
Reference Building Energy Consumption (MWh)	194.31	175.68	147.44
Optimized Energy Consumption (MWh)	138.78	127.22	108.98
Energy Efficiency (MWh)	55.52	48.46	38.45

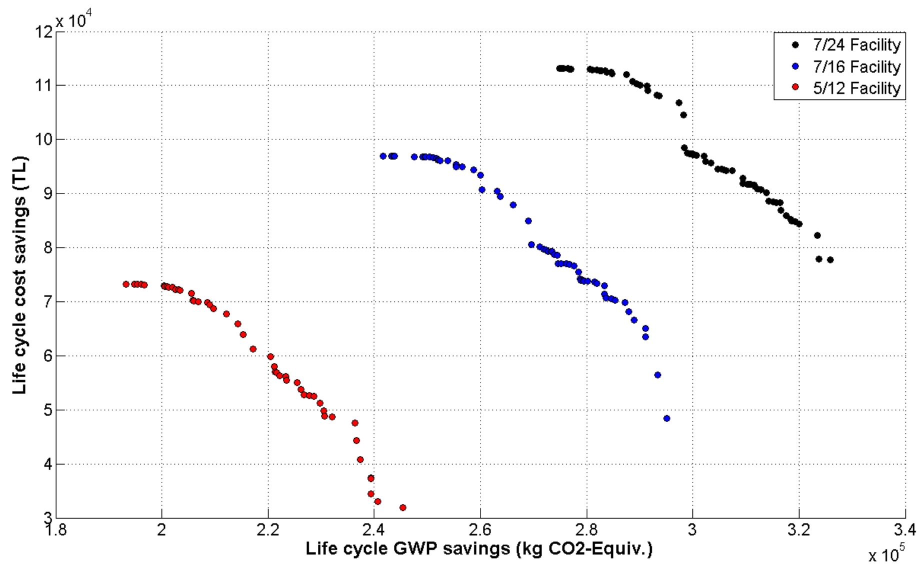


Figure 6.12. Non-dominated Solutions in Different Heating Schedule

6.1.4. Parametric Analysis of Differential Evolution Optimization Model

In this section, performance of Differential Evolution in TOKI building energy optimization is tried to be improved by changing DE specific position update parameters by parametric analyses on control parameter F and crossover rate, C_r.

In parametric analysis, Differential Evolution runs by 200 agents in 1000 iterations to optimize building performance. Moreover, a control run is used by 5000 iterations to check Pareto optimal solution found in 200000 function evaluation runs. Firstly, control parameter F is set 1 and effect of changes in crossover rate on optimization performance is tested by 0.1 intervals. The optimization result in Figure 6.13 explains that no trends in results is observed in non-dominated solution generation, in Pareto optimal solutions where all non-dominated solutions combined and Pareto solutions are generated among them and ranked top 15 optimal solution with respect to main objective performance. On the other hand, among all results, DE with C_r=0.7 performs best with 77 non-dominated solutions and 34 Pareto optimal solutions. Moreover, the algorithm is able to catch all top 15 non-dominated solutions. Therefore, in the following analysis, crossover rate C_r is assigned as 0.7.

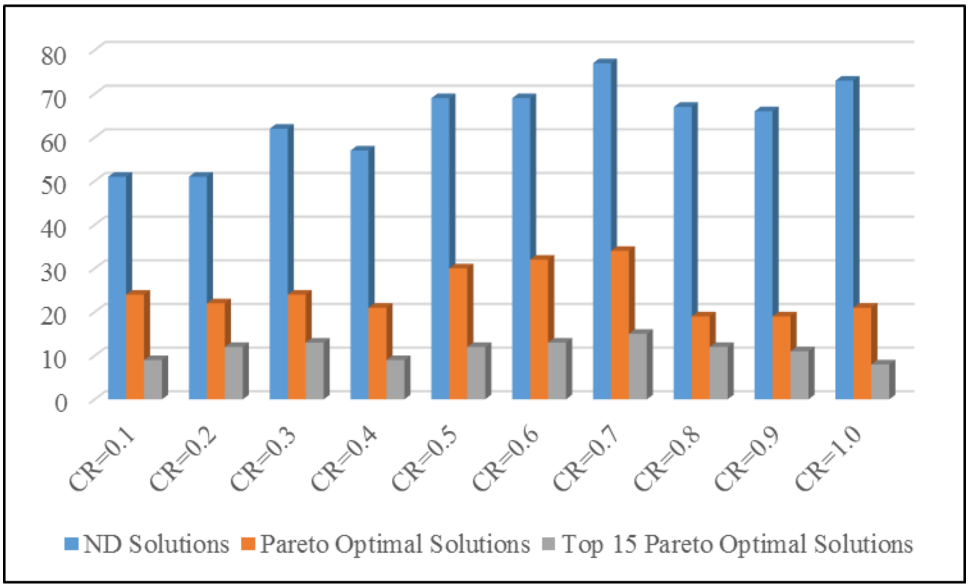


Figure 6.13. Parametric Analysis of Crossover Rate in DE

In the second part of the study, performance of Differential Evolution is tested by changing control parameters F using alternative F values from 0.5 to 2.0 with 0.25 intervals. The optimization results show that F=1.0 and F=1.25 are efficient to generate non-dominated and Pareto optimal solutions whereas F=0.75 works best while find top 20 Pareto optimal solutions with 95% success in 200000 function evaluation.

Parametric analysis results indicates that decision maker should use C_r=0.75 and F should be set in a range of 0.75 to 1.25 for this case. Change in case study parameters may change parametric performance of the study. Therefore, in initial case of EnrOpt interface, crossover rate and control parameter are assigned as 0.7 and 1.0, respectively.

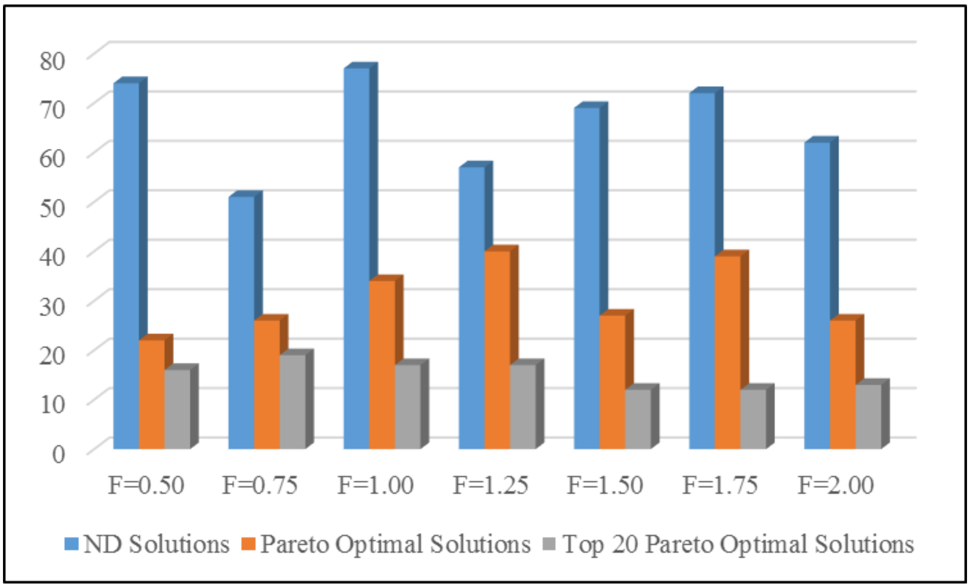


Figure 6.14. Parametric Analysis of Control Parameter F in DE

6.2. Performance Optimization of Simple Cottage Case Study

In this section, energy performance results of simple cottage explained in Section 5.5 are presented and details of non-dominated optimum designs are compared and discussed. In the next step, sensitivity of change in parameters of cost optimal design is analysed to present how parameter changes energy performance of the cottage.

At the end of multi-objective optimization procedure, five non-dominated design solutions are generated by MODE. In Figure 6.15, annual energy cost and carbon footprints are graphed with Pareto optimal solutions. In annual energy consumption based analysis, in general, single optimum design is expected if single energy resource is used in analysis; however, in this case, default energy costs are used that electricity and fuel cost per kWh are $ 0.14 and $ 0.049. On the other hand, renewables generates 61 % of total electricity consumption. Therefore, electricity is much cleaner than fuel resource due to less carbon footprints. Therefore, in design stage, a trade-off between electricity and fuel consumption is expected to find non-dominated optimal design alternatives. Therefore, five non-dominated results are obtained thanks to this trade-offs.

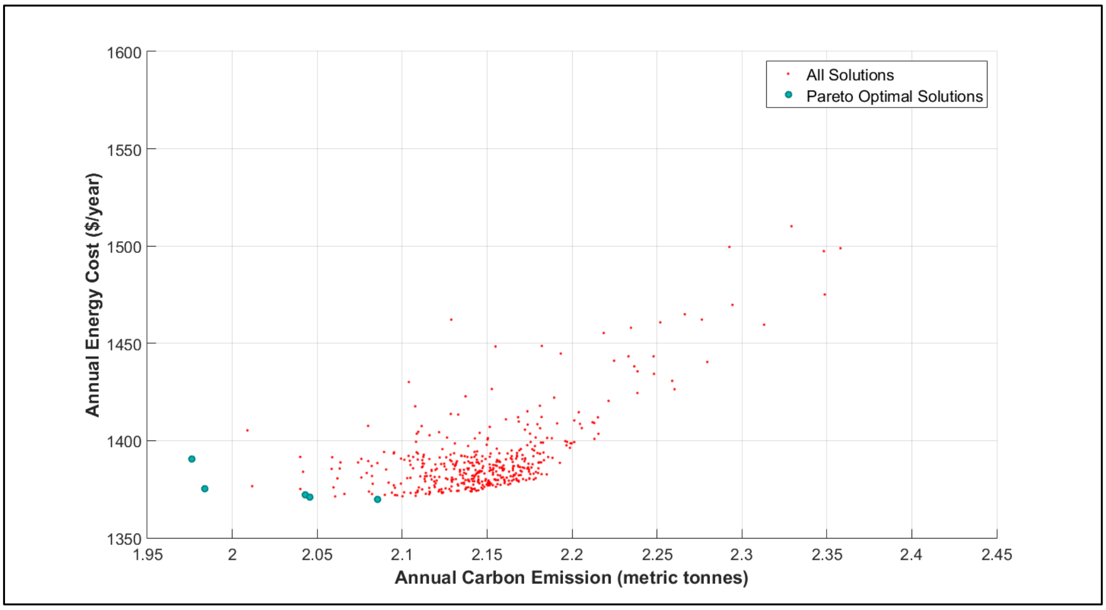


Figure 6.15. Non-dominated Solutions in Cottage

The details of optimum designs show that optimization algorithm tries to minimize heat loss in window glazing system by using different combinations of triple low-e glazing. Similarly, window area of side windows is larger than the one in front windows although side windows are located in both north and south direction.

Therefore, the results indicates that solar gains in south window is much larger than the expected heat loss in north window. Therefore, the size of window is increased in north-south directions. The effect of direction in window system is proved by exchanging geometric property of front and side window by 90 degree counter clockwise orientation where the larger window dimensions are used in south direction and no window exists in north direction. On the other hand, other symmetric window alternative is used in west and east direction. The results prove the idea that existing optimum performance of Alternative 2 in Table 6.12 is improved from \$ 1369.77 to \$ 1337.44 whereas annual carbon footprint decreases from 2.08 ton CO_2 equivalent to 1.95 ton.

In energy analysis, GBS allows parametric analysis by changing design details in base model. In Dynamo based energy analysis, multiple parametric analysis results can be obtained by enabling parametric runs in energy analysis process by using 'Run Energy Analysis' node in model figured in Figure 5.21. After simulating base design energy performance, the model in Dynamo can call parametric analysis results. In this case study, sensitivity analysis of same design parameters that are used in the first case study to show importance of design details in energy analysis. The sensitivity results of wall and roof insulation, operating schedule and window glazing system are presented in Table 6.14. The R value in insulation parts represents thermal resistance of design parameters according to US standard. The results explain that insulation changes building performance significantly especially if the building component is not insulated with any insulation materials. The significance of results can be understood better from minimum 30% change between insulated and uninsulated wall and roof in Table 6.14. On the other hand, glazing effect is limited compared to insulation works. The main reason behind this result is the significant effect of insulation on building performance and window-wall ratio in the cottage. As window-wall ratio increases in the building, building performance is more affected by change in the glazing system. Moreover, change in operating schedule affects building performance significantly due to occupancy condition based energy consumption. These results support addition

Table 6.13. Detailed Analysis of Non-dominated Solutions

Best Results Detailed Analysis	**Best Alternative 1**	**Best Alternative 2**	**Best Alternative 3**	**Best Alternative 4**	**Best Alternative 5**
Annual Energy Cost ($/year)	1375.13	1369.77	1372.24	1370.88	1390.47
Annual Electric Consumption (kWh/year)	7568.78	7266.23	7394.25	7376.12	7728.00
Annual Fuel Consumption (MJ/year)	23605.52	26286.39	25162.71	25251.74	23109.71
Annual Carbon Emission in Electricity Consumption (metric tons)	0.81	0.77	0.79	0.79	0.82
Annual Carbon Emission in Fuel Consumption (metric tons)	1.18	1.31	1.25	1.26	1.15

Table 6.13. Detailed Analysis of Non-dominated Solutions (continued)

Best Results' Design Details	**Best Alternative 1**	**Best Alternative 2**	**Best Alternative 3**	**Best Alternative 4**	**Best Alternative 5**
Front Window Shape	Transom	Awning with Trim	Awning with Trim	Transom	Fixed
Side Window Shape	Archtop with Trim	Casement 3x3	Archtop with Trim	Archtop with Trim	Archtop with Trim
Front Window Dimensions	1220x0610 mm	0406x0610 mm	0406x1220 mm	0610x0610 mm	0610x0610 mm
Side Window Dimensions	1830x2000 mm	0915x1830 mm	1830x1525 mm	1830x1525 mm	1830x2000 mm
Front Window Glazing Type	Triple glazing - 1/4 in thick - low-E/clear/ clear (e = 0.2) glass	Triple glazing - 1/4 in thick -clear/clear/ clear glass	Triple glazing - 1/4 in thick - clear/clear/low-E (e = 0.2) glass	Triple glazing - 1/4 in thick - clear/clear/low-E (e = 0.2) glass	Triple glazing - 1/4 in thick - clear/clear/low-E (e = 0.2) glass
Side Window Glazing Type	Triple glazing - 1/8 in thick clear/clear/clear glass	Triple glazing - 1/8 in thick-clear/clear/ low-E (e = 0.2) glass	Triple glazing - 1/4 in thick - clear/clear/clear glass	Triple glazing - 1/4 in thick - clear/clear/clear glass	Triple glazing - 1/8 in thick - clear/clear/clear glass

of operating schedule in modified TS 825 based energy model to increase energy estimation accuracy. As a result, Dynamo based BIM integrated optimization model provides parametric relations in energy estimation with more accurate results and analyzes sensitivity in design parameters by parametric analysis to understand the change in energy performance of the building from a wider perspective. This enables decision maker to direct optimization process with respect parametric analysis results to reach optimum results in a fast and efficient way.

Table 6.14. Sensitivity Analysis on Optimized Cottage Performance

Wall Insulation	**Annual Energy Cost ($/year)**	**Annual Carbon Footprints (ton/year)**	**U-value if exists**
Uninsulated Wood Frame Wall	1680.75	3.03	1.56
R13 Metal Frame Wall	1399.81	2.17	0.88
R13 Wood Frame Wall, Wood Shingle	1251.29	1.70	0.46
R13 + R10 Metal Frame Wall	1170.09	1.46	0.32
8 inch Concrete Wall	1369.77	2.09	0.84
Roof Insulation			
R0	2120.10	4.29	2.52
R10	1369.77	2.09	0.45
R19	1325.20	1.95	0.33
R38	1249.10	1.72	0.13
R60	1231.37	1.67	0.08
Operating Schedule			
7/24 Facility	1839.31	3.02	
7/12 Facility	1664.87	2.61	
6/12 Facility	1612.50	2.52	
5/12 Facility	1472.23	2.30	
Window Glazing			
Single Clear(6 mm)	1434.69	2.28	6.17
Double Clear	1398.29	2.17	2.74
Double Low-e	1383.21	2.12	1.99
Triple Low-e	1377.53	2.13	1.55

6.3. Comparison of EnrOpt and Dynamo-BIM Model

The developed two energy optimization frameworks, EnrOpt and Dynamo based BIM integrated energy optimization model, are compared according to their energy estimation methodology and their performance in the optimization process in the comparison table in Table 6.15.

Table 6.15. Comparison of EnrOpt and Dynamo-BIM Model

Model Details	**EnrOpt**	**Dynamo-BIM Model**
Energy model	Modified TS 825 standard (steady-state)	Green Building Studio (simulation)
Optimization algorithm(s)	Differential Evolution Particle Swarm Optimizer Modified Cross Entropy Method	Differential Evolution
Run time	Depending on number of non-dominated solutions in each iteration and number of function evaluation 44.8 seconds for 65 non-dominated solutions in 200.000 function evaluation	Depending on complexity of building envelope (10-20 seconds for single run)
Life cycle analysis	Applicable	Applicable
Possible design variables	Insulation Window frames/glazing Wall type	Insulation Window glazing Renewables Orientation All building component details
Design alternative updates	Updated in Excel and simple changes in coding if necessary	Importing into BIM model or Creating design alternative in BIM tool

Table 6.15. Comparison of EnrOpt and Dynamo-BIM Model (continued)

Model Details	EnrOpt	Dynamo-BIM Model
Response to design change	Re-designing reference building in Excel	Automatically updated BIM model if updates are not relevant with design variables Re-design objective function if updates are relevant with energy model
Requirements for tool use	Microsoft Excel Matlab Quantity takeoff Material information/database	BIM tools Building model Material information/database Simple Python coding
Main Advantage	Wieldy tool	Parametric relations for more accurate estimation

CHAPTER 7

CONCLUSION

Energy consumption in buildings comprises a significant amount of total final energy consumption and carbon footprints. Therefore, efficient energy strategies are required to be developed to increase building energy efficiency. In order to develop an efficient strategy to improve building energy performance, previous studies have been focused on the reasons of inefficiency in building energy use. The reasons behind building energy inefficiency are lack of proper scope definition that causes frequent changes in design, short-term thinking by disregarding life cycle effect of design and inefficiency of legal regulations and incentive strategies. Moreover, in traditional construction, performance of designed building is analyzed just after necessary architectural and construction documents preparation to meet legal requirements. Therefore, it is resulted in lost opportunity to provide energy efficiency in the building early design stage. In the next steps of building life cycle, decision makers encounter with more constraint handling to improve building efficiency. Improperness of traditional CAD based solutions and lack of integration between project stakeholders are one of the main barriers to develop energy efficient solutions. Moreover wieldy energy analysis tools are required to evaluate different design alternatives in early design stage in a fast and efficient way.

In building energy optimization process, energy model determines the accuracy of energy optimization model. In energy estimation, energy analyst selects energy prediction methodology based on cost-effectiveness, time efficiency and estimation accuracy of methodology. In early design stage, engineering calculations are preferred in energy analysis due to scarcity of measured data. Engineering calculations are based on steady state energy estimation and dynamic energy simulation models. Steady state energy estimation techniques simplify building envelope and use average climate and all other necessary data to provide time efficiency in energy analysis. On the other hand, dynamic simulation models simulate spontaneous change in building envelope to predict building energy performance more accurately in much more time. Moreover, BIM based energy analysis provides geometry and material information export into energy model and reflects parametric relations of BIM model into energy model to get more accurate energy results in optimization process. Therefore, regarding whole process, in optimization process, accuracy of energy model and run time of optimization model considers a trade-off to develop efficient solution alternatives.

In this study, a flexible excel integrated Matlab based GUI life cycle energy optimization interface based on TS 825 standard and meta-heuristics is developed to provide easy use, fast and accurate non-dominated design solution sets for decision maker in post-decision making process. Performance of energy model is improved by using more accurate and detailed input data. Furthermore, in the second energy optimization model, Dynamo based BIM integrated energy optimization model is proposed to provide effective model based solution that communicates with all project stakeholders to deal with improper scope definitions or conflicts between stakeholders in early design stage. In the following sections, major findings of this study and limitations in the study are explained and recommendation on the study and possible future studies are discussed.

7.1. Major Findings

Outcomes of this study show that energy optimization model improves building energy consumption and optimize building life cycle performance by generating non-dominated solution alternatives for decision maker to consider effective design in post decision making process by changing design alternatives. The results demonstrate that both energy estimation methodology and optimization strategy determines optimization results. Therefore, the major inferences obtained from this study according to both energy model and optimization model can be briefly explained as follows:

Energy model based findings:

- ✓ In building energy prediction, climate data dominates the accuracy level of estimated energy performance. TS 825 standard presents higher heating degree- day data for five different degree –day regions compared to both long-term average temperature data and recent heating degree-day data. Moreover, temperature data categorization for degree-day regions causes deviations up to 25% in energy estimations. This results in 12 % to 23% deviation in life cycle cost optimization process for the case study in this thesis. Moreover, significant change in climate data influences performance of non-dominated solutions and their design details.

- ✓ In optimization process, cost-effectiveness and thermal efficiency of design alternatives consider a trade-off in design selection. In addition, area values of building components as coefficients of design variables increases the importance of trade-off in optimization process.

- ✓ Heating schedule added to modified energy model causes significant change in building energy performance.

- ✓ Elaboration in glazing properties and city specific solar radiation coefficient changes building life cycle performance slightly.

Optimization model based findings:

- ✓ Optimization strategy determines direction of non-dominated solution generations. Main objective based optimization strategy focuses on alternative non-dominated solutions around main objective based optimum design whereas Pareto optimal solution finding strategy scan all solution spaces, especially around all non-dominated solutions.

- ✓ Performance of optimization algorithms on the case study shows that Differential Evolution and Particle Swarm Optimizer works efficiently in main objective based optimization strategy whereas Modified Cross Entropy works properly in Pareto optimal solution finding strategy.

- ✓ Parametric analysis of Differential Evolution on the case study demonstrates that optimization parameters of DE, crossover rate and control parameter F, should be set 0.7 and 1.0.

Energy optimization model based findings:

- ✓ EnrOpt provides 113225.36 ₺ cost savings and nearly 275 metric ton CO_2 GWP savings in TOKI building case in Ankara for 30-year analysis. This provides 175 ₺ annual improvement for each dwelling by 28.57% improvement in building heating whereas 1700 ₺ initial investment is required for each dwelling in the case study.

- ✓ Optimum design recovers its initial investment in nearly 10.5 years whereas this value is just 0.99 year for emission paybacks in the case study.

- ✓ Most of life cycle environmental impacts in the building is reduced except ozone depletion and eutrophication in the case study.

- ✓ Climate conditions and energy prices are key determinants in energy use reduction and life cycle cost optimization for five different cities.

- ✓ Optimum insulation design and design generation strategy of the algorithm changes depending on length of analysis period. In short-term analysis such as 5-year analysis, algorithm tries to minimize initial investment cost regarding payback period of investment whereas in long-term analysis, algorithm considers trade-off between initial investment and thermal performance of whole building design.

- ✓ Different energy resource use changes improvement rate in the building depending on energy resource cost and emission performance.

- ✓ Limitation in material selection and insulation thickness changes building performance and design parameters. In this case study, the algorithm tries to maximize its performance by using upper insulation thickness limits for optimum design. Moreover, in wall design, the limitation changes selected material to reduce heat loss in the wall.

- ✓ In this case study, observed optimization behavior shows that the algorithm, first tries to maximize thermal performance of window glazing systems and roof insulation. On the other hand, the thickness of insulation in foundation is minimized due to less heat loss in the foundation. The non-dominated design solutions indicates that basement ceiling insulation values are most sensitive to generate alternative non-dominated design solutions.

- ✓ Dynamo interacts with BIM model to change geometric and material properties in the model. This change can be followed by all stakeholders to make analysis in terms of different perspective of building. This approach allows analyzing more design alternatives than currently done in practice.

- ✓ BIM integrated energy analysis provides consideration of parametric relations in energy estimation which gives more realistic results.

- ✓ The case study in BIM integrated model shows that window fenestration, operating schedule and insulation details play a key role in building energy performance.

7.2. Limitations of the Study

In this study, energy optimization model is developed based on some assumptions. Therefore, these assumptions draw the limits of the study. The limitations of this study can be summarized as follows:

- ✓ Cost and environmental impact data of design alternatives are obtained from databases. Therefore, change in design inputs is expected to change whole optimization process.

- ✓ Energy prices are entered into model in terms of Turkish Lira to provide consistency in cost units with design alternatives; however, Turkey imports most of consumed energy in terms of US Dollars. Moreover, change in energy inflation is also determined in terms of Turkish Lira. This limits accuracy of life cycle cost analysis.

- ✓ Maintenance cost of optimum design in the following years are excluded in this study. Moreover, change in performance of design alternatives in the upcoming years due to tear and wear in design alternatives are not considered. Lastly, logistic cost of the design alternatives are not taken into consideration.

- ✓ Manual update in BIM integrated energy optimization model decelerates optimization process and limits whole life cycle analysis in the case study. This can be eliminated if the automated run in energy analysis works properly.

7.3. Recommendations and Future Work

This study focuses on generating non-dominated design solutions to improve building life cycle performance according to multiple objectives and analyzes how change in energy optimization model changes building energy performance. The results of this study indicates that heat insulation based strategy provides passive and effective solution in buildings to reduce amount of energy use. Moreover, the results suggest that more insulation thicknesses with cost effective and thermal efficient materials should be used compared to insulation practices in construction industry. Furthermore, heating energy requirement calculation methodology in TS 825 standard should be elaborated by using more specific climate data and replacing shading factor table in TS 825 standard with a detailed database such as Isıcam glazing database. Beside these modifications, heating operating schedule should be included in calculations to reduce the amount of unnecessary energy estimation due to continuous heating during all month.

Visual programming based BIM integrated studies are new and promising studies to evaluate building performance. Therefore, in near future, it is planned to focus on elimination of the internal error in some of the multiple runs of the same input file to automate the building energy optimization process without any extra manual update framework in the energy optimization model. Moreover, Dynamo based BIM integrated studies can be used to optimize building performance by interdisciplinary approach. The integrated model can interact with different tools to maximize whole building efficiency. In future studies, Dynamo based BIM integrated model can be constructed as a brain center of detailed framework such that the model can interact with Autodesk Vasari for lightening analysis and Revit and GBS with energy analysis whereas structural performance of the model is tested by SAP 2000 model that is provided by DynamoSAP. BIM integrated scheduling can be also added into integrated framework. In the upcoming studies, optimization model in visual programming can interact with all these tools to maximize whole building life cycle efficiency in a correct order. Moreover, in the upcoming years, cloud based EnergyPlus simulation will be available for optimization studies to perform fast and more accurate energy analysis in BIM integrated optimization models instead of Green Building Studio.

Elaboration in design parameters and calculations in the energy model in EnrOpt interface improves the estimation accuracy of the energy model. However, the accuracy level of the model should be tested by various building types to validate the improvement and its level in energy estimation. Finally, in future studies, input design database of EnrOpt interface can be enriched to get more accurate optimization results. Moreover, performance of meta-heuristics can be improved by changing optimization strategy in optimization models to generate more effective non-dominated solution sets.

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APPENDIX A

A. TOKI BUILDING CASE STUDY

Table A.1. Energy Resource Details

Energy Resource	Unit Price	Unit Lower Calorific Value (kcal/unit)	Energy Efficiency (%)
Fuel Oil (kg)	2.130 ₺	9875	80
Hard Coal (kg)	0.472 ₺	6650	65
Lignite(kg)	0.374 ₺	4732	65
Natural Gas in İzmir (m^3)	1.110 ₺	8250	90
Natural Gas in İstanbul (m^3)	1.185 ₺	8250	90
Natural Gas in Ankara (m^3)	1.200 ₺	8250	90
Natural Gas in Kayseri (m^3)	1.162 ₺	8250	90
Natural Gas in Erzurum (m^3)	1.107 ₺	8250	90

Wall System I				
	Material	Thermal Conductivity	Thickness(m)	Thermal Performance
Wall Type	HCB 190 x 190 x 135	0,33	0,19	0,575757576
Insulation Type	5 cm-EPS 30 kg/m3	0,03315	0,05	1,508295626
Layer 1	4.2. Cement mortar	1,6	0,028	0,0175
Layer 2	4.1. Lime mortar , lime - cement mortar	1	0,028	0,028
Layer 3	4.3. Gypsum mortar, lime plaster mortar	0,7	0,005	0,007142857
Layer 4	Select			
Layer 5	Select			
Layer 6	Select			
Layer 7	Select			
Wall Location	Exterior Wall			0,17
Wall Area	1115,6816	m2		
Only Layers				0,222642857
Wall System without Insulation				0,798400433
All wall system				2,306696059

Wall System II				
	Material	Thermal Conductivity	Thickness(m)	Thermal Performance
Wall Type	Select			
Insulation Type	6 cm-EPS 30 kg/m3	0,03315	0,06	1,809954751
Layer 1	4.2. Cement mortar	1,6	0,028	0,0175
Layer 2	4.1. Lime mortar , lime - cement mortar	1	0,028	0,028
Layer 3	4.3. Gypsum mortar, lime plaster mortar	0,7	0,005	0,007142857
Layer 4	5.1.2. Reinforced Concrete (Normal concrete (with TS 500) , made using natural aggregate concrete or gravel)	1,65	0,2	0,121212121
Layer 5	Select			
Layer 6	Select			
Layer 7	Select			
Wall Location	Interior Walls(apartment partiating wall,stair, low-temperature surrounding)			0,26
Wall Area	715,9504	m2		
Only Layers	310,6186453			0,433854978
Wall System without Insulation				
All wall system	1606,456473			2,243809729

Figure A.1. Wall Design Details of TOKI Building

Wall System III					
	Material	Thermal Conductivity	Thickness(m)	Thermal Performance	
Wall Type	Select				
Insulation Type	5 cm-EPS 30 kg/m3	0,03315	0,05	1,508295626	
Layer 1	4.2. Cement mortar	1,6	0,028	0,0175	
Layer 2	4.1. Lime mortar , lime - cement mortar	1	0,028	0,028	
Layer 3	4.3. Gypsum mortar, lime plaster mortar	0,7	0,005	0,007142857	
Layer 4	5.1.2. Reinforced Concrete (Normal concrete (with TS 500) , made using natural aggregate concrete or gravel)	1,65	0,2	0,121212121	
Layer 5	7.1.5.2. Horizantal coring brick wall - 700 kg/m3	0,36	0,085	0,236111111	
Layer 6	Select				
Layer 7	Select				
Wall Location	Exterior Wall			0,17	
Wall Area	145,8405	m2			
Only Layers				0,579966089	
Wall System without Insulation					
All wall system				2,088261715	

Wall System IV					
	Material	Thermal Conductivity	Thickness(m)	Thermal Performance	
Wall Type	Select				
Insulation Type	6 cm-EPS 30 kg/m3	0,03315	0,06	1,809954751	
Layer 1	4.2. Cement mortar	1,6	0,028	0,0175	
Layer 2	4.1. Lime mortar , lime - cement mortar	1	0,028	0,028	
Layer 3	4.3. Gypsum mortar, lime plaster mortar	0,7	0,005	0,007142857	
Layer 4	5.1.2. Reinforced Concrete (Normal concrete (with TS 500) , made using natural aggregate concrete or gravel)	1,65	0,2	0,121212121	
Layer 5	Select				
Layer 6	Select				
Layer 7	Select				
Wall Location	Exterior Wall			0,17	
Wall Area	1381,164	m2			
Only Layers	474,9201173			0,343854978	
Wall System without Insulation					
All wall system	2974,764461			2,153809729	

Figure A.1. Wall Design Details of TOKI Building (continued)

Basement System I				
	Material	Thermal Conductivity	Thickness(m)	Thermal Performance
Insulation Type	4 cm-EPS 30 kg/m3	0,03315	0,04	1,206636501
Layer 1	4.6. Cement mortar screed	1,4	0,03	0,021428571
Layer 2	4.6. Cement mortar screed	1,4	0,02	0,014285714
Layer 3	10.3.2.1.2. Extruded polystyrene foam (XPS) boards - TC 035	0,035	0,025	0,714285714
Layer 4	4.3. Gypsum mortar, lime plaster mortar	0,7	0,005	0,007142857
Layer 5	8.1.1. Timber derived from coniferous trees	0,13	0,01	0,076923077
Layer 6	. Reinforced Concrete (Normal concrete (with TS 500) , made using natural aggregate concrete or g	1,65	0,14	0,084848485
Layer 7	Select			
Floor Location	Basement Ceiling			0,34
Floor Area	158,12	m2		
Basement System without Insulation				1,258914419
All basement system				2,46555092

Basement System II				
	Material	Thermal Conductivity	Thickness(m)	Thermal Performance
Insulation Type	4 cm-EPS 30 kg/m3	0,03315	0,04	1,206636501
Layer 1	4.6. Cement mortar screed	1,4	0,03	0,021428571
Layer 2	4.6. Cement mortar screed	1,4	0,02	0,014285714
Layer 3	10.3.2.1.2. Extruded polystyrene foam (XPS) boards - TC 035	0,035	0,025	0,714285714
Layer 4	4.3. Gypsum mortar, lime plaster mortar	0,7	0,005	0,007142857
Layer 5	1.8.Artificial stones	1,3	0,009	0,006923077
Layer 6	. Reinforced Concrete (Normal concrete (with TS 500) , made using natural aggregate concrete or g	1,65	0,14	0,084848485
Layer 7	Select			
Floor Location	Basement Ceiling			0,34
Floor Area	66,28	m2		
Basement System without Insulation				1,188914419
All basement system				2,39555092

Figure A.2. Basement Ceiling Insulation Design Details of TOKI Building

Basement System III				
	Material	*Thermal Conductivity*	*Thickness(m)*	*Thermal Performance*
Insulation Type	6 cm-EPS 35 kg/m3	0,03122	0,06	1,921844971
Layer 1	1.8.Artificial stones	1,3	0,009	0,006923077
Layer 2	9.2.2.1.5. Polymer bitumen waterproofing membranes	0,19	0,003	0,015789474
Layer 3	4.6. Cement mortar screed	1,4	0,03	0,021428571
Layer 4	. Reinforced Concrete (Normal concrete (with TS 500) , made using natural aggregate concrete or g	1,65	0,14	0,084848485
Layer 5	4.3. Gypsum mortar, lime plaster mortar	0,7	0,005	0,007142857
Layer 6	Select			
Layer 7	Select			
Floor Location	Basement Ceiling			0,34
Floor Area	29,44	m2		
Basement System without Insulation				0,476132464
All basement system				2,397977435

Figure A.2. Basement Ceiling Insulation Design Details of TOKI Building (continued)

Basement System IV				
	Material	*Thermal Conductivity*	*Thickness(m)*	*Thermal Performance*
Insulation Type	6 cm-XPS350 30 kg/m3	0,035	0,06	1,714285714
Layer 1	1.6.Marble	3,5	0,02	0,005714286
Layer 2	.1. Plain Concrete (Normal concrete (with TS 500) , made using natural aggregate concrete or grav	2,5	0,15	0,06
Layer 3	4.6. Cement mortar screed	1,4	0,03	0,021428571
Layer 4	. Reinforced Concrete (Normal concrete (with TS 500) , made using natural aggregate concrete or g	1,65	0,35	0,212121212
Layer 5	9.2.2.1.5. Polymer bitumen waterproofing membranes	0,19	0,003	0,015789474
Layer 6	Select			
Layer 7	Select			
Floor Location	Soil-contacted Basement			0,17
Floor Area	46,122	m2		
Basement System without Insulation				0,485053543
All basement system				2,199339257

Figure A.3. Foundation Insulation Design Details of TOKI Building

Roof System I				
	Material	*Thermal Conductivity*	*Thickness(m)*	*Thermal Performance*
Insulation Type	13 cm-Glasswool 18 kg/m3	0,04	0,13	3,25
Layer 1	9.2.2.1.5. Polymer bitumen waterproofing membranes	0,19	0,002	0,010526316
Layer 2	Normal concrete (with TS 500) , made using natural a	1,65	0,14	0,084848485
Layer 3	4.1. Lime mortar , lime - cement mortar	1	0,028	0,028
Layer 4	Select			
Layer 5	Select			
Layer 6	Select			
Layer 7	Select			
Roof Type	Ceiling(unused garret,under ventilated space)			0,21
Roof Area	337,72	m2		
Roof System without Insulation				0,333374801
All roof system				3,583374801

Roof System II				
	Material	*Thermal Conductivity*	*Thickness(m)*	*Thermal Performance*
Insulation Type	14 cm-Glasswool 18 kg/m3	0,04	0,14	3,5
Layer 1	9.2.2.1.5. Polymer bitumen waterproofing membranes	0,19	0,002	0,010526316
Layer 2	4.3. Gypsum mortar, lime plaster mortar	0,7	0,005	0,007142857
Layer 3	Normal concrete (with TS 500) , made using natural a	1,65	0,14	0,084848485
Layer 4	Select			
Layer 5	Select			
Layer 6	Select			
Layer 7	Select			
Roof Type	Ceiling(unused garret,under ventilated space)			0,21
Roof Area	46,122	m2		
Roof System without Insulation				0,312517658
All roof system				3,812517658

Figure A.4. Roof Insulation Design Details of TOKI Building

				Window Geometry		
Window ID	*Window Shape*	*Frame Material*	*Glazing Type*	*Length(m)*	*Width(m)*	*Thickness(m)*
1	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,7	0,04
2	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,6	0,7	0,04
3	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,7	0,04
4	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,7	0,04
5	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,6	0,7	0,04
6	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,7	0,04
7	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,9	0,04
8	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,9	0,04
9		Select	Select			
10		Select	Select			

				Window Geometry		
Window ID	*Window Shape*	*Frame Material*	*Glazing Type*	*Length(m)*	*Width(m)*	*Thickness(m)*
1	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,7	0,04
2	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,6	0,7	0,04
3	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,7	0,04
4	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,7	0,04
5	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,6	0,7	0,04
6	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,7	0,04
7	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,9	0,04
8	Single Casement	PVC (3 chambers)	Double Sinergy Air (4-16-4)	1,3	0,9	0,04
9		Select	Select			
10		Select	Select			

Figure A.5. Window Design Details of TOKI Building

Door ID	*Door Type*	*Length(m)*	*Width(m)*	*Area(m)*	*Thermal Transmittance*	*# of Doors*	*Heat Loss*
1	Exterior Door (Wooden,PVC)	2,2	0,9	1,98	3,5	44	304,92
2	Exterior Door (Metal with thermal break)	2,5	2,7	6,75	5,5	1	37,125
3	Interior Door	2,2	1	2,2	2	44	4,4
4	Select						
5	Select						
6	Select						
7	Select						
8	Select						
9	Select						
10	Select						

Figure A.6. Door Design Details of TOKI Building

Table A.2. Design Details of Reference Buildings for Different Cities

Design Parameters	**İzmir**	**İstanbul**	**Kayseri**	**Erzurum**
Wall Type I	HCB 190 x 190 x 135	HCB 190 x 190 x 135	HCB 190 x 190 x 135	HCB 190 x 190 x 135
Wall Insulation I	3 cm-EPS30	3 cm-EPS30	7 cm-EPS30	7 cm-EPS30
Wall Insulation II	4 cm-EPS30	5 cm-EPS30	8 cm-EPS30	8 cm-EPS30
Wall Insulation III	4 cm-EPS30	4 cm-EPS30	7 cm-EPS30	8 cm-EPS30
Wall Insulation IV	4 cm-EPS30	5 cm-EPS30	8 cm-EPS30	8 cm-EPS35
Base Insulation I	3 cm-EPS30	3 cm-EPS30	5 cm-EPS30	5 cm-EPS35
Base Insulation II	3 cm-EPS30	3 cm-EPS30	5 cm-EPS30	5 cm-EPS35
Base Insulation III	4 cm-EPS30	5 cm-EPS30	7 cm-EPS35	8 cm-EPS30
Base Insulation IV	4 cm-XPS350-30	5 cm-XPS350-30	7 cm-XPS300-30	8 cm-XPS350-30
Roof Insulation I	8 cm-GW18	10 cm-GW18	17 cm-GW18	18 cm-GW18
Roof Insulation I	9 cm-GW18	10 cm-GW18	17 cm-GW18	18 cm-GW18
Window Frames	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)
All Window Glazing Systems	Double Sinergy Air (4-16-4)	Double Sinergy Air (4-16-4)	Double Sinergy Air (4-16-4)	Double Sinergy Air (4-16-4)

Table A.3. Life Cycle Environmental Impact Performance of Optimum Design in TOKI Building in Ankara

Environmental Impact	Life Cycle Performance	Natural Gas Equivalence (MWh)	Source of Result
Life Cycle Global Warming Potential Savings (kg CO2-Equiv.)	275537.26	1152.38	
Life Cycle Acidification Air Savings (kg SO2-Equiv.)	408.49	2049.84	
Life Cycle Acidification Water Savings (kg SO2-Equiv.)	0.03	2318.84	
Life Cycle Ecotoxicity Savings (CTUeco)	43.23	1067.87	
Life Cycle Eutrophication Air Savings (kg N-Equiv.)	-10.40	-978.73	EPS Wall Insulation - Adhesive Mortar
Life Cycle Eutrophication Water Savings (kg N-Equiv.)	-0.17	-247.77	EPS Wall Insulation - EPS, Plaster Mesh, Plastic Dowels
Life Cycle Human Health Particulate Air Savings (kg PM2.5-Equiv.)	34.52	2055.06	
Life Cycle Human Toxicity, Cancer Savings (CTUh)	2.83E-05	1714.90	
Life Cycle Human Toxicity, Non-cancer Savings (CTUh)	4.08E-07	1436.76	
Life Cycle Ozone Depletion Air Savings (kg CFC 11-Equiv.)	-8.09E-04	-442475.52	EPS Wall Insulation- EPS, Adhesive Mortar
Smog Air Savings (kg O3-Equiv.)	6994.58	1950.84	

APPENDIX B

B. OPTIMUM DESIGN DETAILS

Table B.1. Design Details of Optimum Design in Different Analysis Periods

Design Parameters	**5-year Analysis**	**10-year Analysis**	**20-year Analysis**	**40-year Analysis**
Wall Type I	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190
Wall Insulation I-III-IV	7 cm-EPS30	10 cm-EPS30	13 cm-EPS30	18 cm-EPS30
Wall Insulation II	4cm-EPS30	6 cm-EPS30	9 cm-EPS30	12 cm-EPS35
Base Insulation I-II-III	3 cm-EPS35	5 cm-EPS35	8 cm-EPS35	12 cm-EPS35
Base Insulation IV	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25
Roof Insulation	13 cm-GW18	19 cm-GW18	25 cm-GW18	25 cm-GW18
Window Frames	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)
Window Glazing I-II-III IV-V-VII	Double S-Argon (4-16-4)	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VI-VIII	Double S-Argon (4-16-4)	Double S-Argon (4-16-4)	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)

Table B.2. Design Details of Optimum Design for Different Energy Resources

Design Parameters	Natural Gas	Hard Coal	Lignite	Fuel Oil
Wall Type I	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190
Wall Insulation I-III-IV	16 cm-EPS30	13 cm-EPS30	14 cm-EPS30	20 cm-EPS30
Wall Insulation II	11 cm-EPS30	9 cm-EPS30	9 cm-EPS30	14 cm-EPS30
Base Insulation I-II-III	11 cm-EPS35	8 cm-EPS35	9 cm-EPS35	15 cm-EPS35
Base Insulation IV	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25
Roof Insulation	25 cm-GW18	25 cm-GW18	25 cm-GW18	25 cm-GW18
Window Frames	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)
Window Glazing I-II	Low-e S-Argon (4-16-4-16-4)	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing III	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing IV	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing V	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VI	Low-e S-Argon (4-16-4-16-4)	Double S-Argon (4-16-4)	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VIII	Low-e S-Argon (4-16-4-16-4)	Double S-Argon (4-16-4)	Double S-Argon (4-16-4)	Low-e S-Argon (4-16-4-16-4)

Table B.3. Design Details of Optimum Design for Different Insulation Materials in Walls

Design Parameters	**EPS**	**Rockwool**	**XPS**
Wall Type I	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190
Wall Insulation I-III-IV	16 cm-EPS30	18 cm-RW120	14 cm-XPS300-30
Wall Insulation II	11 cm-EPS30	12 cm-RW120	9 cm-XPS300-30
Base Insulation I-II-III	11 cm-EPS35	11 cm-EPS35	11 cm-EPS35
Base Insulation IV	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25
Roof Insulation	25 cm-GW18	25 cm-GW18	25 cm-GW18
Window Frames	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)
Window Glazing I-II	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing III	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing IV	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing V	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VI	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VIII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)

Table B.4. Design Details of Optimum Design in Thickness Limitation

Design Parameters	Unconstrained	Constrained
Wall Type I	HCB 190 x 85 x 190	7.5 cm-AAC400
Wall Insulation I	16 cm-EPS30	10 cm-EPS35
Wall Insulation II	11 cm-EPS30	10 cm-EPS30
Wall Insulation III	16 cm-EPS30	10 cm-EPS35
Wall Insulation IV	16 cm-EPS30	10 cm-EPS35
Base Insulation I	11 cm-EPS35	10 cm-EPS35
Base Insulation II	11 cm-EPS35	10 cm-EPS35
Base Insulation III	11 cm-EPS 35	10 cm-EPS35
Base Insulation IV	3 cm-XPS300-25	3 cm-XPS300-25
Roof Insulation I	25 cm-GW18	15 cm-GW18
Roof Insulation II	25 cm-GW18	15 cm-GW18
Window Frames	PVC (3 chambers)	PVC (3 chambers)
Window Glazing I	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing II	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing III	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing IV	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing V	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VI	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VIII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)

Table B.5. Design Details of Optimum Design for Long-term Average Temperature Data

Design Parameters	**Artvin**	**Isparta**	**Malatya**	**TS 825 3^{rd} DDG**
Wall Type I	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190
Wall Insulation I-III-IV	15 cm-EPS30	16 cm-EPS30	15 cm-EPS30	17 cm-EPS30
Wall Insulation II	10 cm-EPS30	10 cm-EPS30	10 cm-EPS30	12 cm-EPS30
Base Insulation I-II-III	9 cm-EPS35	10 cm-EPS35	10 cm-EPS35	12 cm-EPS35
Base Insulation IV	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25
Roof Insulation	25 cm-GW18	25 cm-GW18	25 cm-GW18	25 cm-GW18
Window Frames	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)
Window Glazing I-II	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing III	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing IV	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing V	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VI	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VIII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)

Table B.6. Design Details of Optimum Design for Recent Heating Degree-Day Data

Design Parameters	**Artvin**	**Isparta**	**Malatya**	**TS 825 3rd DDG**
Wall Type I	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190
Wall Insulation I-III-IV	15 cm-EPS30	15 cm-EPS30	16 cm-EPS30	17 cm-EPS30
Wall Insulation II	10 cm-EPS30	11 cm-EPS30	11 cm-EPS30	12 cm-EPS30
Base Insulation I-II-III	9 cm-EPS35	10 cm-EPS35	11 cm-EPS35	12 cm-EPS35
Base Insulation IV	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25
Roof Insulation	25 cm-GW18	25 cm-GW18	25 cm-GW18	25 cm-GW18
Window Frames	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)
Window Glazing I-II	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing III	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing IV	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing V	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VI	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VIII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)

Table B.7. Design Details of Optimum Design in Different Heating Schedule

Design Parameters	7/24 Facility	7/16 Facility	5/12 Facility
Wall Type I	HCB 190 x 85 x 190	HCB 190 x 85 x 190	HCB 190 x 85 x 190
Wall Insulation I	16 cm-EPS30	15 cm-EPS30	14 cm-EPS30
Wall Insulation II	11 cm-EPS30	10 cm-EPS30	9 cm-EPS30
Wall Insulation III	16 cm-EPS30	15 cm-EPS30	14 cm-EPS30
Wall Insulation IV	16 cm-EPS30	15 cm-EPS30	14 cm-EPS30
Base Insulation I	11 cm-EPS35	10 cm-EPS35	9 cm-EPS35
Base Insulation II	11 cm-EPS35	10 cm-EPS35	9 cm-EPS35
Base Insulation III	11 cm-EPS 35	10 cm-EPS 35	9 cm-EPS 35
Base Insulation IV	3 cm-XPS300-25	3 cm-XPS300-25	3 cm-XPS300-25
Roof Insulation I	25 cm-GW18	25 cm-GW18	25 cm-GW18
Roof Insulation II	25 cm-GW18	25 cm-GW18	25 cm-GW18
Window Frames	PVC (3 chambers)	PVC (3 chambers)	PVC (3 chambers)
Window Glazing I	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing II	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing III	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing IV	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing V	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VI	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Double S-Argon (4-16-4)
Window Glazing VII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)
Window Glazing VIII	Low-e S-Argon (4-16-4-16-4)	Low-e S-Argon (4-16-4-16-4)	Double S-Argon (4-16-4)

APPENDIX C

C. MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION IN DYNAMO

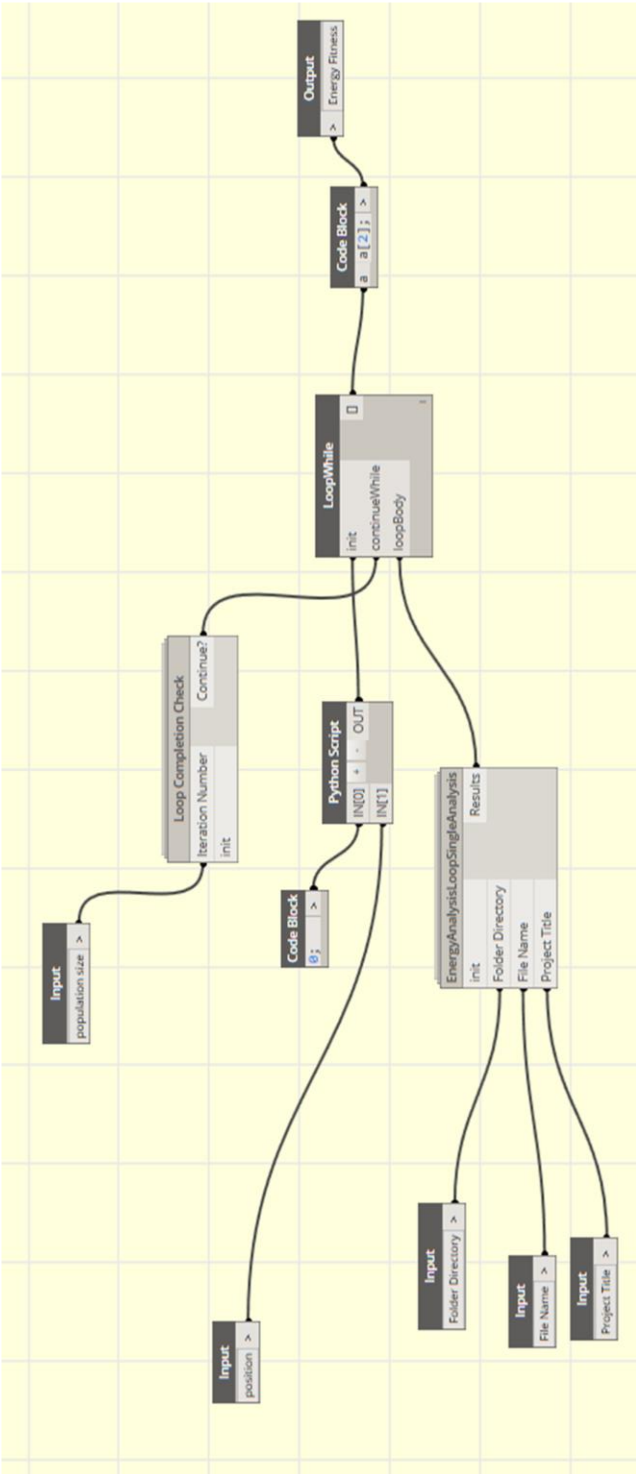

Figure C.1. DE Fitness Evaluation Node in Dynamo

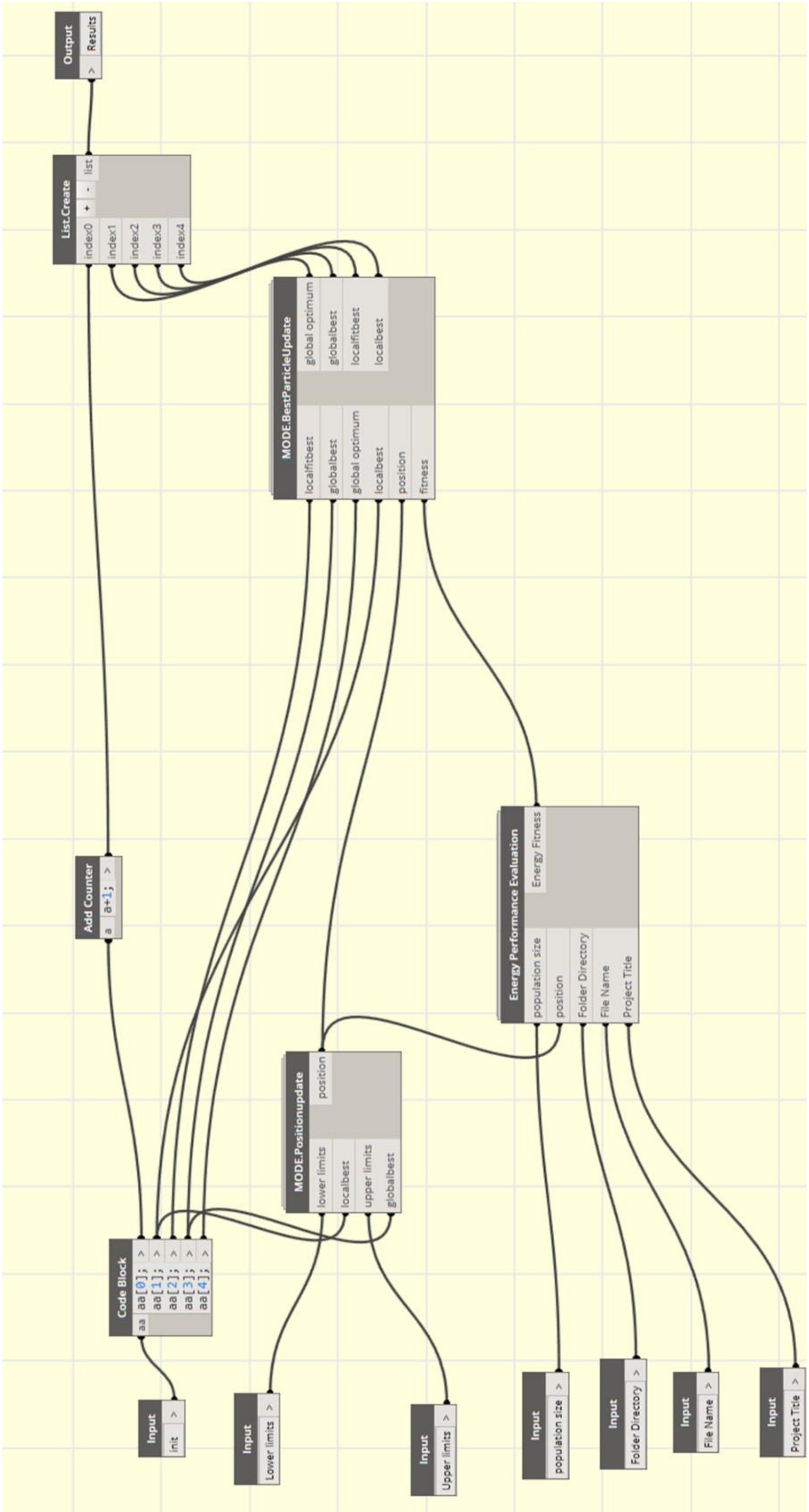

Figure C.2. DE Single Iteration Node in Dynamo

APPENDIX D

D. MANUAL UPDATES IN DYNAMO

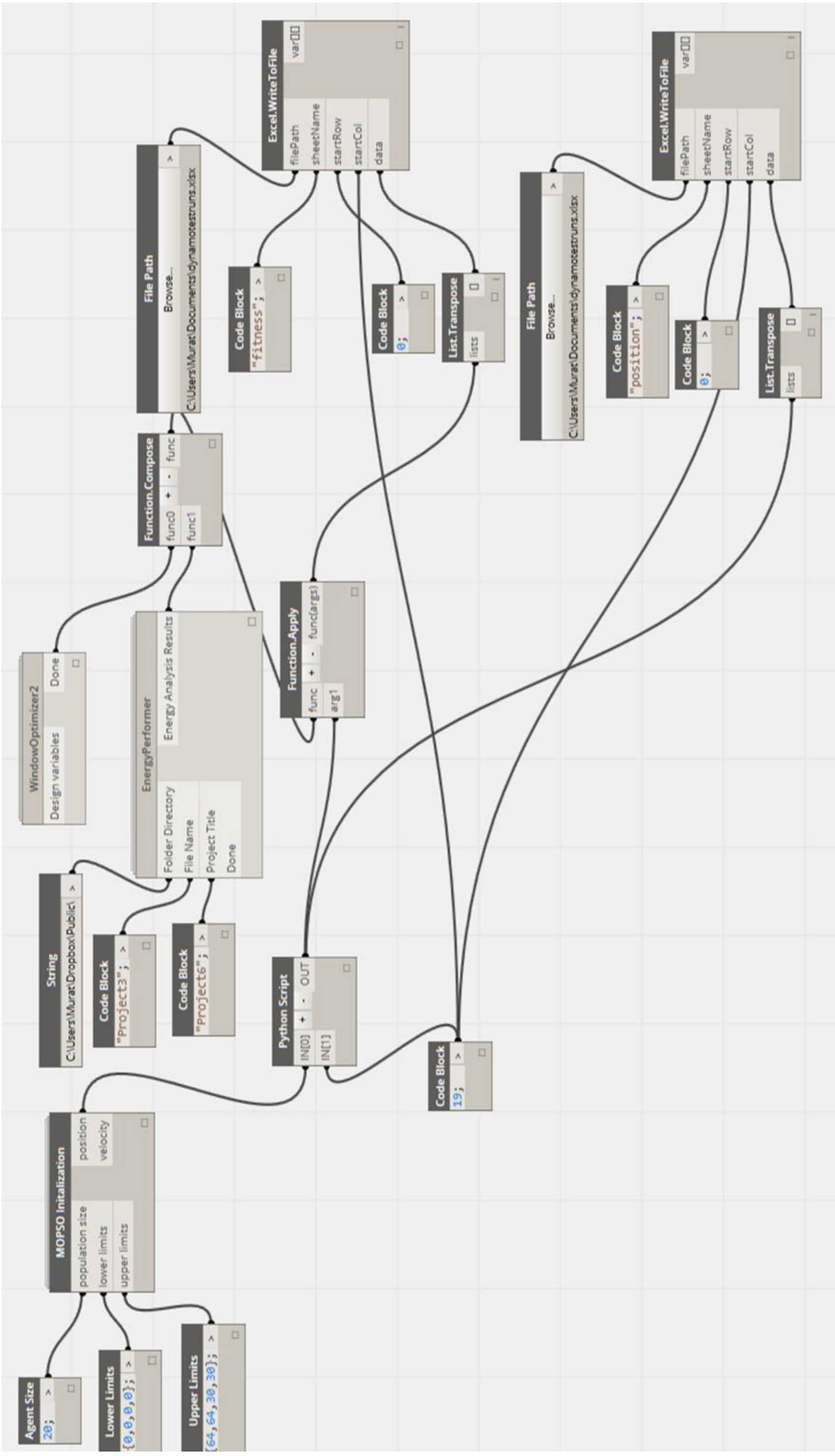

Figure D.1. DE Initialization in Manual Updates

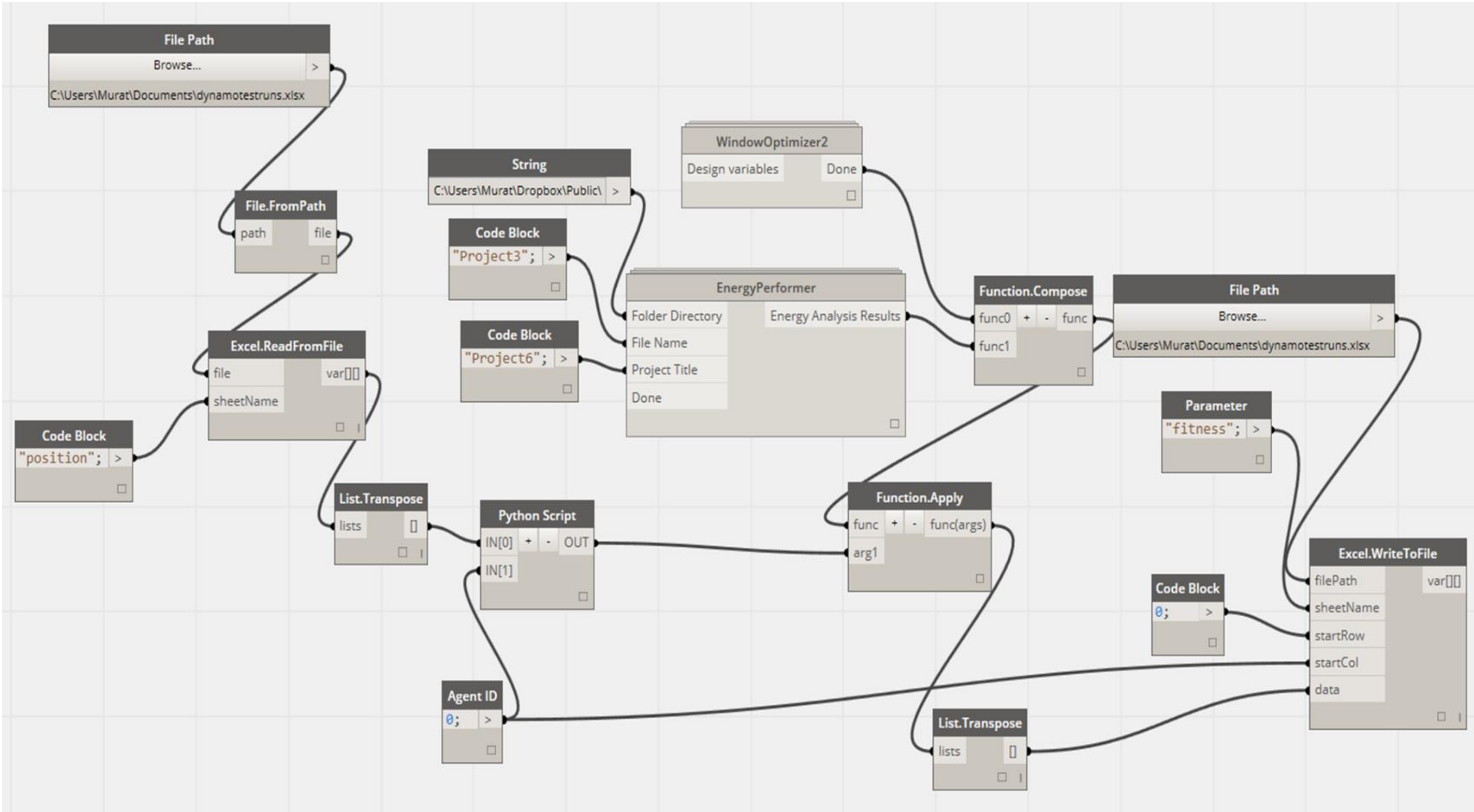

Figure D.2. DE Fitness Evaluation in Manual Updates

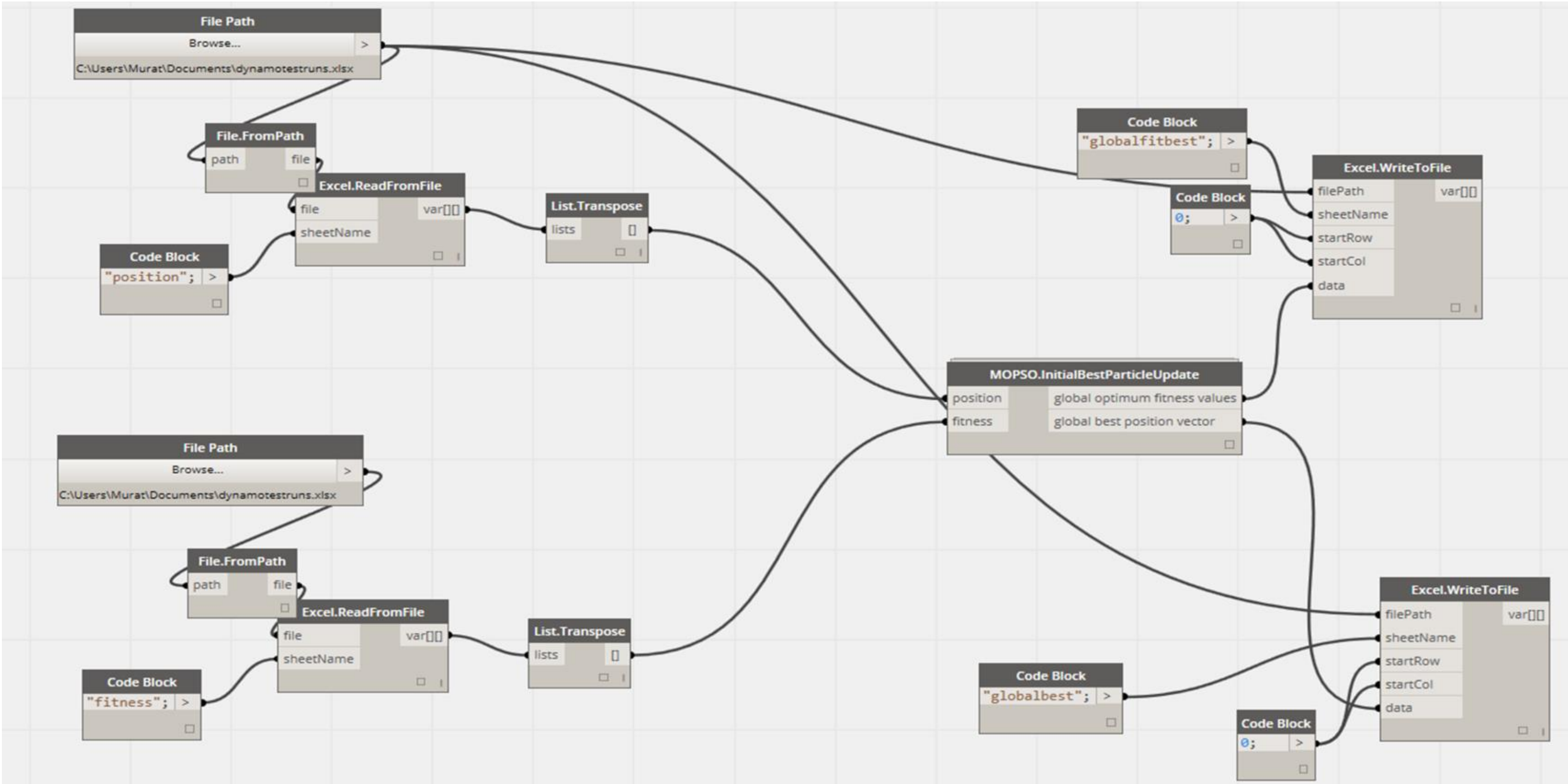

Figure D.3. DE Initial Non-dominated Solution Assignment in Manual Updates

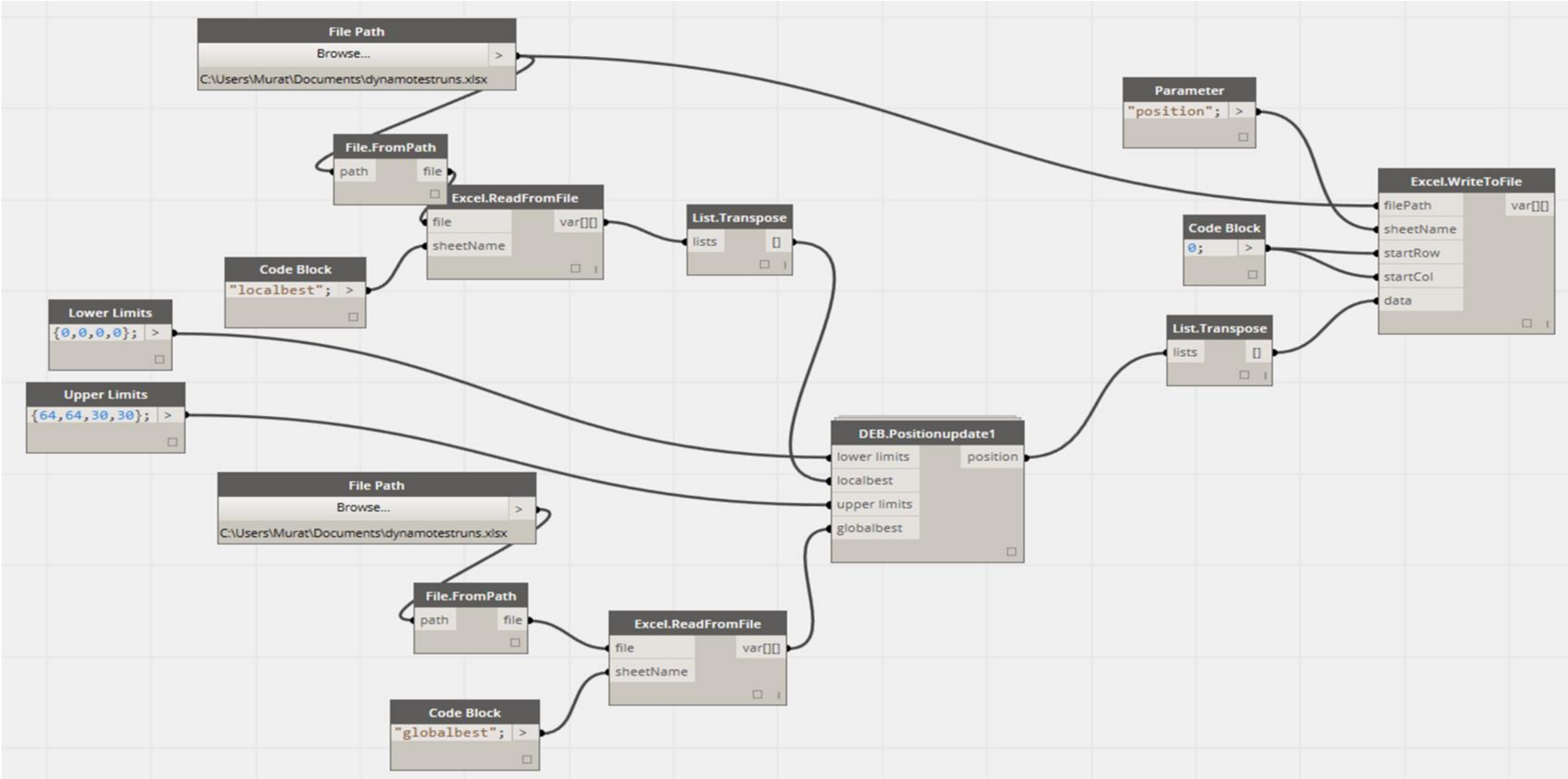

Figure D.4. DE Position Update in Manual Updates

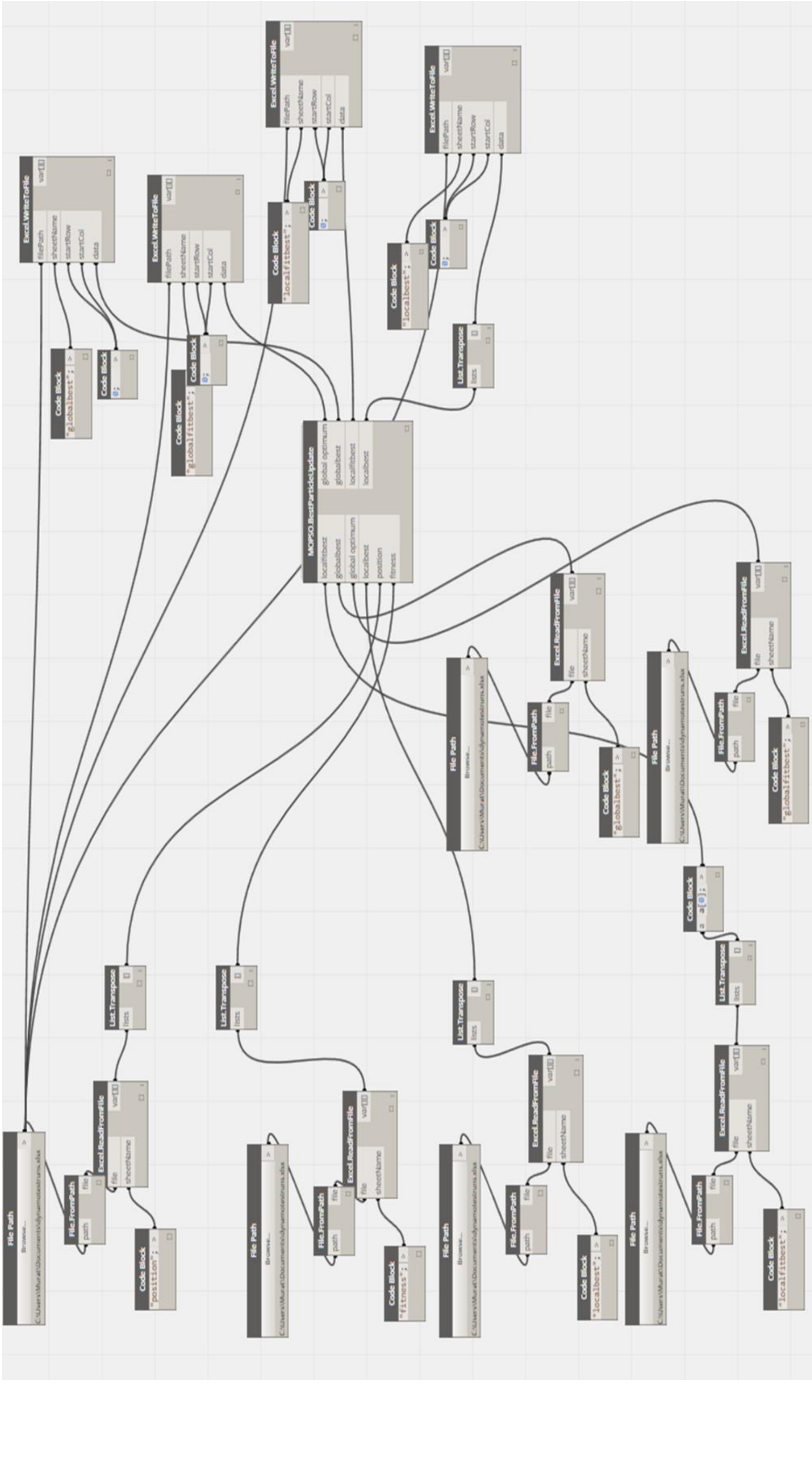

Figure D.5. DE Local and Global Best Updates in Manual Update