MULTI-OBJECTIVE OPTIMIZATION OF A BUILDING'S EMBODIED ENERGY, OPERATIONAL ENERGY, AND EMBODIED WATER

A Thesis

by

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ABSTRACT

Buildings account for approximately 40% of annual energy consumption and 16% of annual water withdrawals globally over their life cycle. Moreover, most building designs consider only the operational energy use of buildings during their life cycle, disregarding the contribution of embodied energy and embodied water to total energy and water consumption. Studies have indicated that minimizing operational energy may increase embodied energy. Likewise, minimizing energy use may not always mean reducing embodied water use. The most effective approach to determine the trade-offs among building design and construction decisions related to building energy and water parameters is to apply multi-objective optimization. In order to quantify the trade-offs between water and energy, this research created a multi-objective optimization model using building information modeling data to simulate energy and water use.

This study created and tested a multi-objective genetic algorithm to examine energy-water trade-offs by computing water consumption, operational energy, and embodied energy of buildings. We tested the tool by conducting a case study of a higher-education building. We applied and compared single-, double-, and triple-objective optimization approaches. First, a triple-objective optimization method was applied to target operational energy, embodied energy, and embodied water as the objective functions. Second, a double-objective optimization was applied excluding embodied water to analyze operational-embodied energy trade-offs. Third, a single-objective embodied water optimization approach was applied to target embodied water individually. We investigated the design variables contributing to total energy and embodied water consumption and the relationship between energy and water. In addition, we examined the building's envelope material quantity and window-to-wall ratio as optimization variables. Results from the multi-objective optimizations suggest that excluding embodied water can produce a set of Pareto solutions that is quite different than when including it. In the double-objective optimization between embodied energy and operational energy, minimizing operational energy increased embodied energy and, consequently, total energy use. Embodied water and energy did not show such a relationship, though. However, in comparing window-to-wall ratios, similar connections were seen between water and energy. Optimal energy solutions had low window-to-wall ratios, while the single-objective embodied water results had significantly higher window-to-wall ratios. Average embodied water values from the triple-objective optimization, double-objective optimization, and single-objective optimization were 338,948, 59,364.3, and 24,600.7 MGal, respectively. Even though single-objective optimization showed the lowest embodied water, the corresponding embodied energy and operational energy were relatively high (8,494,700 and 13,327,000 MJ, respectively). Results clearly suggest that focusing on just one energy or water component during building design may generate solutions that worsen other components.

Keywords: Building information modeling, multi-objective optimization, embodied energy, embodied water, water-energy nexus, genetic algorithm

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NOMENCLATURE

ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
3D	three-dimensional
BIM	building information modeling
BUR	bitumen membrane
DEE	demolition embodied energy
DEW	demolition embodied water
EE	embodied energy
EPDM	ethylene propylene diene terpolymer
EW	embodied water
GA	genetic algorithm
GHG	greenhouse has
IEE	initial embodied energy
IEW	initial embodied water
IO	input-output
IOH	input-output–hybrid
LAAH	Liberal Arts and Humanities
LCE	life cycle energy
LCEE	life cycle embodied energy
MOGA	multi-objective genetic algorithm
NSGA	nondominated sorting genetic algorithm
NZEB	nearly-zero-energy building
OE	operational energy

OW	operational water
PSO	particle swarm optimization
PVC	polyvinyl chloride
REE	recurrent embodied energy
REW	recurrent embodied water
US	United States
WWR	window-to-wall ratio

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CHAPTER I

INTRODUCTION

Because of global warming and climate change, the frequency and intensity of weather disasters have grown over the last decade (Venkatraj and Dixit, 2021). The primary cause of global warming is the release of greenhouse gases (GHGs) into the atmosphere as a result of the combustion of fossil fuels (Dixit, 2017). Approximately 40% of annual energy consumption and 16% of annual water use come from the building sector (Dixit et al., 2013). This sector is a major contributor because the raw material extraction, processing, transportation, construction, service, maintenance, refurbishment, demolition, and disposal phases of a building's life cycle consume significant amounts of energy and water. Nearly 90% of the energy consumed in building construction, operation, maintenance, renovation, and demolition is derived from fossil fuels (Ibn-Mohammed et al., 2013, Dixit, 2017). By reducing overall building life cycle energy (LCE), the building sector can potentially reduce its carbon footprint and GHG emissions (Monteiro et al., 2016). Likewise, building design, construction, and management also incur water use as embodied water (EW) and operational water (OW). EW consumption has an energy component and a nonenergy component. Energy production will consume freshwater, and energy reduction will reduce the water use associated with it. However, there is a non-energy–related component of water in the processes of materials production and construction, operation and maintenance, and building end-of-life, for which reducing energy may not solve the problem of freshwater depletion.

Operational Energy and Embodied Energy

Building consumes energy in two forms: embodied energy (EE) and operational energy (OE) (Menzies and Tsolaki, 2016). OE is considered the energy used during a building's operational phase due to heating, cooling, lighting, heating water, powering equipment, and other similar operating activities to ensure thermal comfort for occupants (Dixit et al., 2012, Giordano et al., 2017). The total energy consumed by buildings due to raw materials extraction, materials production, transportation, construction, equipment, labor, maintenance, and demolition is considered life cycle embodied energy (LCEE) (Hernandez and Kenny, 2011, Dixit et al., 2010). LCEE consists of three components distributed across the three main stages of a building's life cycle: initial construction, operation and maintenance, and end-of-life (Venkatraj and Dixit, 2021). The three components of EE are initial embodied energy (IEE), recurrent embodied energy (REE), and demolition embodied energy (DEE) (Giordano et al., 2015).

- IEE is the energy demanded in manufacturing building materials (indirect energy use) and the construction phase of a building (direct energy use).
    - Indirect energy includes extracting raw materials, transportation to the production unit, manufacturing, and transportation to the site.
    - Direct energy includes construction, prefabrication, assembly, transportation, and administration.
- REE is the energy consumed to maintain a building during its operational phase (Venkatraj and Dixit, 2021). It is the energy consumed in repair or replacement because of damaged materials or retrofitting. REE is a result of how people utilize the building, their maintenance needs, the facility's service life, and the life span and quality of materials and components (Azari and Abbasabadi, 2018).
- DEE is the net energy associated with end-of-life activities like deconstructing a building and recycling, reusing, or disposing of building elements (Azari and Abbasabadi, 2018,

Giordano et al., 2015, Jiao et al., 2012). Recycling and reusing material may actually save some EE.

Until recently, most studies have investigated only OE because of its significant contribution to a building's life cycle. However, recent research has shown the significance of EE, especially IEE, given the processes of materials and product manufacturing.

Operational Water and Embodied Water

One of the most precious assets on the planet is freshwater. Just 0.1% of the world's available water is freshwater available for use to animals and humans (Jain and Shrivastava, 2016). Water shortage is, unfortunately, becoming a significant issue, with growing events of drought. Many areas of the globe are concerned about the imbalanced withdrawal and consumption of freshwater.

Excessive freshwater usage coupled with population explosion, especially in urban areas, poses serious questions about the sustainability of water resources (Hurlimann, 2009). Another aspect influencing the water crisis is the widespread withdrawal of groundwater and surface water for energy production, which causes resource depletion and environmental issues such as a reduction in groundwater resources, land subsidence, seawater contamination, and loss of surface water quality (Mo et al., 2011).

EW corresponds to the total amount of water consumed in manufacturing products or services used to construct and manage a building (Chen et al., 2012). In the early 1990s, Professor John Anthony Allan first proposed the concept of EW, also known as "virtual water" (Han et al., 2015, Mellor, 2017, Hurlimann, 2009). Previous research has primarily focused on EW in the food sector, as food-processing systems use three-quarters of all water supplies directly (Chen et al., 2012, Xiao et al., 2019, World Bank, 2011). However, much research has been published on the virtual water of nonfood goods in the last decade (Chen et al., 2012, Fang et al., 2014, Han et al., 2014, Liu et al., 2018, Franco Solís and De Miguel Vélez, 2018, Zhao et al., 2009, Fan et al., 2019, Wang et al., 2020).

Buildings consume water in two forms: energy-related water and non-energy–related water. Energy-related water is water consumption directly related to energy sources like fossil fuel extraction or energy source production such as electricity, natural gas, coil, and petroleum. Energy-related water is the sum of water use due to EE and OE sources. Non-energy–related water, on the other hand, is the water used directly and indirectly in building processes like materials manufacturing and production, construction, transportation, maintenance, and end-of-life. Non-energy–related EW, like EE, is the sum of initial embodied water (IEW), recurrent embodied water (REW), and demolition embodied water (DEW). Limited research has been performed to quantify and assess all EW components, including both energy and nonenergy EW (Hong et al., 2019, Fang et al., 2014, Stephan and Crawford, 2014). Analyzing both EE and EW is necessary to produce environmentally sustainable constructed environments (Li et al., 2012, Rios, 2018). A recent unpublished study in our research laboratory investigated the water consumption of five case-study buildings and showed the dominant role of non-energy–related EW. Fig. 1 shows the energy-related water of these buildings to be between 9.8% and 12%. Furthermore, EW is a significant contributor to total water use during a building's life cycle.

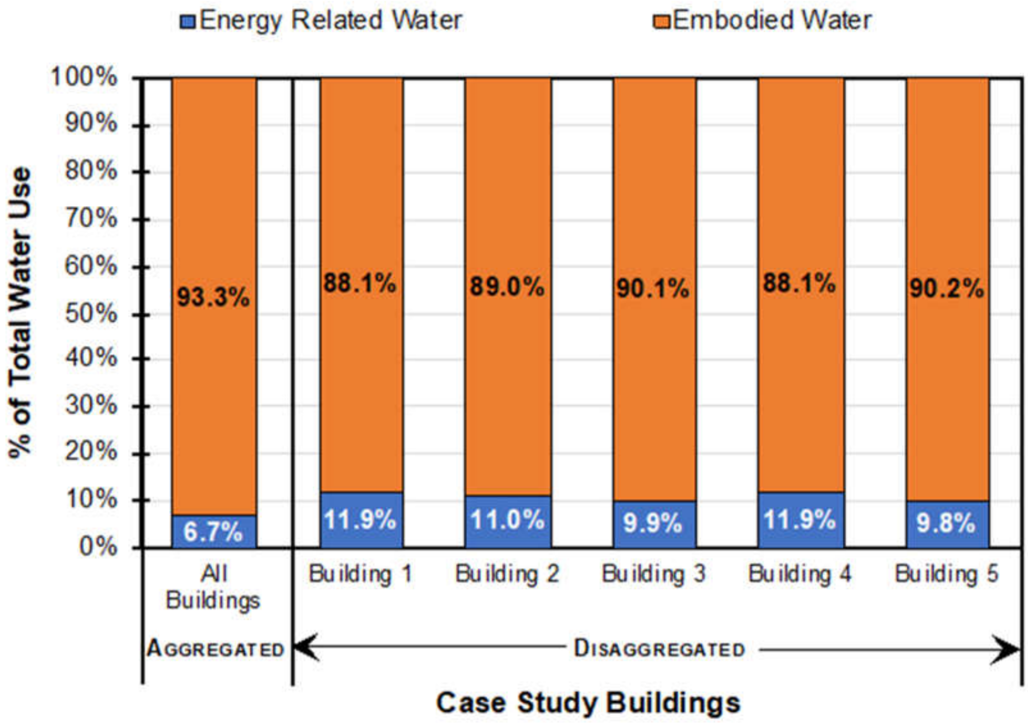

Figure 1. Comparison between energy-related water and non-energy–related water

EW, like EE, is a relatively new concept in the building industry. There is a lack of research on EW in the construction sector (Bardhan and Choudhuri, 2016). Buildings are heavily water-dependent, with a high rate of freshwater consumption during their life cycle. According to Abd El-Hameed (2018), the building sector uses about 20% of the world's water; green buildings can reduce usage by 40%. Previously, emphasis has been placed mostly on computing OW usage and less on EW consumption. Water embedded in building materials in the processes of raw materials extraction, shipping, materials processing, and direct water usage during construction is considered preoperational EW use (Crawford and Treloar, 2005, Jain and Shrivastava, 2016, Choudhuri and Roy, 2015). Because of the various types of consumption that may be involved, indirect water is more difficult to quantify and attribute to any product (Abd El-Hameed et al., 2017).

Calculating Embodied Energy and Embodied Water

Three commonly used calculation methods for EE and EW are process, input-output (IO), and hybrid approaches. Each technique is different in system boundary coverage and type and source of data (Dixit, 2017). The process-based method gathers and adds the actual energy data from construction sites and manufacturers. Because of the use of actual energy data, the process-based method is more reliable. However, because of the unavailability of data, the process-based approach may deliver incomplete results mainly due to "truncation error" (Venkatraj and Dixit, 2021, Crawford, 2004). The IO-based method utilizes the national average data from each economic sector and translates the monetary flow into energy and product flows (Chang et al., 2016, Hong et al., 2019). IO-based calculation covers a broader system boundary because of the usage of IO data, which makes it more complete than the process-based method. However, IO-based EE and EW calculation is considered less reliable than the process-based method (Treloar, 1998, Dixit and Singh, 2018).

Moreover, the IO approach computes the energy and water values that are sector-based rather than product-specific, which may cause inaccurate calculation (Dixit and Singh, 2018). The hybrid method utilizes both process and IO analyses to calculate energy and water, thus improving the completeness and reliability of results. The IO-hybrid (IOH) approach is currently the most complete method for EE calculation; it combines the completeness of the IO method and the reliability of the process technique (Meng et al., 2014, McCormack et al., 2007). Dixit and Singh (2018) provided a detailed overview of the development and data sources of the IOH method and applied EE and EW calculations and data from recent IOH studies. Venkatraj and Dixit (2021) utilized an IOH method to quantify EE consumption of education buildings. EW factors of each material's production were also calculated in an unpublished study conducted in our laboratory.

System Boundary

Fig. 2 shows the system boundary of the present study. This study aimed to calculate only IEE and exclude REE and DEE given the scope of the study. Future studies can include REE and DEE in the total EE use during a building's life cycle. IEE was computed by the sum of direct and indirect energy due to materials production and actual construction. In addition to EE, heating and cooling load served as an OE use factor. Lighting, plug load, and ventilation are other possible factors of OE but were out of the scope of this study. There was no need to include energy-related water use because optimizing OE and EE will automatically optimize energy-related water. Consequently, non-energy–related water, which makes a significant contribution compared with total water use, was considered in energy optimization. Furthermore, this research aimed to calculate and find the trade-offs among non-energy–related EW, IEE, and OE use.

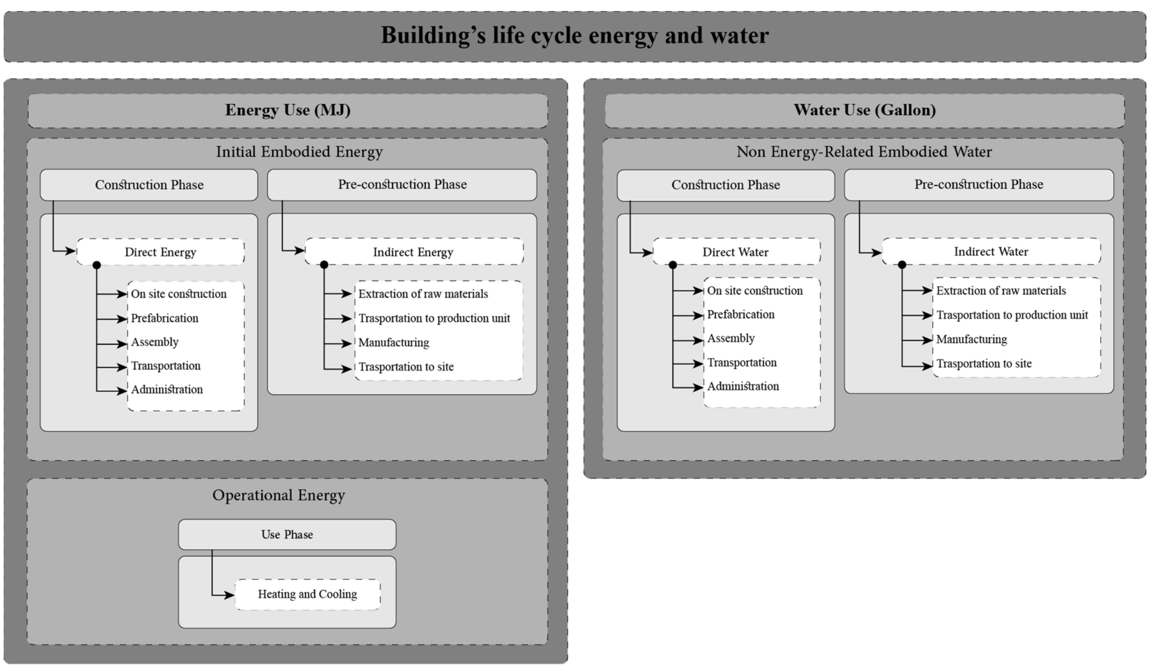

Figure 2. System boundary

Multi-Objective Optimization

Determining the best solution based on a collection of constraints and variables is known as optimization. Multi-objective, or multi-criteria, optimization is a technique that seeks to find trade-offs for design goals in building design with more than one objective (Shadram and Mukkavaara, 2018).

Several optimization approaches exist, with the genetic algorithm (GA) being one of the most powerful for retrofitting problems. Material types such as insulation and windows are considered discrete values, while variables such as window-to-wall ratio (WWR) are considered continuous values of energy optimization. When working with discrete and continuous values, GA is a wonderful tool. Furthermore, there are conflicting criteria in building energy optimization, such that changing one criterion will cause another fitness function to change in a different way (Murray et al., 2014). For example, recent studies have shown that although nearly-zero-energy buildings (NZEBs) significantly reduce OE, EE is increased in some cases (Shadram and Mukkavaara, 2018, Ibn-Mohammed et al., 2013). This conflict has raised the attention to EE and EW and finding the trade-offs between them.

This study aimed to investigate the trade-offs among OE, EE, and EW by implementing a building information model (BIM)–based multi-objective genetic algorithm (MOGA). This research sought to find optimal solutions in new-construction projects and rank them based on energy and water use performance.

CHAPTER II

LITERATURE REVIEW

Several studies have addressed the trade-offs in building energy simulation by implementing optimization techniques. Diakaki et al. (2010) implemented a compromise programming method to optimize annual primary energy demand, annual carbon dioxide emissions, and initial investment cost. Asadi et al. (2012) developed a model to minimize retrofit cost and maximize energy savings, with window type, external wall insulation, roof insulation, and solar collector type being the design variables used. In another study, a particle swarm optimization (PSO) method was utilized to investigate the nexus among annual cooling, heating, and lighting electricity and to minimize buildings' annual energy consumption (Delgarm et al., 2016). Fesanghary et al. (2012) developed a Harmony search algorithm model to optimize building life cycle cost and carbon dioxide emissions.

Although a few studies have reported using optimization methods other than GA, most previous research has implemented MOGA for optimization modeling, revealing the popularity and effectiveness of this method in the building sector. Wang et al. (2005) implemented MOGA to investigate the trade-offs between the environmental and cost impacts of buildings to assist designers in green building design. They implemented a life cycle analysis method to assess design alternatives. Asadi et al. (2014) developed a multi-objective method to investigate the relationship among energy usage, retrofit costs, and thermal discomfort hours. Azari et al. (2016) explored insulation materials, window types, framing materials, wall thermal resistance, and WWR to optimize OE and reduce environmental impact. Harkouss et al. (2018) utilized a nondominated sorting genetic algorithm (NSGA-II) to minimize thermal, electrical demands and building life cycle costs. Among the economic aspects of building retrofitting are investment cost, energy cost, life cycle cost, and payback period. Jafari and Valentin (2017) developed a model to minimize the operational use of buildings and life cycle cost due to retrofitting processes. In another study, Murray et al. (2014) analyzed simple payback, carbon emissions, and energy cost as design objectives to address the importance of investigating the trade-offs between the cost and environmental impacts of retrofitting in the planning phase of a project. These studies implemented life cycle analysis to investigate the trade-offs among OE, GHG emissions, economic impact, and environmental impact. However, previous energy optimization models have not explored EE and EW because of data unavailability and complexity in determining building EE and EW.

Recently, two studies reported the use of BIM tools in energy optimization problems. Sandberg et al. (2019) proposed a model to automate design and analysis workflows. Using BIM, collecting data, calculating objective functions, and optimizing design can be automated, leading to reduced calculation time. Shadram and Mukkavaara (2018) utilized BIM as a multidisciplinary information-sharing system to collect relevant data and optimize OE and EE trade-offs in three-dimensional (3D) environment software. Studies on EE have shown that energy use embedded in building materials and construction is significant. One study concluded that a reduction of 140 GJ in OE potentially increases EE by 340 GJ (Shadram and Mukkavaara, 2018).

EW, like EE, has been overlooked in the literature. It has been suggested that EW exceeds water consumed in the operational stage of a building and at its end-of-life (Abd El-Hameed et al., 2017). Furthermore, it is essential to evaluate IEW and REW in the construction sector.

Table 1 shows an overview of related literature on building energy optimization and its objectives. Most studies have investigated the trade-offs between OE and other green building measures like economic and environmental impacts. Few studies have addressed the trade-offs between EE and OE, and no literature has considered water use in life cycle energy optimization.

Table 1. Overview of literature on multi-objective optimization

Reference	Location	OE	EE	Economic impact	Environmental impact	EW
Wang et al. (2005)	Montreal, Canada	✗	✗	✓	✓	✗
Diakaki et al. (2010)	Athens, Greece	✓	✗	✓	✓	✗
Asadi et al. (2012)	Portugal	✓	✗	✓	✗	✗
Fesanghary et al. (2012)	Louisiana, USA	✗	✗	✓	✓	✗
Asadi et al. (2014)	Coimbra, Portugal	✓	✗	✓	✗	✗
Murray et al. (2014)	Cork, Ireland	✗	✗	✓	✓	✗
Lu et al. (2015)	Hong Kong	✗	✗	✓	✓	✗
Delgarm et al. (2016)	Tehran, Iran	✓	✗	✓	✗	✗
Azari et al. (2016)	-	✓	✗	✗	✓	✗
Schwartz et al. (2016)	Sheffield, England	✓	✓	✓	✗	✗
Jafari and Valentin (2017)	Albuquerque, New Mexico	✓	✗	✓	✗	✗
Harkouss et al. (2018)	Lebanon and France	✓	✗	✓	✗	✗
Shadram and Mukkavaara (2018)	Sweden	✓	✓	✗	✗	✗
Ascione et al. (2019)	Milan, Italy	✓	✗	✓	✓	✗
Amani and Kiaee (2020)	Tehran, Iran	✓	✗	✗	✓	✗

Problem Statement and Questions

The construction industry is a significant energy and water consumer globally; it contributes 40% of energy and 16% of water withdrawals. These numbers emphasize the importance of energy retrofitting in the industry. Moreover, different components of a building's energy use have a conflicting relationship, making it challenging to optimize the life cycle environmental footprint. A significant number of databases and tools can help calculate and analyze OE during a building's life cycle; however, recent studies have revealed that in many cases, reducing OE causes a noticeable increase in EE (Ibn-Mohammed et al., 2013, Shadram and Mukkavaara, 2018). In addition, the EW impacts of a building are not well understood. For instance, like EE, EW may be consumed directly and indirectly, both of which must be assessed to reduce energy use, carbon emissions, and freshwater consumption holistically. Furthermore, each energy source used as EE or OE also consumes water associated with the building life cycle and therefore must also be explored.

Efficient energy use has become demanded in construction, and recently, more attention has been paid to EE and EW. However, the lack of comprehensive data on EE, especially during the initial phase of a building, raises the question of how to find the best design measures in building design and construction to reduce energy and water usage. Also, the existing knowledge on optimizing energy and water is limited. Furthermore, different factors such as geographic location affect results, requiring further investigation. A detailed analysis is needed of OE and EE, along with EW, to understand whether decisions align based on each individually and all three collectively.

Research Objectives

This study proposes a comprehensive model to understand potential trade-offs among different energy and water use components of a building to help designers, engineers, and clients in their decision-making processes by minimizing the energy and water consumption of buildings during their life cycle. Objectives of this study were as follows.

- Quantify and examine trade-offs among energy and water components of OE and EE, with the key tasks to:
    - Implement a comprehensive EE and EW model to quantify energy and water components.
    - Develop a BIM-based tool that makes the information sharing among BIM software, EE, and water databases easier and more manageable.
- Optimize total life cycle energy and water use to identify design measures that may help reduce the overall environmental impacts of new-construction education buildings, with the key tasks to:
    - Link the BIM software, energy and water data, and optimization model.
    - Conduct analysis using different GAs based on design variables, constraints, and fitness objectives by creating and applying (1) triple-objective optimization for OE, EE, and EW, (2) double-objective optimization for OE and EE, and (3) single-objective optimization for EW.
    - Test the model with a case study of a new higher-education building.
- Select and compare Pareto front solutions from the single-, double-, and triple-objective optimizations, with the key tasks to:

- Select Pareto solutions of the triple-objective optimization with three fitness objectives.
- Select Pareto solutions of the double-objective optimization with two fitness objectives.
- Select three separate Pareto solutions of the single-objective optimization.
- Compare the multi-objective solutions to investigate the effects of EW and its significance in building design and construction.
- Compare multi-objective solutions with single-objective results to check the feasibility of the multi-objective optimization tool in finding trade-offs among OE, EE, and EW.

CHAPTER III

METHODOLOGY

OE use in this study included annual heating and cooling load. In terms of EE and EW, this research included only IEE and non-energy–related EW. This study focused on the building envelope; therefore, mechanical systems like plumbing, heating, and air-conditioning were excluded. In addition, use of REE, DEE, REW, DEW, and OW was out of the scope of this study.

This study used a quantitative method to calculate the energy and water factors during a building's life cycle. This section presents a framework for the multi-objective optimization, as well as a prototype to examine the trade-off problem. This study proposes a BIM-based method to make the energy and water calculations easier and more manageable within a design software. The proposed method will assist designers in the decision-making process during the design stage of a building. The framework section discusses the method and steps for creating the multi-objective optimization. The developed prototype section presents detailed information on the model, software utilized in the study, data sources, and calculations.

Framework

The framework consists of four parts: a BIM component, a data repository interface, an energy simulation model, and a multi-objective optimization model. This framework utilizes existing BIM and design tools to investigate the effect of materials and their quantities on buildings' energy and water performance. Fig. 3 shows the framework for assessing the trade-offs among OE, EE, and EW use.

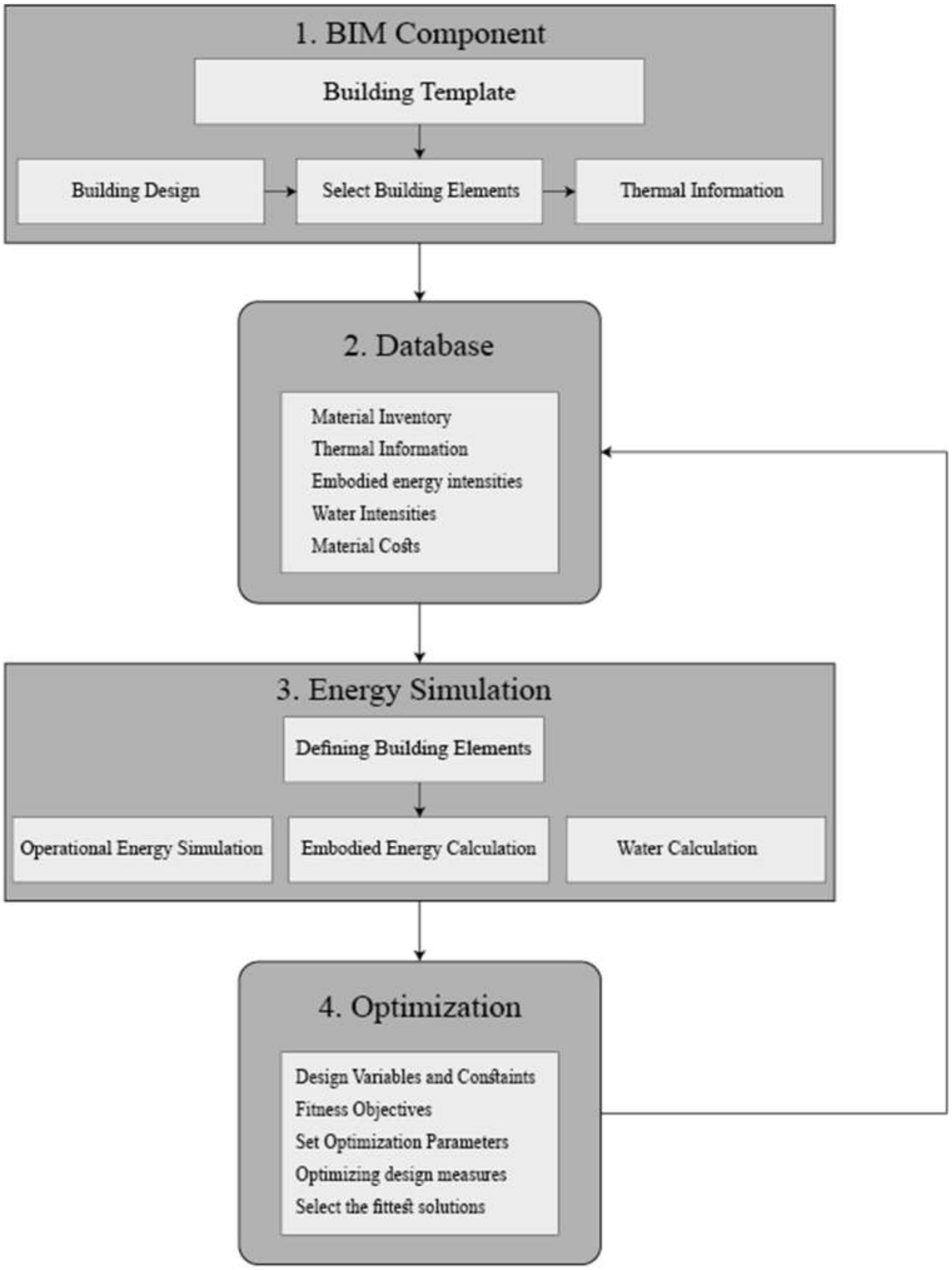

Figure 3. Framework for energy and water optimization

Building Information Modeling

BIM enables sharing information among different parts of the framework. It is considered a tool to manage the thermal and physical properties of building elements. BIM software stores all the building information required for solving the trade-off problem. The materials library of the BIM software contains various building elements with their related thermal information like conductivity, specific heat, and density, which are essential for energy simulation.

Data Repository

The data repository interface stores the data of interest for the energy simulation EE calculation and EW assessment. The database includes the building's physical and thermal information such as the bill of materials, thermal conductivity, specific heat, and density from the BIM software. Additionally, EE and EW intensities are used to calculate the EE and EW of building materials. The framework collects energy and water data from the existing energy and water database, which implements an IOH calculation to determine the energy and water intensity of building materials based on each energy source.

Energy Simulation Model

We used computer-aided design software (Rhino and Grasshopper) to import the building geometry from the BIM software (Autodesk Revit), extract the building boundary, and create building blocks. The rest of the model was created by implementing a visual-programming plug-in within the design software.

The next step was to set up building elements using the thermal information from the data repository interface. Setting up construction elements allowed for calculating OE, EE, and non-energy–related water associated with each material.

Set-up zones based on the building geometry allowed the energy simulation engine to recognize construction elements (i.e., floors, interior and exterior walls, roof). Furthermore, it enabled the ability to assign building elements to construction components.

Finally, we used an energy simulation engine to calculate annual heating and cooling load based on design variables (e.g., building elements, cooling and heating setpoint, site location, occupancy schedule, and weather data) during the operational phase of the building.

Multi-Objective Optimization Model

Multi-objective optimization is an approach to finding the nexus among different design objectives. In this study, we implemented NSGA-II to investigate the trade-offs among OE, EE, and EW to find a set of optimum solutions based on building materials. GA is a great optimization method when the design variables are both continuous and discrete. Additionally, NSGA-II can perform better in terms of the spread of optimum solutions and distance to the true Pareto front in comparison with other evolutionary algorithms (Harkouss et al., 2018, Lu et al., 2015).

Design Variables and Constraints

An important step to using multi-objective optimization is to set up variables and their constraints. The optimization model finds the optimum solutions based on variables and constraints defined by a user. Design variables could be discrete or continuous and could represent a boundary with lower and upper values as constraints. In this framework, the discrete variables are building materials (e.g., insulation, window type, exterior finish), each constrained to a specific integer value (e.g., vinyl siding = 1, cedar clapboard siding = 2). Continuous variables are the bill of materials defined in a boundary (e.g., $0.2 \leq WWR \leq 0.95$). Tables 2 and 3 show a complete list of discrete and continuous variables used in the optimization model, along with their constraints.

Table 2. Discrete variables used in the optimization with the index number of each individual variable

DESIGN VARIABLE (DISCRETE)	SLIDER NUMBER	MATERIAL NAME	INDEX MIN	INDEX MAX
EXTERIOR FINISH	1	Wood Siding	0	6
		Vinyl Siding		
		Stone Veneer		
		Aluminum Wall Panels		
		Brick Veneer		
		Fiber Cement		
		Stucco		
EXTERIOR WALL INSULATION	2	Rigid Foam Insulation Board	0	4
		Fiberglass Batt Insulation		
		Mineral Wool		
		Cellulose Fill		
		Polystyrene Foam		
ROOFING SYSTEM	3	Bitumen Membrane (BUR)	0	4
		Ethylene Propylene Diene Terpolymer (EPDM) Rubber Roofing Membrane		
		Aluminum Metal Roofing		
		Copper Metal Roofing		
		Polyvinyl Chloride (PVC) Roofing		
WINDOW SYSTEM	4	Single Clear_1/4"	0	5
		Double Clear_1/4"		
		Triple Clear_1/4"		
		Single Clear_3/16"		
		Double Clear_3/16"		
		Triple Clear_3/16"		

Table 3. Continuous variables used in the optimization with their ranges

DESIGN VARIABLE (CONTINUOUS)	SLIDER NUMBER	MIN VALUE	MAX VALUE
WWR EAST	5	0.2	0.95
WWR NORTH	6	0.2	0.95
WWR SOUTH	7	0.2	0.95
WWR WEST	8	0.2	0.95

Objective Functions

The next step was to define objective functions, which in this study were OE, IEE, and IEW uses.

The first objective function, OE, is the result of the energy simulation engine. In this study, we decided to calculate the annual heating and cooling load during the operational phase of the building, making the total OE the sum of all the energy zones' yearly heating and cooling load.

The second objective function, IEE, was evaluated using:

(1) $EE_j = \sum_{i=1}^{4} EE_{i,\ j} * C_j$

(2) $IEE = \sum_{j=1}^{n} EE_j + \sum_{i=1}^{4} EEC_i * C_{bldg}$

where in Eq. 1, EE_j (MJ) is the EE of building element *j*; $EE_{i,j}$ (MJ/$) is the energy source; *i* is the energy intensity of a representing material collected from the IOH EE model in *j* (Kumar et al., 2021, Venkatraj and Dixit, 2021), with the four energy sources being coal, natural gas, electricity, and petroleum; and C_j ($) is the cost of material *j*, with the 2017 National Construction Estimator used to obtain the cost data of building materials. Eq. 2 computes IEE by summing the EE_j and EE of the construction process, where *n* is the number of materials; EEC_i (MJ/$) is the energy source–specific energy intensity of education buildings considering coal, natural gas, electricity, and petroleum as the four energy sources, with the data collected from the same EE model in Eq 1; and C_{bldg} ($) is the total construction cost of the building.

The quantity of building elements was taken from the design software (Rhino), which in this study was the surface area of construction elements (i.e., exterior walls, insulation, windows, roof).

The third objective function is the non-energy–related virtual water or, in other words, the IEW, calculated by:

(3) $EW_m = \sum_{j=1}^{n} EW_j * C_j$

(4) $IEW = EW_m + EWC * C_{bldg}$

where in Eq. (3), EW_m (Gal) is the total EW of materials; EW_j (Gal/\$) is the EW intensity of representing material j collected from the IOH EW model currently under review; and C_j (\$) is the cost of material j from the 2017 National Construction Estimator. Eq. 4 computes IEW (Gal) as the total non-energy–related EW due to materials manufacturing and construction, where EWC (Gal/\$) is the water intensity of construction collected by the same EW model in Eq. 3; and C_{bldg} (\$) is the total construction cost of the building.

EE and EW intensities use values per United States (US) dollar because the energy and water model implemented an IOH method to calculate EE and EW.

Producing Optimum Solutions

This framework applies NSGA-II as the MOGA method. A GA performs design iterations to find the best design solutions based on the design variables, constraints (gene pools), and a set of GA parameters (e.g., population, mutation, crossover, iterations). Classical optimization methods lack the ability to find the global optimum, and they can get trapped in local optima (Mishra et al., 2017). Therefore, GA is a preferred method to deal with nonlinear and nonconvex problems because of its random nature and the fact that it can increase the chances of finding the global optimum. Additionally, GA is an excellent method for dealing with discrete values, making it suitable for energy optimization (Mishra et al., 2017, Arabali et al., 2012).

Case Study

The MOGA was used for a new-construction education building to test the feasibility and applicability of the framework as a decision-making system. The Liberal Arts and Humanities (LAAH) building at Texas A&M University was chosen as the case study. LAAH was built in 2012 in College Station, Texas, a hot, humid climate in the southern US. It is a five-story education building with approximately 2300-m^2 floor area. The initial design was used in this case study as the baseline building to find the optimal solutions related to building materials and WWR. A total of eight design variables, four discrete and four continuous, were defined. Detailed information on these variables can be found in the next section, which explains the developed prototype. Figs. 4 and 5 shows images of LAAH and its location on the Texas A&M University campus. LAAH is located in climate zone 2A based on the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) climate zone map of the US (Fig. 6), which is considered a hot, humid zone.

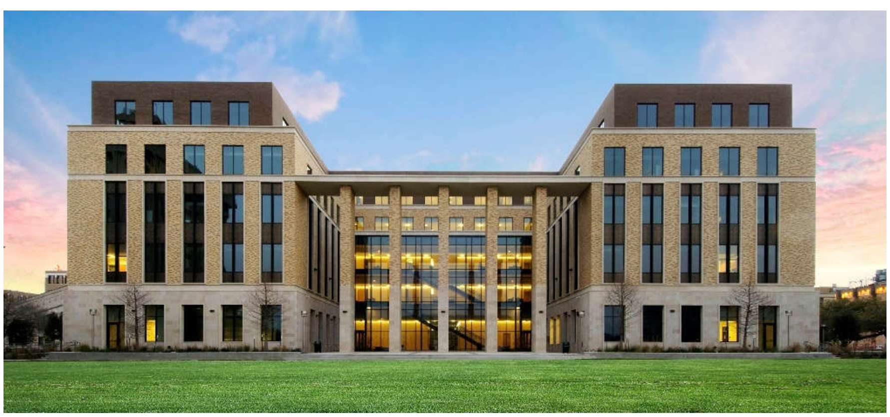

Figure 4. LAAH building

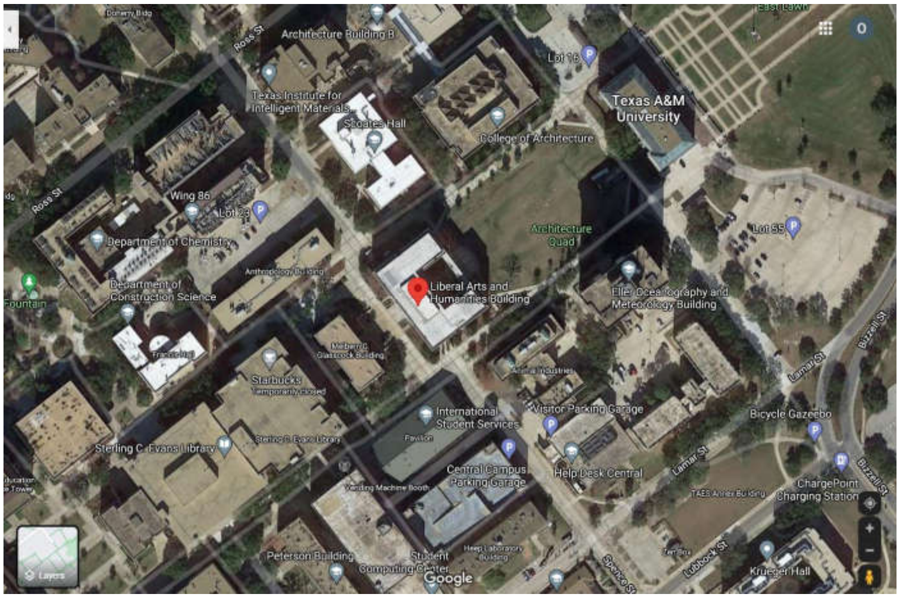

Figure 6. Google Maps view of LAAH on the Texas A&M University campus

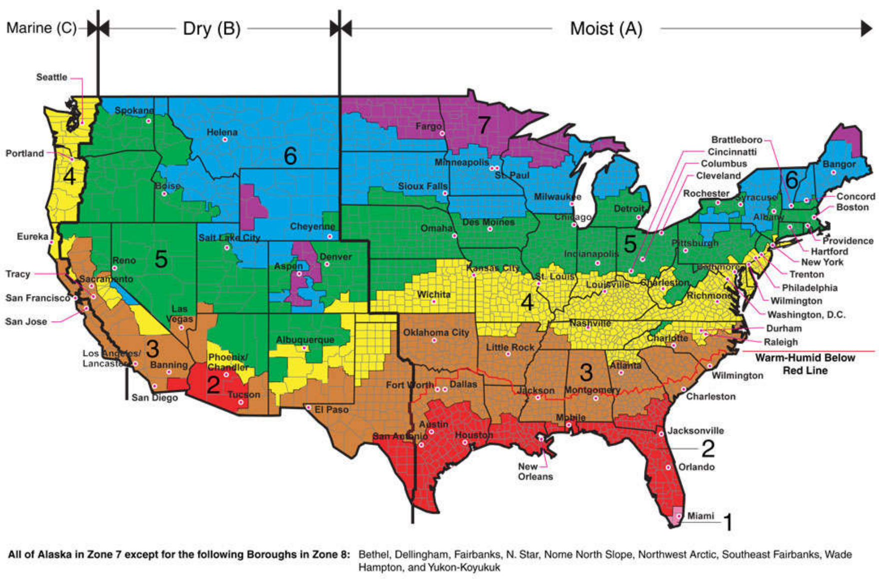

Figure 5. ASHRAE climate zone map of the US

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Developed Prototype

This study sought to develop a multi-objective optimization model to find the optimum solutions for a case-study higher-education building. Therefore, the prototype implemented different tools and plug-ins, as shown in Fig. 7. Like the framework section, the developed prototype section has four sections showing detailed information of the software and method.

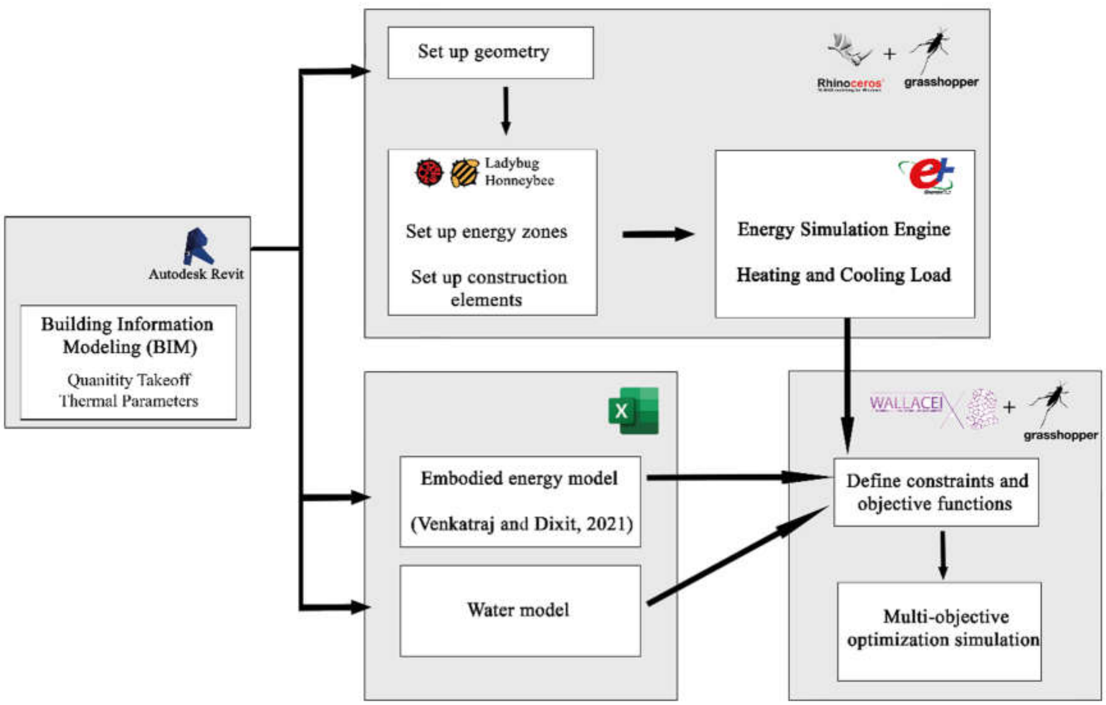


Figure 7. Developed prototype

Building Information Modeling Tool

Autodesk Revit is a BIM-based software that contains building physical and thermal information. We used Autodesk Revit to create the baseline building model and decide the level of detail of the model. The level of detail in this study is the building envelope, interior walls, and floors.

To set up construction elements, we needed the thermal conductivity, specific heat, density, and thickness of each material. Autodesk Revit was used to obtain this information and create the materials inventory. The data from the Revit library were extracted manually to Microsoft Excel for use in the optimization model.

Data Sources

Microsoft Excel was used to store related information (e.g., bill of materials, primary energy factor, EE factors, EW factors) and create a link between the BIM software and the multi-objective optimization model. Table 4 shows a complete list of materials used in the study with their thickness and thermal information. Materials were considered either fixed or variable. Rigid foam board, vapor barrier, polyisocyanurate roof insulation, structural elements, and interior finishes were fixed elements, meaning that they do not change and therefore will not change EE or EW. Fixed materials are those used only for the purpose of creating building elements for the OE simulation. Exterior wall insulation, exterior wall finishes, and roofing systems are considered variables that affect OE, EE, and EW and were considered genes in the optimization process. Material quantities were extracted from Autodesk Revit. These data were then used to create the material elements in the optimization method in Rhino and Grasshopper.

Table 4. Complete list of materials used in the study

		THICKNESS (M)	CONDUCTIVITY W/(M·K)	DENSITY (KG/M³)	SPECIFIC HEAT J/(KG·°C)
INSULATION	Rigid foam insulation board	0.0500	0.04	23.00	1470.00
	Fiberglass batt insulation	0.1400	0.02	32.00	920.00
	Mineral wool	0.1400	0.03	200.00	710.00
	Cellulose fill	0.1400	0.04	43.00	1380.00
	Polystyrene foam	0.1400	0.04	23.00	1470.00
	Vapor barrier	0.0002	0.33	920.00	2092.00
	Polyisocyanurate roof insulation	0.0380	0.03	45.00	1470.00
	Plywood sheathing	0.0200	0.11	552.00	1420.00
STRUCTURE	Metal stud	0.0900	0.12	560.00	190.00
	Metal deck	0.0012	45.00	7850.00	480.00
	Concrete floor	0.1500	0.42	2300.00	657.00
FLOOR FINISH	Ceramic tiles	0.1200	1.20	2000.00	850.00
EXT FINISH	Cedar clapboard siding	0.0160	0.12	496.00	190.00
	Vinyl siding	0.0090	0.71	1200.00	836.00
	Stone veneer siding	0.1000	1.88	2760.00	836.00
	Aluminum wall panels	0.0025	230.00	2700.00	897.00
	Brick veneer	0.0250	0.54	1550.00	840.00
	Fiber cement	0.0080	0.58	1900.00	1000.00
	Stucco	0.0150	0.72	1856.00	840.00
INT FINISH	Gypsum board	0.0150	0.65	1100.00	840.00
ROOFING	BUR	0.0035	0.50	1700.00	1000.00
	EPDM rubber roofing membrane	0.0015	0.14	930.00	2092.00
	Aluminum metal roofing	0.0010	230.00	2700.00	897.00
	Copper metal roofing	0.0250	401.00	8940.00	450.00

In addition to the types of material considered discrete variables, WWR was considered a continuous variable. Because WWR affects the quantity of the materials, it will also change OE, EE, and EW. Therefore, this study excluded the calculation of EE and EW for the fixed materials and did not change with changing WWR. Tables 5 to 8 show the EE intensity of energy sources representing each building element, the EW intensity of materials, and the cost of each component based on the 2017 National Construction Estimator. After importing the EE and EW data into the optimization model, the values were converted from MBTU/$ to MJ/$ so that Energy Plus would calculate the OE based on MJ, making the energy data uniform.

Table 5. EE and EW intensity of exterior wall insulation

					2012 (MJ/$)		EW
	Unit	Cost ($/unit)	Oil and gas extraction	Coal mining	Electric power generation, transmission, and distribution	Natural gas distribution	100,000 Gal/$
PLYWOOD SHEATING	SF	0.57	15.20019	0.24826	9.02454	5.16241	
VAPOR BARRIER	SF	0.07	33.17735	0.66402	6.17637	31.43270	
RIGID FOAM INSULATION BOARD	SF	1.75	3.83921	0.45335	7.75515	12.62354	
FIBERGLASS BATT INSULATION	SF	0.88	2.36618	0.69618	12.55016	9.53028	
MINERAL WOOL	SF	1.11	2.36618	0.69618	12.55016	9.53028	
CELLULOSE FILL	SF	0.63	19.58715	2.80493	11.30354	8.62871	
POLYSTYRENE FOAM	SF	0.68	3.83921	0.45335	7.75515	12.62354	

Table 6. EE and EW intensity of exterior wall finish

			2012 (MJ/$)				EW
	Unit	Cost ($/unit)	Oil and gas extraction	Coal mining	Electric power generation, transmission, and distribution	Natural gas distribution	100,000 Gal/$
WOOD SIDING	SF	4.84	12.7367	0.12543	5.49418	1.69212	0.000974
VINYL SIDING	SF	0.88	7.42165	0.66402	6.17637	31.43270	0.001738
STONE VENEER	SF	31.00	2.50811	0.35971	6.32018	4.77670	0.000421
ALUMINUM WALL PANELS	SF	40.00	3.45537	0.29397	36.68641	5.29598	0.000255
BRICK VENEER	SF	5.51	2.04232	0.49491	5.39853	8.70067	0.000367
FIBER CEMENT	SF	1.24	11.76215	18.95796	19.13552	3.97818	0.000221
STUCCO	SF	1.03	4.01691	18.95796	19.13552	3.97818	0.000221

Table 7. EE and EW intensity of roofing

			2012 (MJ/$)				EW
	Unit	Cost ($/unit)	Oil and gas extraction	Coal mining	Electric power generation, transmission, and distribution	Natural gas distribution	100,000 Gal/$
BUR	SF	0.56	24.49608	0.27779	2.62882	6.69364	0.000212
EPDM RUBBER ROOFING MEMBRANE	SF	0.75	5.52937	0.83717	7.69120	16.26661	0.001749
METAL ROOFING	SF	1.81	3.45537	0.29397	36.68641	5.29598	0.000255
COPPER METAL ROOFING	SF	13.90	2.53881	0.52627	8.75045	3.19648	0.000240

Table 8. EE and EW intensity of glass

	Unit	Cost ($/unit)	2012 (MJ/$) Oil and gas extraction	Coal mining	Electric power generation, transmission, and distribution	Natural gas distribution	EW 100,000 Gal/$
SINGLE CLEAR 1/4"	SF	9.45	2.32161	0.26241	9.48683	10.82746	0.000403
DOUBLE CLEAR 1/4"	SF	18.90	2.32161	0.26241	9.48683	10.82746	0.000403
TRIPLE CLEAR 1/4"	SF	28.35	2.32161	0.26241	9.48683	10.82746	0.000403
SINGLE CLEAR 3/16"	SF	8.89	2.32161	0.26241	9.48683	10.82746	0.000403
DOUBLE CLEAR 3/16"	SF	17.78	2.32161	0.26241	9.48683	10.82746	0.000403
TRIPLE CLEAR 3/16"	SF	26.67	2.32161	0.26241	9.48683	10.82746	0.000403

Energy Simulation Model

Grasshopper, which is a visual-programming tool in Rhinoceros, coupled with Honeybee and Ladybug plug-ins, was used (1) to create building blocks and thermal zones, (2) to import data from the IO interface, (3) to set up building elements from the BIM software, and (4) to assign building elements to thermal zones and set up variables and constraints (e.g., cooling and heating setpoint, occupancy schedule, setup location from standard weather data). Energy Plus, an energy simulation engine embedded in the Honeybee plug-in, simulated the energy performance of the building to calculate annual energy use.

Multi-Objective Optimization

Wallacei, a Grasshopper plug-in, was used to find the trade-offs among OE, EE, and EW. The optimization model consists of (1) importing EE and EW data from the IO data interface, (2) setting up optimization variables and constraints, (3) defining objective functions, (4) setting up optimization parameters (e.g., iteration, mutation, crossover, population), (5) running the optimization model and finding the optimum solutions, and (6) exporting the final solutions to the IO data interface.

CHAPTER IV

RESULTS AND DISCUSSION

The simulations and multi-objective optimization were performed on a computer with an Intel Core i7-9750H processor, 32-GB RAM, and Microsoft 11 operating system. The multi-objective optimizations took 60 hours on average, with approximately 12 minutes to run each solution. The single-objective optimization took 14 hours. GA parameters used in this study were population size = 10, maximum generations = 30, crossover probability = 0.9, and mutation probability = 0.125.

One of the limitations of the study was the optimization process being time-consuming. The model was a large five-story building, making each solution run several minutes. Furthermore, we decided to simulate a total of 300 populations, which generally is a slightly low total. In most models, the minimum population size is suggested to be at least 3,000, with more populations within the generation.

In this study, we conducted different multi-objective and single-objective optimizations to investigate the trade-offs between energy and water and to examine the importance of multi-objective optimization in sustainable design. The results show that trade-offs exist among OE, EE, and EW. Furthermore, after conducting triple-objective optimization among the three objectives, double-objective optimization between OE and EE, and single-objective optimization for EW, triple-objective optimization showed different results from the other solutions, suggesting the need for multi-objective optimization to determine the trade-offs between energy and water.

Triple-Objective Optimization

Fig. 8 shows the fitness values for 10 Pareto front solutions of the triple-objective optimization among OE, EE, and EW. In most cases, decreasing OE increased EE. Solutions with the lowest OE had the highest EE and, consequently, the highest total energy use, indicating a potentially conflicting trade-off. In the case of EW, results do not show such a linear relationship between energy and water. Some solutions with low EW had low EE but higher OE. In addition, there were solutions with low EW and OE but high EE. However, one solution showed relatively low OE and EE, along with EW. Solution 4 had the lowest total energy use: 2,788,000-MJ EE, 10,537,000-MJ OE, and 254,260-MGal EW. Most solutions had an EW value between 200,000 and 25,000 MGal. EE values were between 2,788,000 and 8,042,500 MJ, and OE values were between 9,885,400 and 11,857,000 MJ. Solution 4 had the best fitness values in all three objectives, with a low EE, OE, and EW. The genes creating this solution were stucco, fiberglass batt insulation, BUR, and 3/16" single clear window. The WWRs associated with solution 4 were 0.39 eastside, 0.22 northside, 0.21 southside, and 0.33 westside.

The worst solution, having high EE and EW values, was solution 5. Comparing the materials constructing the best and worst solutions (solutions 4 and 5, respectively) shows the difference to be the roofing and glazing system, suggesting the need to reduce the EE and EW of the exterior wall finish and the inner layers of steel studs and insulation.

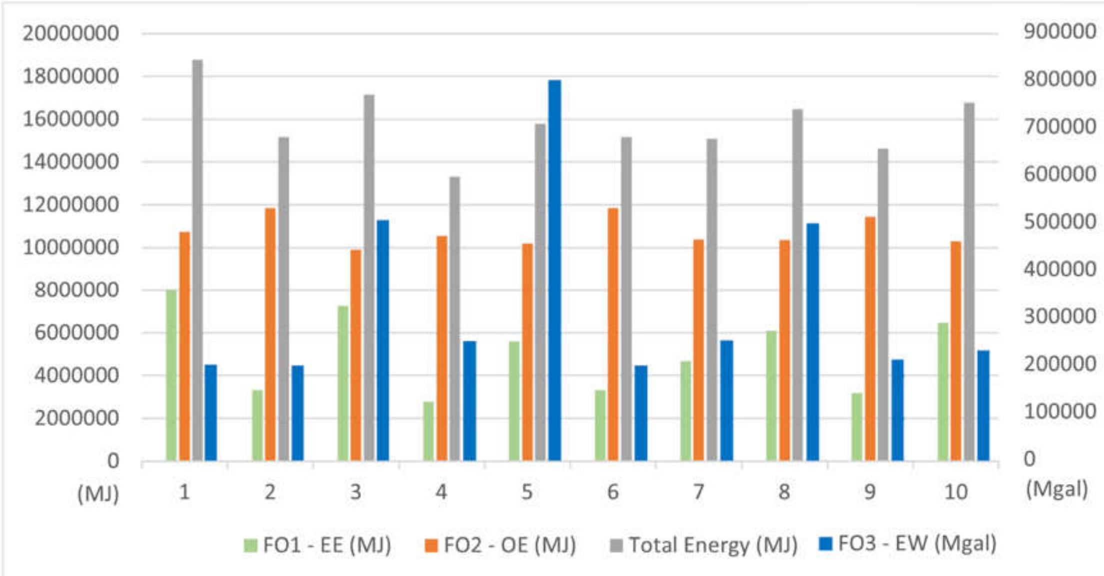


Figure 8. EE, OE, and EW values from the Pareto front solutions

Tables 9 and 10 show the genes associated with each solution. The most frequent design variables from the results suggest stucco as the exterior finish, fiberglass batt insulation as the wall insulation, BUR as the roofing system, and different window systems (mostly single or double clear windows). Moreover, continuous variables for the fittest solutions are approximately 0.45 eastside WWR, 0.25 southside WWR, and 0.35 westside WWR. Northside WWR in six solutions was around 0.23 and in four other solutions was approximately 0.75.

Table 9. Discrete variables considered genes associated with each solution

VARIABLES (DISCRETE)				
	EXT Finish (1)	EXT Insulation (2)	Roofing (3)	Window (4)
1	Stucco	Fiberglass Batt Insulation	BUR	Triple_Clear_1/4"
2	Stucco	Fiberglass Batt Insulation	BUR	Single_Clear_3/16"
3	Stucco	Fiberglass Batt Insulation	Copper Metal Roofing	Triple_Clear_1/4"
4	Stucco	Fiberglass Batt Insulation	BUR	Single_Clear_3/16"
5	Stucco	Fiberglass Batt Insulation	PVC Roofing	Double_Clear_1/4"
6	Stucco	Fiberglass Batt Insulation	BUR	Single_Clear_3/16"
7	Fiber Cement	Cellulose Fill	BUR	Double_Clear_1/4"
8	Stucco	Fiberglass Batt Insulation	Copper Metal Roofing	Double_Clear_1/4"
9	Stucco	Fiberglass Batt Insulation	BUR	Single_Clear_3/16"
10	Stucco	Fiberglass Batt Insulation	BUR	Triple_Clear_1/4"

Table 10. Continuous values considered genes associated with each solution

VARIABLES (CONTINUOUS)				
	WWR East (5)	WWR North (6)	WWR South (7)	WWR West (8)
1	0.53	0.76	0.39	0.36
2	0.49	0.75	0.39	0.44
3	0.43	0.26	0.25	0.29
4	0.39	0.22	0.21	0.33
5	0.39	0.23	0.22	0.36
6	0.49	0.75	0.39	0.44
7	0.51	0.23	0.21	0.36
8	0.53	0.3	0.25	0.29
9	0.45	0.78	0.22	0.41
10	0.53	0.24	0.39	0.33

Figs. 9 and 10 present scatterplots for the Pareto front solutions to show correlations among EE, OE, total energy use, and EW. The results suggest a strong relationship between EE and OE, in which an increase in EE will reduce the OE of buildings (Fig. 9). On the other hand, such a strong correlation does not exist between total energy consumption and EW (Fig. 10). Having a low population size and low number of Pareto front solutions could cause such results. Increasing the population size of the optimization and, consequently, having more Pareto solutions may show different and more accurate results.

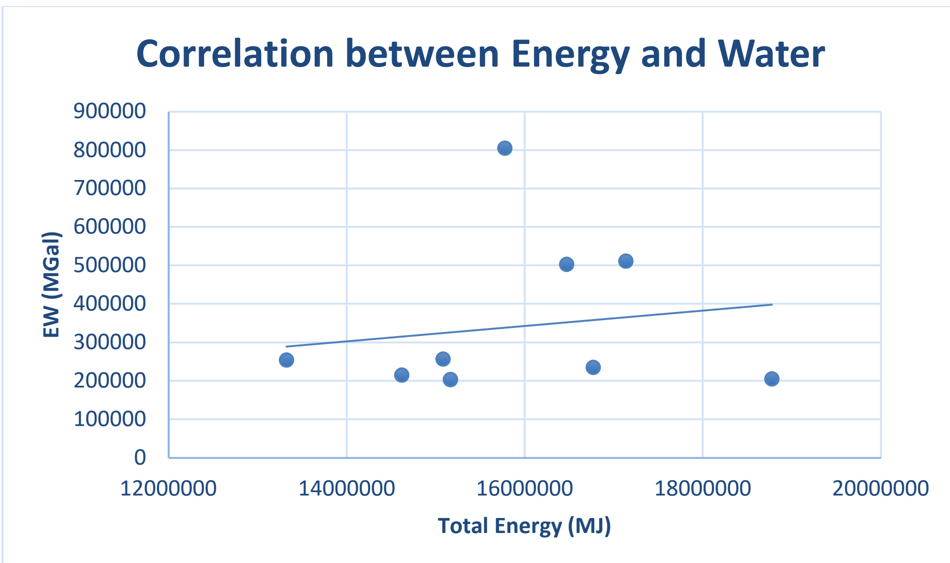


Figure 9. Scatterplot between EE and OE values

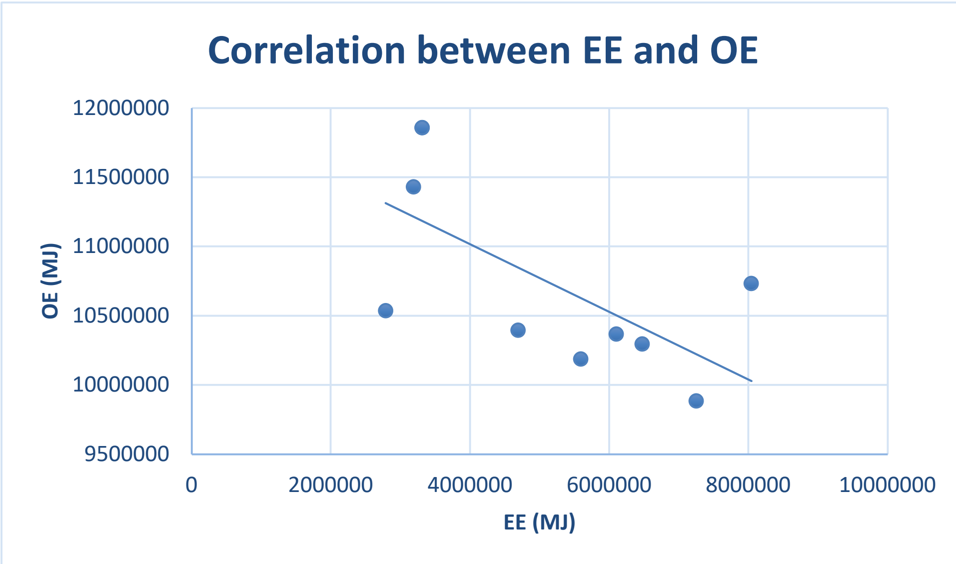


Figure 10. Scatterplot between total energy and EW values

Double-Objective Optimization

We implemented double-objective optimization between OE and EE to compare the results with the triple-objective optimization and to justify the existing trade-offs between water and energy and the importance of including water consumption in the design and construction process. We used the same model as in the triple-objective optimization to identify any changes in the results and their related genes when considering water and when excluding water from our objective functions. Fig. 11 shows the Pareto front solutions of the optimization between OE and EE. Fig. 12 illustrates the EW values associated with each solution in Fig. 11. Comparing the results of the double-objective optimization and EW values corresponding to each solution with the results from triple-objective optimization shows a significant difference between the EW values considering water as one of the objective functions. The best solution for triple-objective optimization was solution 4. However, in double-objective optimization, solutions 2 and 7 had the best fitness values. Most solutions from triple-objective optimization had significantly lower EW consumption than the double-objective optimization results. The average EW of the double-objective optimization solutions was 59,364.3 MGal, with the lowest and highest values being 3,361,387 and 1,057,000 MGal, respectively. Triple-objective optimization solutions, on the other hand, had an average EW of 338,948 MGal. This suggests that excluding water from the optimization could potentially lead to a higher EW.

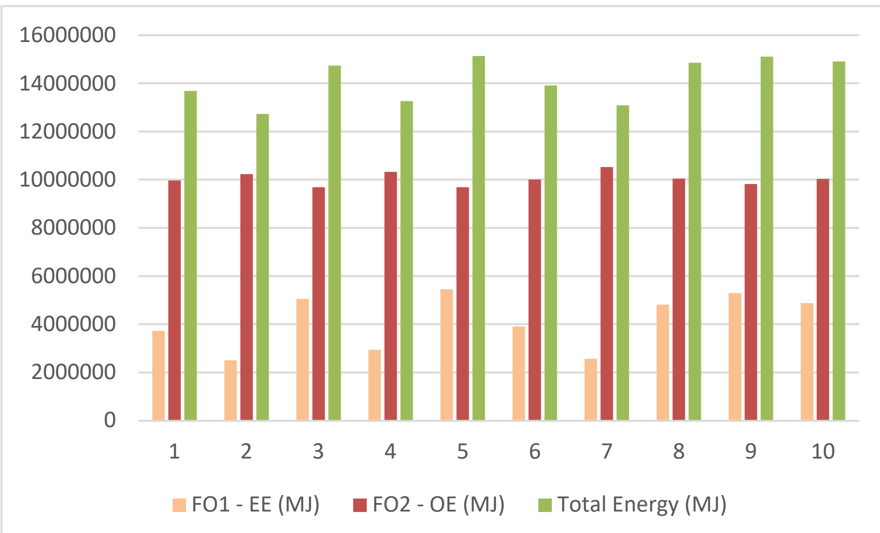
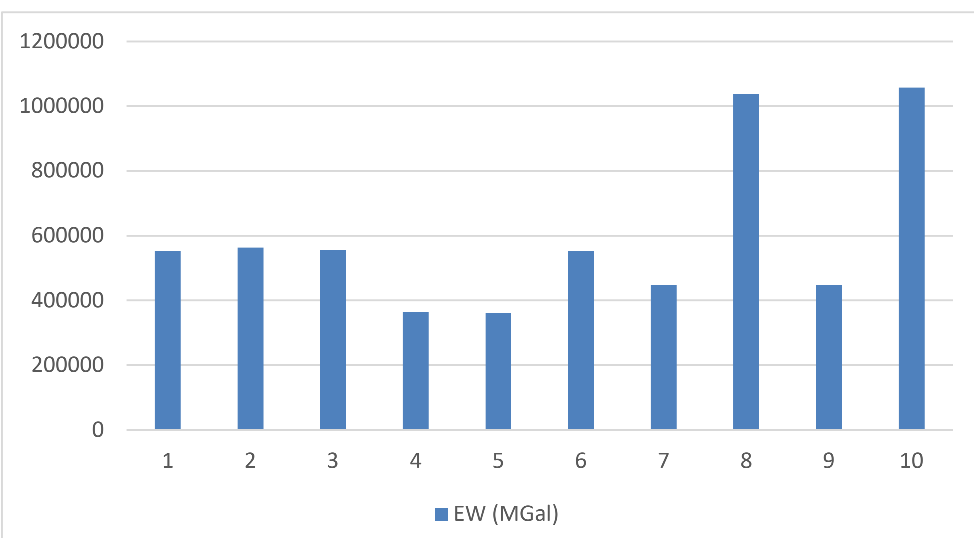


Figure 11. Fitness values for each solution from double-objective optimization

Figure 12. EW values associated with each solution from double-objective optimization



Tables 11 and 12 show genes associated with each solution of double-objective optimization. The fittest solutions mostly have vinyl siding as the exterior finish, fiberglass batt insulation, EPDM roofing membrane, and a single or double clear glazing system. Among the genes, the exterior finish and roofing system had different results in double-objective optimization compared with triple-objective optimization.

Exterior finishes associated with the Pareto front solutions of double-objective optimization are mostly vinyl siding. However, the fittest solutions of triple-objective optimization have stucco as their exterior finish. In the case of the roofing system, double-objective optimization results suggest EPDM roofing membrane, whereas triple-objective optimization results mostly suggest BUR as the best roofing system. The worst solution was number 9; comparing it with the materials of the best solution, there is a difference in their exterior finishes and glazing systems, meaning that the inner layers of the wall and insulation must be reduced to minimize OE and EE. WWRs were almost the same in all the solutions, suggesting that reducing WWR will reduce the energy consumption of the building.

In terms of WWR, by comparing double- and triple-objective optimization results, eastside and southside WWRs had almost the same values, 0.45 and 0.23, respectively. However, northside and westside WWR values were near 0.2, which is the lowest bound of the variable constraint. In the triple-objective optimization including EW, some solutions tended to have a higher WWR, especially on the north side, suggesting that the model not only focuses on reducing the WWR, but also tries to increase the ratio of window, which can be seen in Table 10. In optimizing energy and water together, solutions with higher WWRs had lower EWs, which could suggest that a conflicting variable between energy and water is WWR.

Table 11. Discrete variables considered genes associated with each solution

VARIABLES (DISCRETE)

	EXT Finish (1)	EXT Insulation (2)	Roofing (3)	Window (4)
1	Vinyl Siding	Fiberglass Batt Insulation	EPDM Roofing Membrane	Double_Clear_3/16"
2	Vinyl Siding	Fiberglass Batt Insulation	EPDM Roofing Membrane	Single_Clear_3/16"
3	Vinyl Siding	Fiberglass Batt Insulation	EPDM Roofing Membrane	Triple_Clear_1/4"
4	Fiber Cement	Fiberglass Batt Insulation	EPDM Roofing Membrane	Single_Clear_3/16"
5	Fiber Cement	Fiberglass Batt Insulation	EPDM Roofing Membrane	Triple_Clear_1/4"
6	Vinyl Siding	Fiberglass Batt Insulation	EPDM Roofing Membrane	Double_Clear_1/4"
7	Vinyl Siding	Fiberglass Batt Insulation	BUR	Single_Clear_3/16"
8	Wood Siding	Fiberglass Batt Insulation	EPDM Roofing Membrane	Double_Clear_1/4"
9	Vinyl Siding	Fiberglass Batt Insulation	BUR	Triple_Clear_1/4"
10	Wood Siding	Mineral Wool	EPDM Roofing Membrane	Double_Clear_1/4"

Table 12. Continuous variables considered as genes associated to each solution

VARIABLES (CONTINUOUS)

	WWR East (5)	WWR North (6)	WWR South (7)	WWR West (8)
1	0.46	0.21	0.22	0.2
2	0.39	0.21	0.21	0.2
3	0.46	0.21	0.2	0.2
4	0.45	0.2	0.21	0.2
5	0.44	0.21	0.22	0.2
6	0.46	0.21	0.23	0.21
7	0.46	0.23	0.23	0.24
8	0.49	0.22	0.23	0.2
9	0.46	0.23	0.23	0.24
10	0.49	0.21	0.23	0.2

Single-Objective Optimization

Fig. 13 shows the Pareto front solutions of single-objective optimization. Single-objective optimization showed lower EW values compared with triple-objective optimization, suggesting a conflicting relationship between energy and water. This means that only considering EW may produce better EW results, but not necessarily the same result as multi-objective optimization. Solutions 7, 8, and 9 had the lowest EWs. Especially when deciding construction elements for a building envelope, it is crucial to consider both the energy and water factors of materials and find the trade-offs between them to reach the most optimum design measures. Table 13 shows the construction elements and EW values related to each solution.

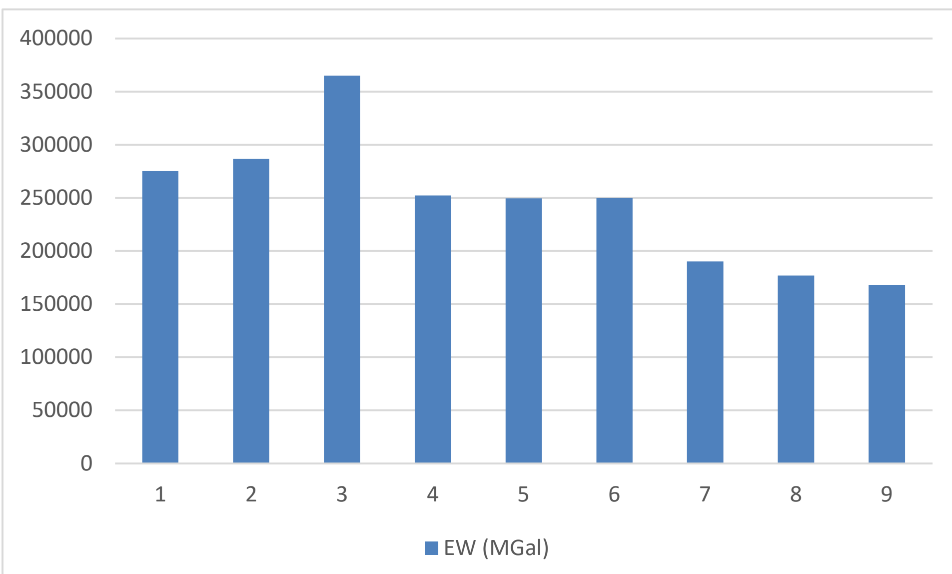


Figure 13. Pareto front solutions of single-objective optimization

Table 13. Discrete variables considered genes associated with each solution

	VARIABLES (DISCRETE)				
	EXT Finish (1)	EXT Insulation (2)	Roofing (3)	Window (4)	EW (MGal)
1	Vinyl Siding	Fiberglass Batt Insulation	BUR	Triple_Clear_1/4"	275,339.3441
2	Vinyl Siding	Cellulose Fill	Aluminum Metal Roofing	Double_Clear_3/16"	286,693.1969
3	Vinyl Siding	Rigid Foam Insulation Board	Aluminum Metal Roofing	Double_Clear_3/16"	365,062.6717
4	Fiber Cement	Rigid Foam Insulation Board	Aluminum Metal Roofing	Triple_Clear_3/16"	252,239.8044
5	Vinyl Siding	Cellulose Fill	BUR	Double_Clear_1/4"	249,596.9926
6	Vinyl Siding	Fiberglass Batt Insulation	EPDM Roofing Membrane	Triple_Clear_3/16"	249,862.0366
7	Vinyl Siding	Fiberglass Batt Insulation	EPDM Roofing Membrane	Single_Clear_1/4"	190,235.4374
8	Vinyl Siding	Fiberglass Batt Insulation	EPDM Roofing Membrane	Triple_Clear_1/4"	176,781.8068
9	Vinyl Siding	Fiberglass Batt Insulation	EPDM Roofing Membrane	Double_Clear_1/4"	168,255.6177

The Pareto solutions of single-objective optimization had an average EW value of 24,600.7 MGal, the lowest compared to triple- and double-objective optimization. However, EE and OE values corresponding to these low EW values were relatively high compared to the double- and triple-objective optimizations. The OE and EE of the best solution from single-objective optimization (solution 9) were 8,494,700 and 13,327,000 MJ, respectively. The fittest solution was number 9, which included vinyl siding, fiberglass batt insulation, EPDM roofing membrane, and double clear glazing as its related variables. The worst solution was number 3, having the highest EW value among the nine Pareto solutions. Materials constructing the best and worst solutions were all different, with the exception of exterior finish, meaning that the EW of the outer layers of walls must be reduced.

Table 14 shows the WWR values for each solution. WWR on each side of the building tended to have a high value, suggesting that window area plays a significant role in the final EW value. On the other hand, the fittest solutions had a minimum window ratio over the wall area for energy optimization, revealing the conflict between water and energy. This emphasizes the applicability of implementing multi-objective optimization to find the trade-offs between energy and water. Most WWRs were close to the highest bound of the constraint.

Table 14. Continuous variables considered genes associated with each solution

	VARIABLES (CONTINUOUS)				
	WWR East (5)	WWR North (6)	WWR South (7)	WWR West (9)	EW (MGal)
1	0.95	0.93	0.94	0.95	275,339.3441
2	0.51	0.78	0.7	0.71	286,693.1969
3	0.7	0.52	0.47	0.9	365,062.6717
4	0.95	0.86	0.8	0.75	252,239.8044
5	0.44	0.94	0.71	0.69	249,596.9926
6	0.95	0.86	0.85	0.8	249,862.0366
7	0.95	0.86	0.84	0.8	190,235.4374
8	0.94	0.93	0.94	0.9	176,781.8068
9	0.95	0.85	0.94	0.85	168,255.6177

CHAPTER V

CONCLUSIONS

Optimization methods are useful in investigating and addressing the trade-offs among different building functions. However, limited research has focused on including EE in energy optimization problems. Recent studies addressing the nexus between OE and EE have found that most design measures that minimize OE have a higher impact on EE, making the total energy consumption insufficient (Chastas et al., 2016, Shadram and Mukkavaara, 2018). On the other hand, water scarcity has become a severe problem in most countries. Previous literature has addressed freshwater consumption and has tried to propose a method to reduce water consumption. However, like EE, EW has been overlooked in previous research, especially in optimization problems. No study exists that includes EW to find the trade-offs between water and energy. Many factors in building design contribute to total energy and water consumption, which means it is possible that there is a conflict among OE, EE, and EW.

This study aimed to investigate this conflict and propose a BIM-based method to optimize OE, EE, and EW in new-construction education buildings. A model was created and applied for a case-study building to find optimal solutions. In this model, energy simulation and multi-objective optimization were designed in a single software to make the building's design process easier and more manageable. To analyze and present the results, we conducted (1) triple-objective optimization among EE, EW, and OE, (2) double-objective optimization excluding EW, and (3) single-objective optimization with EW. The purpose of running different optimizations was to compare the results to help us understand the trade-offs between energy and water and determine the elements that affect objective functions. Design variables used in this study were building envelope material elements and WWRs for each side of the building. Results show different optimization approaches to produce different design measures as their final solutions, meaning that different materials contribute to total energy and water consumption differently. Furthermore, there is, in fact, a trade-off between energy and water that should be addressed.

Moreover, WWRs of energy and water affect total usage contrarily. For example, in single-objective optimization with EW, solutions with higher WWRs had lower water consumption. However, the best solutions had a low WWR in optimizing OE and EE, meaning that there is a conflict among OE, EE, and EW that should be calculated and included in sustainable design.

Ten Pareto front solutions were selected from the triple-objective optimization. Among the 10, only 1 solution had relatively low OE, EE, and EW. Comparing the 10 solutions, a linear relationship was found between OE and EE, in which reduced OE leads to increased EE. However, the relationship between energy and water consumption was found to be nonlinear.

Because of the complexity of the model and the optimization simulation being time-consuming, we only ran the optimization for a total of 300 populations. In general, more iterations and generations (3,000 populations) are preferred for optimization. Having a larger population size like 3,000 could lead to a different set of results and could help us better understand the relationship between energy and water and the measures contributing to total EE and EW consumption. This study mainly focused on creating a framework for EE and EW optimization so that it can be used in the future for different buildings with different design measures. Because the model was complex and made the simulation time-consuming, we had to reduce the total population size to stay within the time constraints of the study and to be able to test the feasibility of the model. The main purpose of the study was to create a BIM-based method to enable information sharing among design software.

Results from the optimizations are specific to one case study (LAAH building on the Texas A&M University campus) and may only represent higher-education buildings; they may not be generalized to all commercial or residential buildings. In addition, the results are just for one climate zone in the US; using the model for buildings located in other climate zones may produce different results.

The purpose of this study was to make a framework to calculate and optimize OE, EE, and EW in a single software to make the process easier and more manageable for other buildings in any location. The current design software is limited in terms of information sharing among each other. Even though there are software like Athena that calculate EE, they still have the problem of automation in sharing data with other design software like Rhino and Grasshopper. This limitation is also the case between Revit and Rhino, as presented in this study. In addition, limited tools exist to calculate EE and EW together.

Future Study

This study aimed to address the trade-offs between energy and water. However, future study is needed to improve the model proposed in this study. Many elements affect total energy and water consumption, not all of which were addressed in this research. We studied only one building in a hot, humid climate zone in the southern US. Other climate zones could find significantly different results. Moreover, we only addressed IEE and IEW and excluded other stages as out of the scope of the thesis. We implemented an existing IOH method for EE and EW to calculate the objective functions. Although it is a complete method, the calculation may not be accurate because it uses price data.

In addition, the simulation and optimization processes were time-consuming. The optimization was conducted on a single laptop, which limited time and, therefore, the number of iterations allowed. Thus, the optimization may have been constrained to the local optima. Using better resources and operating systems with faster optimization could help the simulation run at least 3,000 solutions, leading to more accurate results.

Investigating EW is just a start in identifying trade-off problems in a building's energy consumption. Our model performs well in the specific case-study building with specific design variables and could be implemented for different buildings. The current model is considered semiautomated. The energy and water calculations are usable in other buildings, yet the energy zoning was done manually for our specific building. Future development could be done to fully automate the creation of building geometry, creation of energy zones, and selection of Pareto front solutions so that the model can be utilized for different buildings with different shapes and sizes. In addition, other objectives could be considered with water consumption, such as cost, carbon footprint, and GHG emissions.

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