YAŞAR UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

MASTER THESIS

A NOVEL FRAMEWORK TO EVALUATE THE PERFORMANCE OF RESPONSIVE KINETIC SHADING DEVICES IN THE EARLY DESIGN STAGES

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ABSTRACT

A NOVEL FRAMEWORK TO EVALUATE THE PERFORMANCE OF RESPONSIVE KINETIC SHADING DEVICES IN THE EARLY DESIGN STAGES

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Computational tools offer a great potential in the conceptual phase of architectural design, towards exploring numerous design alternatives that provide better environmental impact. Particularly in the domain of solar control with help of kinetic shading devices that respond to its environment, the function of computational tools is even more significant, since the determination of the control parameters introduces a dynamic problem. However, critical review of relevant literature suggests that the utilization of computational tools have failed to address some vital aspects. This has led exclusion of many design alternatives and weather conditions due to the high computational expenses. To this end, the current study aims to investigate the problem of adequately exploring the design space and evaluating the performance of responsive-kinetic shading devices (RKSD). For this purpose, we proposed a novel framework by implementing a surrogate-based technique for multi-objective optimization of control parameters of a conceptual RKSD on randomly sampled daylight hours. To test the adequacy of the proposed framework, an experimental research was designed. In this design, such methods as parameter initiation, variable randomization, simulation, database generation, neural networks, optimization, and hypothesis test were used in combination. Results revealed that using proposed framework one can adequately reach to optimum set of solutions in a fraction of a time when compared to traditional simulation-based optimization methods. More, utilizing proposed framework one can formally compare the performances between static shading and RKSD. In the case of our experimental design, RKSD outperforms the static one in daylighting and view metrics. However, considering indoor temperature no significant differences observed. To the best of our knowledge, the current work is the first to propose a framework, which allows an end user to conduct a formal comparison of selected performance metrics between responsive-kinetic and optimized-static shadings. The further works shall focus on the relationships between the weather conditions, design parameters, and the performance objectives. Due complex interactions among employed techniques, a user-friendly graphical user interface establishment shall also be in the agenda.

Key Words: responsive, kinetic, shading, simulation, artificial neural networks, multi-objective optimization

ÖZ

TEPKİSEL KİNETİK GÖLGELEME ARAÇLARININ ERKEN TASARIM AŞAMALARINDA PERFORMANS DEĞERLENDİRMESİ İÇİN ÖZGÜN BİR YAKLAŞIM

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Mayıs 2017

Hesaplama araçları, mimari tasarımın erken aşamasında daha iyi çevresel etki sağlayan çok sayıda tasarım alternatifini keşfetmek için büyük bir potansiyel sunmaktadır. Özellikle, tepkisel kinetik gölgeleme araçları aracılığıyla günışığı kontrolünde hesaplama araçlarının işlevi daha da önemlidir; çünkü, kontrol parametrelerinin belirlenmesi dinamik bir problem teşkil eder. Bununla birlikte, konu ilgili literatür eleştirel bir gözle incelendiğinde, tasarım hesaplama araçlarının kullanımında bazı hayati yönlerin ele alındığını görülmüştür. Uzun hesaplama süreleri, birçok tasarım alternatifi ve hava koşullarının gözardı edilmesine neden olmuştur. Bu nedenle, bu çalışmada, tasarım alanını yeterince araştırmayı ve tepkisel kinetik gölgeleme aygıtlarının (TKGA) performansının değerlendirilmesi sorunu araştırıldı. Bu doğrultuda, rasgele seçilen gündüz saatlerinde, kavramsal bir TKGA' nin kontrol parametrelerini, denk-model tekniğine dayalı çok amaçlı optimizasyon uygulayarak bulan yeni bir yaklaşım önerdik. Önerilen yaklaşımın yeterliliğini test etmek için deneysel bir araştırma yapılmıştır. Bu tasarımda, öncül parametrelerin saptanması, rastsal değişken üretimi, simülasyon, veritabanı oluşturma, yapay sinir ağları, optimizasyon ve hipotez testi gibi yöntemler ardısıra kullanılmıştır. Sonuçlar, önerilen yaklaşımı kullanmanın, geleneksel simülasyon tabanlı optimizasyon yöntemlerine kıyasla, çok daha kısa bir zaman zarfında optimum çözüm setine ulaşabildiğini ortaya koymuştur. Dahası, önerilen yaklaşım kullanılarak statik gölgeleme ve TKGA performansları hipotez testi ile kıyaslanmıştır. Oluşturulan deneyde, TKGA, günışığı aydınlatması ve manzaraya bakış metriklerinde optimize edilmiş statik olandan daha iyi performans göstermiştir. Bununla birlikte, iç sıcaklık dikkate alındığında önemli

bir fark gözlenmemiştir. Bildiğimiz kadarıyla bu çalışma, son kullanıcıya, tepki veren kinetik ve optimize edilmiş statik gölgeleme arasında seçilmiş performans metriklerini resmi bir karşılaştırma yapmasını sağlayan bir çerçeve önermekte olan ilk çalışmadır. Gelecekteki çalışmalar, hava koşulları, tasarım parametreleri ve performans hedefleri arasındaki ilişkilere odaklanacaktır. Kullanılan teknikler arasındaki karmaşık etkileşimler nedeniyle, kullanıcı dostu bir grafik arayüz geliştirilmesi de gündeme gelecektir.

Anahtar Kelimeler: tepkisel tasarım, kinetik-statik gölgeleme sistemleri, simülasyon, yapay sinir ağları, çok amaçlı optimizasyon

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I also would like to express my deepest gratitude to my family for their unconditional love and support in every aspect of my life.

Mustafa Teksoy
İzmir, 2017

TEXT OF OATH

I declare and honestly confirm that my study, titled "A NOVEL FRAMEWORK TO EVALUATE THE PERFORMANCE OF RESPONSIVE KINETIC SHADING DEVICES IN THE EARLY DESIGN STAGES" and presented as a Master's Thesis, has been written without applying to any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.

Mustafa Teksoy

Signature

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June 23, 2017

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SYMBOLS AND ABBREVIATIONS

ABBREVIATIONS:

UV	Ultraviolet
PV	Photovoltaic
ANN	Artificial Neural Network
CA	Cellular Automata
W	Watt
m	Meter
K	Kelvin
s	Second
ppl	People
EPW	EnergyPlus Weather Data
X_n	Shading Control Parameters
Y_n	Performance Objectives (Response Variables)
CSV	Coma-Separated Values
lx	Lux
°C	Celsius degree
T	Temperature Objective
L	Illuminance Objectives
V	View to Outside Objective
CV	Cross Validation
RMSE	Root Mean Square Error
RProp	Resilient Back-Propagation
MLP	Multi-Layer Perceptron
exp	Exponential

R	Responsive
S	Static
NN	Neural Networks
T_{in}	Temperature Inside
ID	Identification Number
N	Number of Observation
St.Dev.	Standart Deviation
SE	Standart Error
approx.	Approximately

SYMBOLS:

Δ	Difference
%	Percentage
$\sum$	Mass Summation

CHAPTER ONE
INTRODUCTION

1.1. BACKGROUND

Solar control has been historically an important strategy in building design, since it is highly relevant with the concepts of energy and comfort. A proper control strategy by means of shading devices has considerable influence on room temperature and natural lighting, accordingly, contributes to energy savings while providing comfort for the occupants (Hausladen, de Saldanha, & Liedl, 2008).

Regulating the sunlight on the exterior of a facade, before solar beams enter the room and radiate its energy inside, is a much efficient strategy for sun control. (Fathy, 1986; Hausladen et al., 2008; Olgyay & Olgyay, 1977). Conventionally, static shading devices are integrated to facades in order to perform this task. However, static devices fail in responding to fluctuating environmental and comfort demands. Lechner (2015) put forward a critical question:

> "Is it logical that a static system can respond to a dynamic problem?"

In the midst of 19th century, influenced by the developments in the field of computer science, particularly cybernetics, architects began utilizing computation in an experimental fashion (Frazer, 1995; Usman, 2007). Thus emerged the idea of a pro-active built environment that responds, and further, interacts with its dynamic context.

In the beginning of 21st century, such hardware as microcontrollers, sensors, and motors, has become significantly cheaper and easy to access, along with more powerful computers and display technologies. These developments paved the way to realize once utopian ideas of responsive architectural systems.

Dynamic shading systems have received increasing interest in the recent years, as they have potential for responding to environmental stimuli for energy efficiency. It is well acknowledged that kinetic shading devices that can change its configuration due to the indoor thermal and comfort goals have the potential for contributing to lower energy consumption and higher thermal/visual comfort. In response, design and construction of responsive kinetic shading devices require advanced computational tools and techniques.

Responsive kinetic shading devices has begun to be implemented in large scale building projects, as integral components of the facades, with both functional and aesthetic concerns. One of the recent examples is the Al-Bahr Towers, which was built in Abu Dhabi in 2012. A team of multi-disciplinary design professionals developed a custom computer program for design and analysis of the responsive exterior shading system (see Figure 1). They simulated performance of responsive kinetic shading system prior to its construction in order to reduce energy consumption and increase comfort of the building.

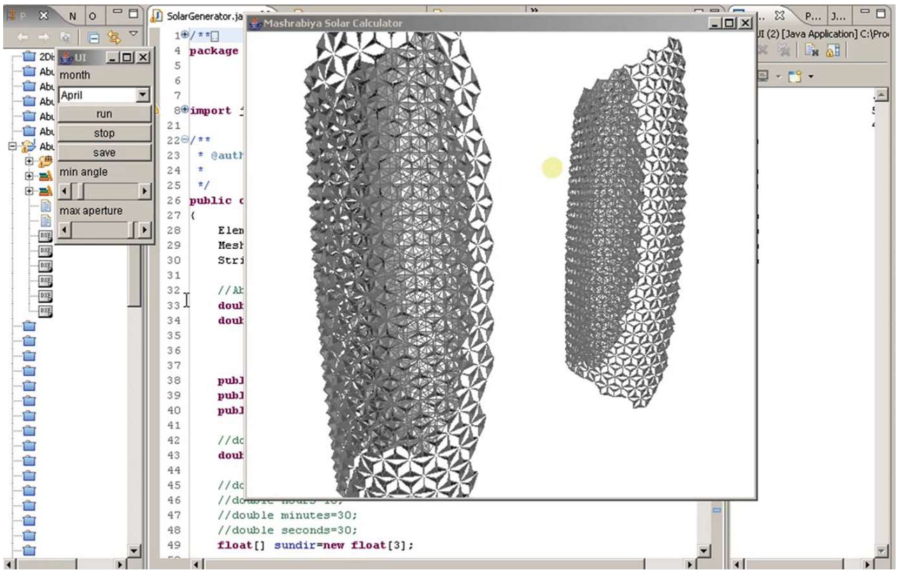

Figure 1. Custom program developed for the simulation of responsive kinetic shading system and performance for Al-Bahr Towers. (Karanouh & Kerber, 2015)

1.2. STATEMENT OF THE PROBLEM

Architectural design problems are inherently complex. When designing a kinetic system, which accounts for change in time, the complexity of the design problem increases substantially. On the other hand, with the developments in the computer technology along with new computational approaches, researchers gained the ability to deal with such complexity. Despite availability of tools and techniques, there is a lack of acknowledged approach for decision-support in the conceptual design of responsive kinetic systems. Therefore, designers and researchers are developing custom approaches for handling the complexity of the design problems.

Performance integrated parametric design and performance optimization for the early design stages help making well-informed design decisions. However, information feedback in the design process comes at a price, which is computation time. Most of the simulation engines that generate such design information are computationally expensive. In the study of solar control with help of kinetic shading devices that respond to its environment, the problem of high computational times is even more significant. Because the determination of the values for the shading control parameters requires to be based on minor fractions of time. A critical review of the literature on responsive kinetic shading devices revealed that most of the studies over-simplified the design problems due to the high levels of complexity and computational costs (Du Montier et al., 2013; Grobman et al., 2016; Kensek and Hansanuwat, 2011; Lee et al., 2016; Nielsen et al., 2011). Such simplifications may lead to deficiency in the exploration of the design space. In two of the studies, researchers employed a meta-heuristic search method, namely genetic algorithm, towards exploration of design alternatives that have better daylight performance (El Sheikh & Gerber, 2011; Sharaidin, Burry, & Salim, 2012). To achieve this task, they required running higher number of simulations until converging to optimum design alternatives. In their approach, computational cost was still high, because meta-heuristic methods require longer time to come up with a satisfying solution. In response, Wortmann et al., (2015) argued that surrogate model based optimization outperforms simulation-based optimization in solving architectural design problems, both at computational cost and finding better solutions. In her research, Skavara (2009) implemented artificial neural networks for controlling the emergent behavior of an exterior shading system that is driven by cellular automata for daylight performance. However, her focus was more on the training techniques of the neural networks, than the comfort and energy related influence of the responsive-kinetic shading device that she proposed.

A responsive-kinetic shading device should optimize its movement for the smaller time intervals. That is, it is necessary to conduct point in time analysis for investigating its performance. However, simulation engine based techniques require longer times to predict satisfying results. Therefore, using artificial neural networks, which establish functions between input and output parameters, as surrogates for optimization seems suitable for the problem of exploring and evaluating the performance of responsive-kinetic shading devices.

There are several studies in the literature that made comparison between static and responsive-kinetic shading devices (Kensek & Hansanuwat, 2011; E. S. Lee, DiBartolomeo, & Selkowitz, 1998; Nielsen et al., 2011; Wagdy, Fathy, & Altomonte, 2016). In all of these studies, researchers concluded that kinetic shading devices outperform static ones. However, in none of them, the static shading systems that they examined was not optimized for better performance. Moreover, in none of the previous studies in the literature, view was not considered as a performance objective, along with thermal and daylight objectives in the same design problem.

With this motivation, we investigate the following questions throughout the research:

- To what extent, can the current work reduce computational cost that is required to optimize the performance of hourly responsive shading control parameters due to thermal, daylight and view to outside objectives?
- Is there a significant performance difference between, annually optimized static and hourly- optimized responsive-kinetic shading devices with respect to thermal, daylight and view to outside objectives?

1.3. RESEARCH AIMS

In line with the issues stated in Section 1.2, the current research aims to overcome the problem of vast computational expenses that the design process of responsive kinetic shading devices necessitates for performance optimization. Therefore, a novel framework is proposed for aiding the exploration of design alternatives and the decision-making in the early design stages of responsive kinetic shading devices.

One of the main aims of the current investigation is to develop a novel framework for aiding the conceptual design of responsive-kinetic shading devices, which can respond to changing environmental conditions for the purpose of energy efficiency and improved occupant comfort.

Another aim of the research is to explore if there is a significant difference between performances of annually optimized static and hourly responsive kinetic shading devices for the climate of Izmir, Turkey. Thermal, daylight and view to outside are the performance objectives, assessed for the two dependent observations. The research utilizes a method for performance comparison between optimum static and responsive-kinetic shading devices on an hourly basis.

1.4. METHODOLOGY OF RESEARCH

The research employs a quantitative approach for assessing performance of the conceptual shading devices. It proposes a novel computational framework for the investigation of responsive-kinetic shading devices. The framework is then implemented in a case study, in which a formal comparison is performed between optimized-static and responsive-kinetic shading types.

The research utilizes computational tools and techniques for quantifying the potential performance of the design alternatives. Such computational tools as Grasshopper (a visual algorithm editor plug-in for Rhinoceros, which is solid modeling software), Ladybug Analysis Tools (a plug-in for Grasshopper, which allows integrating analysis tools and simulation engines, namely EnergyPlus and Radiance), CIDEA (a computational decision-support environment for architectural design), Microsoft Excel and Minitab (a data analysis and statistics tool) are incorporated in the process. The computational tools are utilized for performing data generation, performance simulation, model development, surrogate-based optimization and test of hypothesis.

At first, the parameter initialization process is conducted for a hypothetical space, which formed the base case for further investigation. Then, parametric models are established for the static and responsive shading devices, which are mounted on the south-facing fully glazed façade of the base case. Both shading devices have the same shading control parameters, which are rotation angles of horizontal slats in six different zones of the shading systems. The variable randomization process updates the simulation model iteratively by generating random values for shading control and time of year parameters. The impact of the shading types on indoor temperature, daylight intensity and view to outside are selected as performance indicators, which are the response variables in the study. The values for shading control and response parameters of the design alternatives are stored in spreadsheets by coupling parametric models with thermal, daylighting and view simulation engines in an automated manner.

In order to reduce the number of simulations required for the performance optimization, the artificial neural networks are utilized for function approximation, which are subsequently used in the multi-objective optimization of the control parameters of the static and responsive shading devices. While the static shading control parameters are optimized for average annual performance, the responsive shading control parameters are optimized on an hourly basis, for the randomly sampled daylight hours.

It is hypothesized that responsive-kinetic shading devices will outperform annually optimized-static shading devices regarding the given performance criteria, for the climate of Izmir, Turkey. Paired-T tests are conducted for formal test of hypothesis.

1.5. SCOPE AND LIMITATIONS

The thesis examines conceptual design of shading devices from the perspective of solar control and comfort. It employs parametric modeling and simulation engines for quantifying the performance of the two exterior shading devices. The examined static and responsive shading devices have the same shading control parameters. Influence of the shading geometries on indoor space is studied. While static shading's control parameters are optimized on an annual basis, responsive shading is optimized for reacting hourly fluctuations.

The impact of the two examples on indoor space is observed on 50 randomly sampled daylight hours in a year. The study presents an approach for hourly comparison for the sampled hours. In order to drive an annual inference, all of the weather conditions in daylight hours should be examined.

For the study, structural aspects are neglected. Influence of wind on shading devices are out of the scope of the thesis.

The proposed framework is tested by using EnergyPlus weather data (EPW) of Izmir, Turkey. However, it can easily applied for diverse climates by using related EPW files.

1.6. OUTLINE OF THE THESIS

The thesis is composed of six chapters. After the introduction, Chapter 2 surveys the background and literature review for the study. First, development of computational design in architecture is reviewed, starting from the foundations of parametric design. Then, the implications of computational design in architecture are examined, particularly, with respect to the conceptual design of kinetic shading devices.

In Chapter 3, the methodology of the thesis is explained in detail. The chapter demonstrates the computational approach for decision-making of control parameters and performance assessment for the conceptual design of responsive-kinetic shading devices. The processes of parameter initialization, data generation, model development, surrogate-based optimization and test of hypothesis are revealed in this section. The results that are obtained through the processes are demonstrated in Chapter 4.

Chapter 5 discusses the proposed approach for the conceptual design of responsive-kinetic shading devices and the results of the computational experiment that is designed to compare two diverse type of shadings, which use same shading control parameters.

Finally, in Chapter 6, a summary of the research process and projections for future research are illustrated.

2CHAPTER TWO
BACKGROUND AND LITERATURE REVIEW

The chapter overviews the utilization of computational design approach in architecture, as well as, focuses on a specific design problem in architecture, namely the early design decision-making of responsive-kinetic shading devices.

First, a short definition section overviews static and responsive kinetic shading devices. Then, parametric design approach is traced back to its origins; and, its definition is clarified for grasping the essence of the concept. Then, implications of such computational approaches as performance-based design and design exploration, which rely on parametric design, in the early design stages are revealed. The use of artificial neural networks, a special information processing system, in building design problems is examined at the end of the first section.

The second section overviews the use of the computational design approaches in the conceptual design of responsive-kinetic shading for facades. It demonstrates the prior studies that utilized parametric design, performance-integration and solution exploration in the process of designing environment responsive kinetic shading devices.

The last part of the chapter presents a summary of the literature review and discusses the current state of computational design integrated to the conceptual design phase of kinetic shading devices.

2.1. DEFINITION OF STATIC AND RESPONSIVE SHADING DEVICES

Static shading devices are conventional means of passive solar design, which provides certain amount of solar control for buildings but cannot react to environmental changes. Their type, size, geometry and positioning, varying with respect to the local climate that it is present, are constant throughout the year. It is one of the oldest components in building design (Fathy, 1986; Olgyay & Olgyay, 1977).

With the scientific and technological developments in the 20th Century, advanced building components were begun to be integrated to the built environment. Concepts such as “intelligent” or “responsive” architecture were no more architectural visions of 1960s, but realized building components that define integration of advanced computation and mechatronics for responding to real-time environmental data from both the interior and the exterior. Responsive architecture marks the change in the built environment towards being pro-active in relation to data. Responsive architecture or building components are not inert as opposed to static ones. (Kroner, 1997; Wigginton & Harris, 2002) Within this scope, responsive kinetic shading devices, which presents the focus of the current research, are defined as active shading systems, which consist of components with the ability to change themselves due to the change in the environment with help of kinetic movement in an automated manner. In order to be responsive, a shading device have to be comprise of moving parts, actuators, a control system, sensors and be programmed to respond in a certain way due to the sensor data.

2.2. DEVELOPMENTS IN COMPUTATIONAL DESIGN IN ARCHITECTURE

2.2.1. PARAMETRIC DESIGN: ORIGINS AND DEFINITION

The term *parametric* is originally a mathematical term and its use in describing three-dimensional models dates to first half of the 19th Century. Almost a hundred years later in 1940s, the first use of the term in architecture discipline emerged in the writings of Luigi Moretti. He coined the term parametric architecture (originally “Architettura Parametrica”). This was before the development of computers (Davis, 2013). Antoni Gaudi and Frei Otto are other pre-digital precursors of parametric design approach in architecture. In their flexible physical models, they both used gravity as a parameter that informs the architectural form (Burry, 2016).

Moretti defined *parametric architecture* as the study of defining the relationships between the dimensions of architectural systems with the various dependent parameters. In 1960s, Moretti’s research works of parametric stadiums were presented in his Parametric Architecture exhibition as part of the 12th Milan Triennial (Davis, 2013; Tedeschi, 2014). In his studies, Moretti made use of pseudo isocurves for the form-finding process, in which he attempted to optimize the stadium forms regarding such parameters as views and cost. Moretti collaborated with the mathematician Bruno De Finetti and made use of computers in his research (Tedeschi, 2014).

Few years later, Ivan Sutherland (1963) developed the first interactive Computer-aided Design (CAD) program, called the Sketchpad, which was essentially a parametric system. The invention was relying on an advanced associative logic and parametric change was at the center of the Sketchpad system. Sutherland designed it so that, if there is any change in a model's part, it will result in changing the related parts automatically (Davis, 2013; Tedeschi, 2014; Woodbury, 2010).

Despite the promising endeavors in parametric approaches, which utilize computers starting from the 1960s, the first commercial computer-aided design programs did not employ parametric features. Rather, they aimed at aiding technical drawings and representation. It was 1988 when the first commercially successful parametric modeling software, Pro/ENGINEER, was released. The aim of the software was to enable engineers to consider easily a variety of design alternatives. The parametric modeling feature of the software was achieved by recording the operator's command steps, which was termed as “history tree”. With use of the recorded history tree, in case of any change of parameters, the software would automatically regenerate the model. This feature of the program was a time-saver when working on large models (Weisberg, 2008).

In the field of architecture, the influence of parametric modeling started only about the year 2000 (Woodbury, 2010)Today, there is a variety of software platforms for architects and researchers to work with parametric models. Those softwares vary from history-based modelers such as Catia, Solidworks, Pro/ENGINEER, to visual scripting platforms such as Generative Components, ParaCloud Modeler, Grasshopper, Dynamo and textual programming environments, which are included with most computer-aided design programs. (Davis, 2013)

Parametric design is a computer based design approach that makes use of parametric modeling and scripting techniques to deal with the geometric properties of any design. In this technique, geometric properties of a design are considered as variables. A network of relations and dependencies constructed by the designer, which allows continuous design adjustments along with generating options and variations, is called a parametric design model. At any time, the parametric model outputs a determinate instance of the design depending on the set of currently chosen values. However, the essential characteristic of the parametric design resides in the way in which constituent parts of the model are interrelated and arranged. It is the relationships and dependencies that is designed, not a single determinate instance. (Schumacher, 2016)

Parametric design is a process based on algorithmic thinking, which allows parameters and rules to control design variants. These parameters and rules together define the logic and the intent of a parametric and associative geometry. The superiority of this method lies in its ability to adapt to changes. It is possible to change the associative model by changing few parameters (Jabi, 2013). Dino (2012) stated that parametric design is a sub-category of algorithmic design. There is a strong relationship between parameters and algorithms. While algorithms operate on parameters, on the other hand a parametric system graph is an algorithm itself. The essential difference of a parametric system is its emphasis on explicit and direct manipulation of the parameters in order to change the design geometry (Dino, 2012).

In parametric design approach, designers compose explicit functions. Then, the parametric modeling software handles calculations and displays the resulting associative geometric model. Davis (2013) argued that the significance of a parametric equation lies in its characteristic of relating parameters to outcomes through explicit functions. Because this explicit connection is observable the process becomes disambiguate.

Designers gained the power of generating a range of possibilities with this method. They can generate an infinite number of design objects by assigning specific values to the parameters in the algorithmic schemata, which they created previously (Kolarevic, 2003). Thus, a parametric model signifies many possible designs. Different specific designs can be produced by changing the inputs. Hudson (2010) made a categorization for the parametric design tasks: the process of creating a parametric model and using this model to explore better alternatives in the design space. Woodbury et al. (2006) put forward that exploring the design space of parametric models is one of the main challenges for future parametric modeling researchers. Choosing the best alternative gains importance after generating the logic that produces multiple outcomes.

2.2.2. PERFORMANCE BASED DESIGN AND SOLUTION EXPLORATION

With the development of parametric and associative geometry, the problem of how to evaluate the design alternatives gathered attention. The next phase in the computer-aided design was coupling analytical simulation tools to simulate solutions that are generated by parametric models. This approach brought in new tools that made architects, designers and engineers collaborate in an integrated manner for designing better performing novel forms (Shea et al., 2005). Integration of performance simulations to architectural models and taking performance as the driving notion for design is called performance-based design. In this approach, a geometric model is formulated in a way that it allows transformation and generation in order to be evaluated with criteria from such domains as structural, mechanical, environmental, acoustic and so forth (Oxman, 2008).

Contemporary approaches in the field of performance-based architectural design employ generation-evaluation methods in the early conceptual phase of design. In the conceptual stage of performance-based design, arranging parametric geometry in connection with information about various performances is crucial. The editable definitions and associations are determined in the parameterization process. Consequently, a hierarchical structure describing a dependency chain is produced. In order to explore the goals of parametric modeling, it is necessary to target these goals properly from the beginning (Turrin et al., 2013). Turrin et al. (2013) proposed a three-phase approach for performance-based parameterization, which includes interrelated phases of strategy-definition, model building, and solution-assessment.

Design optimization using performance simulation and functions constitutes the framework for the use of computational techniques to solve performance-based decision-making problems. In this approach, design is perceived as a goal-oriented decision-making process where goals are set by the designers as performance criteria. In order to increase the integration of simulation to decision-support environments several methods and techniques can be utilized. Specific algorithms have been implemented to performance-based exploration in design (Malkawi, 2004). Gagne (2011) classified optimization algorithms generally as either gradient-based or heuristic and suggested that heuristic search algorithms are more suitable for most the problems related with building performance. The reason for this is building performance optimization problems are more complex for being solved by gradient-based algorithms (Gagne, 2011). Exploration of solution space to find better alternatives that satisfy some specified criteria requires iterative evaluations in the numerical design optimization model. Although not being widespread, these kind of decision-support tools are being used in building design research since 1970s (Choudhary & Michalek, 2005).

2.2.3. COMPUTATIONAL DECISION-SUPPORT TECHNIQUES FOR ARCHITECTURAL DESIGN PROBLEMS

Use of computational decision-support techniques to solve practical problems is a long-established method in science and engineering domain. However, its use in architecture design is yet developing. In architectural design research, utilizing metaheuristic search algorithms are relatively popular techniques in exploration of better performing design alternatives. By utilizing those algorithms, researchers aim at exploring design alternatives and make better design decisions. For extensive reviews, please see Evins (2013) and Nguyen et al (2014).

Several studies integrated surrogate models into architectural design problems. Chatzikonstantinou and Sariyildiz (2016) pointed out that most of these studies, which use machine-learning approaches, were intended to prediction of energy-related aspects of buildings; but only a limited number of these focused on function approximation based on simulation-derived knowledge.

Kazanasmaz et al. (2009) developed a predictive model by using artificial neural networks in order to predict daylight intensity for the office buildings in Izmir, Turkey. They made use of multi-layer feedforward artificial neural networks and trained the network with backpropagation algorithm. As input variables, they used two time variables (date, hour) , 5 weather variables (outdoor temperature, solar radiation, humidity, UV index and UV dose) which they acquired from weather data from the local weather station and 6 building variables (distance to window, number of windows, orientation of the rooms, floor identification, room dimensions and point identification). Collected illuminance data for 3 months from the field were used as output of the neural network. By using sensitivity analysis, they investigated the relationship between the input and the output variables of artificial neural network.

Tsanas and Xifara (2012) established a statistical machine learning model in order to tackle the relationship between eight input variables (relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, glazing area distribution) and two output variables (heating load and cooling load) of residential buildings. They investigated for the most influential input variables on the associative response variables by using linear regression and non-linear random forest methods. A dataset generated by simulation of 768 diverse residential buildings were studied in order to predict heating and cooling loads with low mean absolute error deviations.

2.3. DESIGN COMPUTATION IN RESPONSIVE-KINETIC SHADING OF FACADES

2.3.1. PARAMETRIC APPROACH FOR FAÇADE KINEMATICS

Without parametric design approach, it is impossible to realize any kinetic design, since time parameter is an inseparable aspect of anything that moves. Although there are many other parameters that make up a kinetic design, time parameter is the only one that every kinetic design problem has in common.

With the developments in contemporary parametric design in architecture, designers gained the freedom to animate, once static, design alternatives. Moloney (2011) asserted that the inheritance of modernist free façade and the "digital granularity" of contemporary parametric design coincides and suggests the motion in the free façade. He conducted an extensive research on exploring kinetic composition for facades. His work takes place in between theoretical and practical aspect of motion on facade. In the study, the emphasis is on locating the underlying parameters that determine the design of motion. According to Moloney, there is strong resemblance between parametric design and kinetic design. Both results with a process not a single object. In kinetic architectural design, design outcome is the process that determines a multiplicity of kinetic pattern. The mode of designing that parametric techniques introduced is applicable to designing dynamic systems. Out of most influential design variables, Moloney developed the idea of "decision plane" as a way to visualize the design space (Figure 2). Diagram of parameters were conceived as a planar continuum between two extremes and vertical axis represented time in each of the planes. These parameters were used for producing a series of animation studies for dynamic facade morphology. A space of possibilities of motion patterns were explored by means of these animations. In his research, Moloney reduced design of kinetic facades to abstract diagrams in order to focus on morphology that is the configuration of geometric transformations in space, free from scale or materiality. (Moloney, 2011)

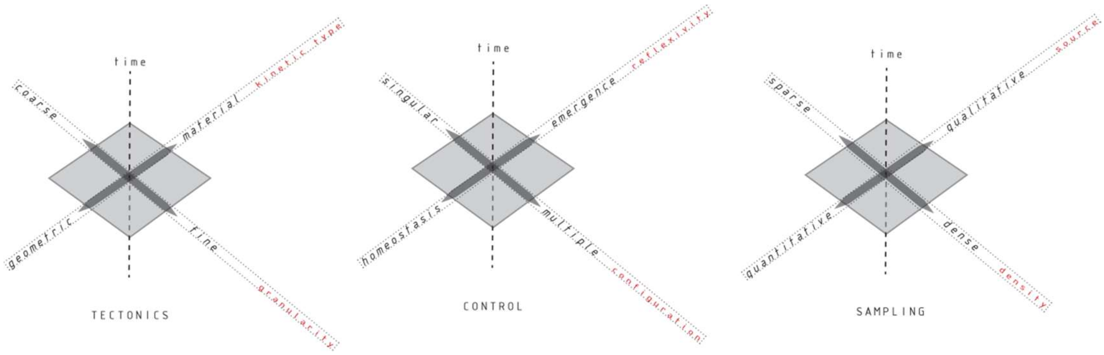

Figure 2. Moloney's decision planes (2011)

Schleicher et al. (2015) studied bio-inspired flexible shading components, which can be applied to curved geometries, from a structural point of view. They implemented elastic shading module on conceptual façade surfaces as a parametric component. Making use of parametric models allowed them to study elastic kinematics of the components on surfaces (Figure 3).

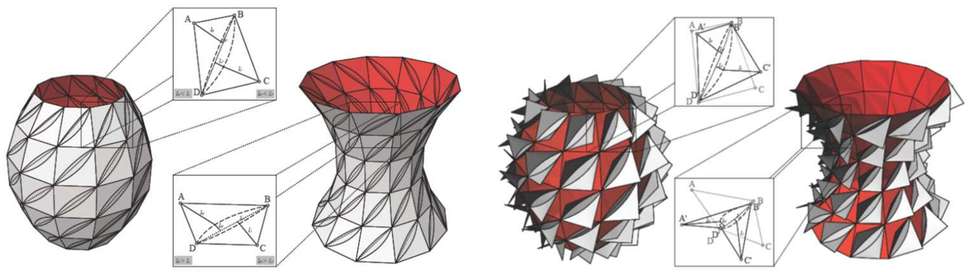

Figure 3. Parametric folding components on diverse geometries Schleicher et al. (2015)

Sharaidin et al. (2012) studied patterns of conceptual kinetic façade components by using a parametric approach. Bu utilizing of parametric modeling technique they investigated various types of motion patterns (see Figure 4). The types of motion patterns that they studied for a conceptual building façade was rotation, elastic, retractable, sliding and self-adjusting, for further performance integration and selecting the best performing option.

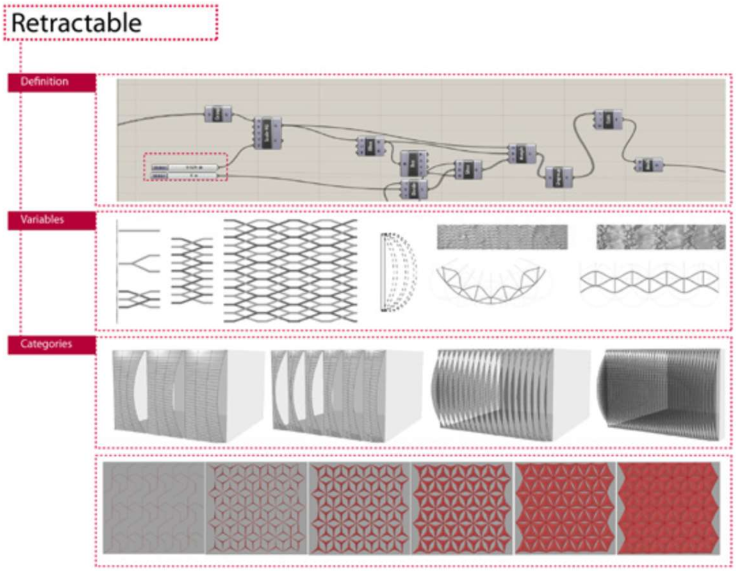

Figure 4. Parametric motion study for kinetic façade (Sharaidin et al. 2012)

In another study, Mahmoud and Elghazi (2016) made use of parametric modeling for exploration of folding modules on the façade of a hypothetical office space. Modulation type and movement of the modules controlled by parameters helped them explore various design alternatives. They divided the façade surface in cells and used each cell like a paper to be fold. By doing this, they obtained origami patterns, which can be actuated regarding a parameter that contains values for rotation, without any surface deformation (see Figure 5).

Datta et al. (2014) investigated conceptual design of a responsive–kinetic facade by means of the parametric model that they developed for the design and control of the facade components. The algorithm that they created generates pentagonal Cairo tessellation on the facade surface of the model and stirs a random rotation movement along the rotation points for each of the pentagonal components independently (Figure 6).

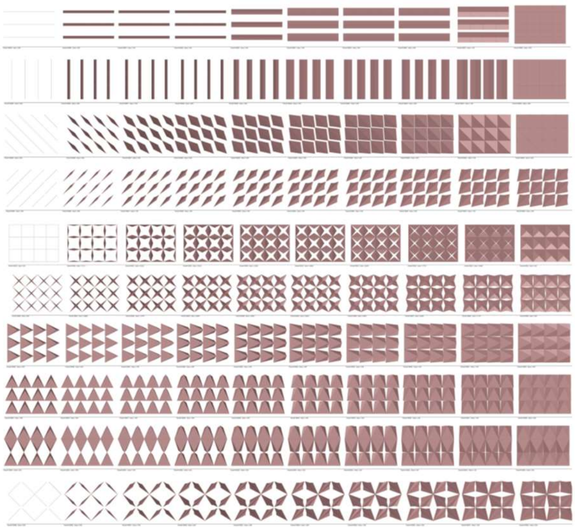

Figure 5. Parametric control of folding patterns. (Mahmoud and Elghazi, 2016)

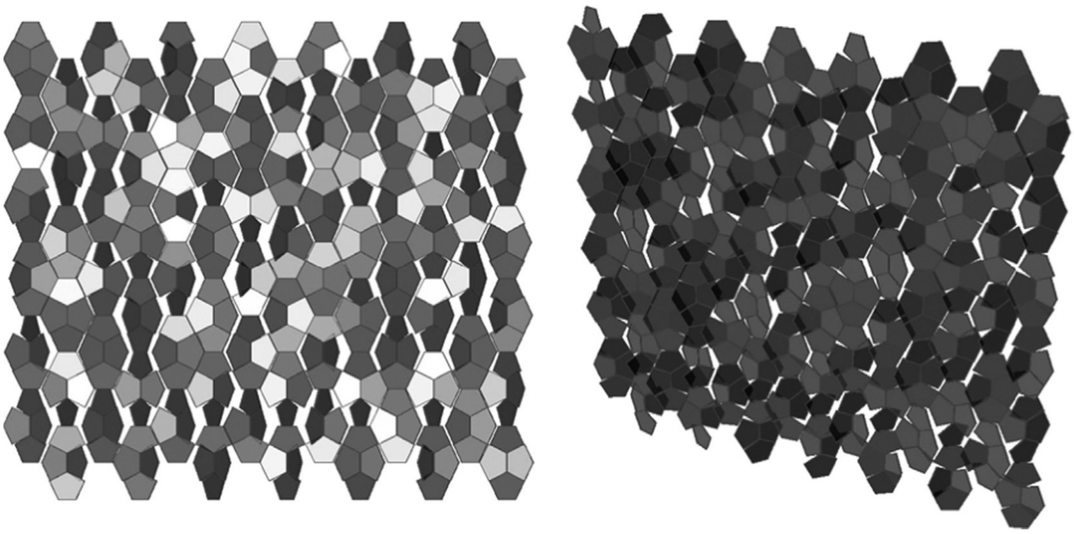

Figure 6. Façade composition based on rotation of random rotations (Datta et al.,2014)

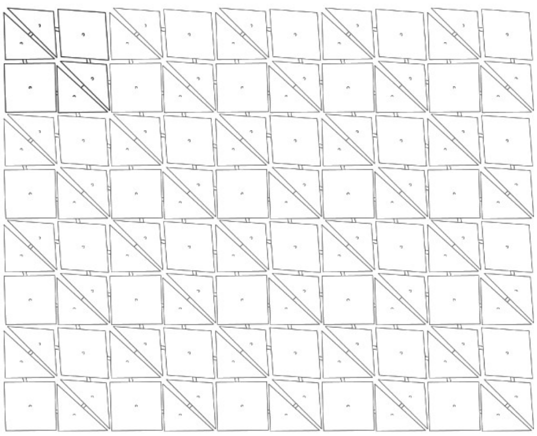

Figure 7. Semi-regular tiling pattern that Rossi et al. (2012) used for their prototype

Rossi et al. (2012) used a semi regular tiling pattern, which is composed of triangular and square panels for distribution of modules, for their kinetic facade prototype (Figure 7). They suggested that it is not mandatory to design and fabricate complex geometries for achieving complex surface patterns, since complexity may emerge because of simple components moving independently of each other in response to varying internal and external environmental influences. Similarly, Nagy et al., (2016) designed autonomous modules with square shape tessellated over the facade forming a diamond tiling for the purpose of energy generation, solar control and luminous distribution for interior office space (Figure 8).

Figure 8. Orientation parameter drives each of the PV panels. (Nagy et al., 2016)

Zawidzki (2015) utilized cellular automaton algorithm for generating dynamic shading patterns for a building facade. Each of the cells in the facade consists of rotating polarized-film modules whose opacity is a function of rotation angle. Regular tiling pattern such as triangular, square and hexagonal were examined in this study. Zawidzki's work is a unique sample for the study of shading geometry as it utilized a different computational approach in the design process. Rules of the algorithm and number of iteration of these rules influence the resultant facade composition (Figure 9 & Figure 10). Parameters used in this study were type of tiling pattern, rotation angle and opacity of each component.

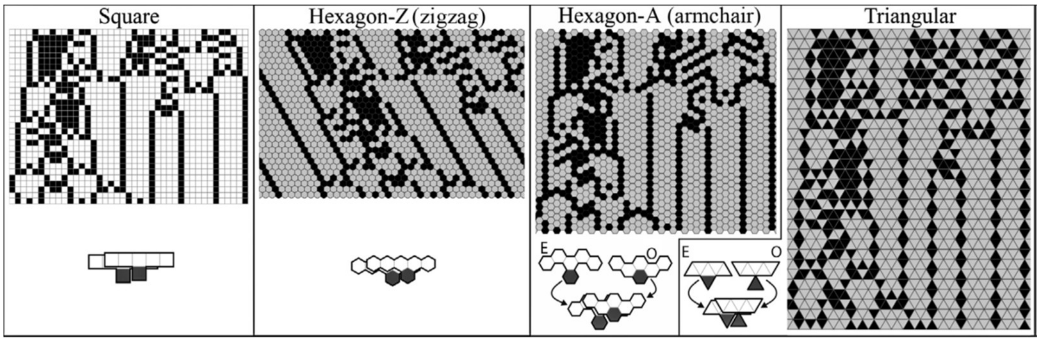

Figure 9. Types of façade tilings and application of cellular automaton for shading composition on façade. (Zawidzki, 2015)

Figure 10. Visualization of Zawidski's cellular automaton shading system (2015).

2.3.2. PERFORMANCE ANALYSIS OF KINETIC SHADING SYSTEMS

A better understanding of the complex relationship between facade system's geometry and its performance metrics is necessary for designing for adaptive, responsive and low-energy architecture (Datta et al., 2014; Hudson, 2010).

Kensek & Hansanuwat (2011) made use of various software platforms in order to simulate and analyze solar thermal, daylighting, ventilation and energy generation performances of four types of kinetic shading systems. For simulations, they used eQuest, 3ds Max Design, Ecotect and WinAir4, Solar Advisor Model, respectively. In their extensive research, kinetic shading systems that they analyzed were overhang, folding, horizontal louver and vertical louver with predefined positions. They compared performances of each shading devices. However, they did not take advantage of parametric modeling coupled with performance simulation engines for their search process. The various programs were not coupled with each other, but performed separately. That is, there was a need for developing a 3D model for each of the programs, except for the Solar Advisor model, which only accepts numeric values. Therefore, they had to keep the search space for kinetic shading devices limited.

Mahmoud and Elghazi (2016) aimed at developing a method for aiding the early design phase of a kinetic shading system by coupling parametric modeling with daylight simulation engine. They investigated the impact of rotational and translational motions of kinetic exterior shading on the daylighting performance of a south facing office room. In this study, parametric models are used for tuning the shading configuration manually for specific times in a year and monitoring its daylight performance for the interior space. It was intended to keep illuminance values that were read from the test points between 300 lx and 3000 lx. However, they did not automate the process for finding the better results as in the previous study above.

Pesenti et al. (2015) also utilized parametric modeling to study the daylight and energy analysis of an office space with an origami inspired exterior shading module, which has twenty-seven variations (Figure 11). The facade module that they designed was kinetic. That is why they pick an origami pattern for the study of kinetic shading, since origami patterns work with retractable rigid planes. Incorporating a parametric model allowed them to study motion of the facade modules. However, they postulated each of twenty-seven pattern variations to be static during the year for the daylight and energy simulations that they conducted. They made comparison of predetermined variations on a yearly basis.

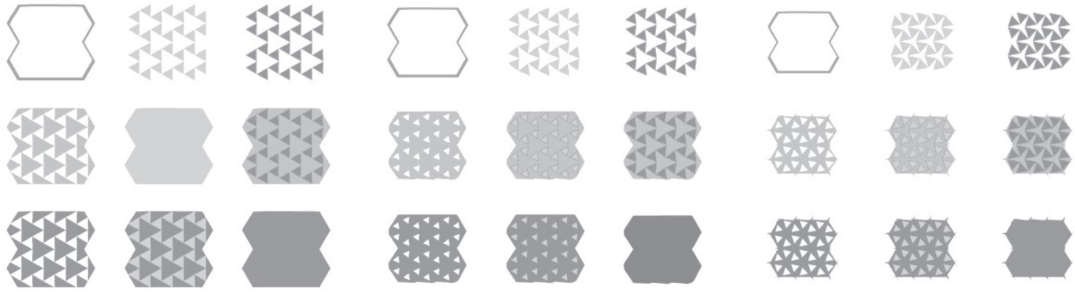

Figure 11. Pesenti et al. (2015) Parametric study of various shading configurations

Nielsen et al. (2011) investigated the potential of kinetic shading by making a quantitative comparison between three observations of an office space located in Denmark, with no shading, fixed horizontal and responsive kinetic venetian blinds. They made use of a tool, called iDbuild, which performs hourly-based calculations of total energy demand and daylight simulations for buildings. They used Daylight Factor for evaluating daylight performance, which is a static daylight performance metric that ignores any change in the sky conditions, location and orientation as well (Glassman, Glassman and Reinhart, 2015). The kinetic venetian blind that they offered is responsive to indoor air-temperature and risk of glare, as they stated. Nevertheless, how it responds to various situations was not revealed in the paper. The operation that it carried out is rotating along pivotal axis for blocking the direct sun light and retracting for no shading. However, neither rotation angle nor degree of retraction is within their variables. Design variables that they stated were orientation of the room and window height. According to their findings, dynamic shading case outperforms the static one in most of the situations, in both thermal and daylight performance criteria.

Grobman et al. (2016) made use of parametric modeling combined with an environmental simulation engine and assessed the performance of no shading, static, seasonally adjusted and dynamic exterior shading devices for a hypothetical office room in Tel Aviv, Israel. They calculated and recorded associated illuminance values for predefined time, orientation and louver angle for a shoebox office model by means of using Grasshopper, a visual script editor that works on 3D modeling software Rhinoceros and an environmental simulation tool called DIVA. The rotation angle variable is defined for horizontal louvers with seven steps between the range of 45° and - 45°. Simulations are performed for each of the variables between 9 am and 6 pm for every 21^{st} day of each month. By generating a matrix from the results, they aimed at monitoring and finding the best performing louver angle and orientation for the room. According to their findings from the simulation based quantitative study that was conducted by using Tel Aviv weather data, automatically adjusted kinetic shading devices performed better than other alternatives.

2.3.3. USE OF COMPUTATIONAL SEARCH METHODS IN THE DESIGN OF KINETIC SHADING DEVICES

Use of computational methods in architectural design problems is gaining popularity due to the new tools and techniques along with increased computation power. These tools and techniques help designers and researchers for evaluating alternatives and make better design decisions. Search methods and information systems can further help solving complex problems. However, few studies utilized those approaches for the early design stages of kinetic shading devices.

Wagdy et al. (2016) made use of an exhaustive search method and carried out simulations for all possible configurations within the predefined range. For assessing the performance of kinetic facade system that they developed, they proposed hourly adaptations of annual metrics of spatial daylight autonomy and annual sunlight exposure. They tested the approach that they proposed for evaluating the daylight performance of the dynamic shading system that is consisted of a modular grid of hollow boxes, which was mounted on the window of the reference, shoebox office model. Parametric modeling and daylight analysis engines were coupled for evaluating daylight performance. Variables of the conceptual dynamic screen mechanism that they designed were horizontal and vertical axial rotation angles of the screen components. For each of the configurations of the shading mechanism, analyses performed iteratively in an automated way for each of the occupied and day-lit hours in a year. They created a tool for speeding up the calculation process of the simulation engine, because their search method was taking too much time. After placing all the illuminance values in a list, they sorted the list for finding the best performing configuration for each specific moment in time.

El Sheikh and Gerber (2011) proposed a method for daylight performance optimization of an exterior shading system consisting of two independent groups of louvers with two different rotation angles. They proposed an early phase decision-support tool for the design of the shading system. The autonomous responsive kinetic louver system that they designed, responds both changing daylighting conditions and preferences of occupants. For their study, they utilized parametric modelling, daylight simulation engine and genetic algorithm. In a similar manner, Sharaidin et al., (2012) conducted digital experiments in order to tackle daylight performance optimization of different kinetic facade systems that have diverse motion behaviors. The types of motions of kinetic facades that they examined are rotation, elastic, retractable, sliding and self-adjusting. They made parametric models of various types of motions for kinetic facades, coupled the models with a daylight simulation engine, and evaluated their daylight performances by using genetic algorithm. Both studies were based on daylight performance integrated parametric modeling and used single objective optimization, with help of Galapagos optimization engine. Galapagos is a component in Grasshopper, which solves single objective optimization problems by means of a genetic algorithm.

Lee et al., (2016) pointed out the crucial role of the operation of shading devices when evaluating their performance, and focused on a calculation method, which assesses the thermal and lighting energy performance of a drop awning that has 10 operational steps. The influence of ten different steps of operations of a single drop awning on the thermal and lighting energy consumption of the reference case are simulated and the sum of thermal and lighting energy load as a single objective is minimized for each hourly moment in time. They concluded their study with the comparison that proves the advantage of having in between steps of operation other than just having on/off state for the kinetic external shading device.

There are just two studies in the literature, which integrate artificial neural networks (ANNs) in conceptual design of kinetic shading devices. In their study, Hu and Olbina, (2011) criticized existing automated shading systems for running short in controlling complex blind systems such as split-blinds. They developed a model based on multi-layer feedforward ANNs, in order to find optimum slat angles of automated interior split-blinds for performing a desired indoor illuminance. For training the network model, they made use of back-propagation algorithm.

Skavara (2009) experimented whether a neural network can handle a complex problem, which is controlling the emergent behavior of cellular automata (CA) forming a shading system on south-facing façade. She aimed at mapping an input layer of an array of 11 daylight values to the output layer of the 11 panels on the first row of shading system. The other rows in the lattice of shading system would respond to the first row by following the deterministic rules of CA. She generated a list of 1000 random CA patterns in order to find optimum first row for each sun position. Using the dataset, she incorporated a feed-forward multi-layer neural network. For adjusting the weights in the connections, she employed back propagation and genetic algorithm. She tested both training methods for finding the minimum error for the ANN.

2.4. SUMMARY AND DISCUSSION

One of the advances in the contemporary design field was the introduction of parametric design approach. By adopting this new approach, designers started to construct relationships and dependencies that output a possible design, just like constructing an explicit function that outputs a dependent variable. Schumacher (2016) underlined the shift in the focus, from the design of final artifact to the design of process that generates variations. This idea infers a fundamental change in the design thinking. Parametric design approach opens room for thinking about alternatives and variation itself. From a philosophical perspective, adopting this approach replaces singularity with multiplicity. Furthermore, as Davis (2013) also pointed out, parametric design is a process-oriented approach in which dependencies in the logic of a design are visible and subject to direct manipulation. This means that the design process is not a black box that relies merely on intuition of the designer anymore. The relation between input and output are apparent. Another fundamental aspect in this approach is that, with a previously created algorithmic schemata, designers can generate an infinite number of design objects by assigning values to parameters (Kolarevic, 2003). Exploring better solutions is a challenge that is brought out by these multiplicity of solutions (Hudson, 2010; Woodbury et al., 2006). This approach leads to new research questions about how to explore and select from the set of design alternatives that parametric model generates.

Seeking for answer to the problem of how to evaluate design alternatives and environmental concerns gave rise to performance-based design, which is an approach driven by information. Parametric models coupled with simulation engines allowed for predicting performance of any design instance. Therefore, the designers are informed about how possible design solutions perform; thus, make better decisions (Oxman, 2008; Shea et al., 2005; Turrin et al., 2013). Integration of performance criteria made the endless variations generated by parametric models more meaningful. However, searching for better design alternatives, parametrically in a wide design space requires more than manually changing values in the design parameters and monitoring the associative values of performance indicators. Computer power comes into place again for repetitive task of searching for better design alternatives within the designer-defined boundaries. Search methods such as optimization algorithms have been integrated to performance-based design process in order to evaluate better solutions. This approach generates an automated decision support workflow, which makes use of search methods. There are gradient-based and heuristic techniques utilized for optimization problems in building design (Choudhary and Michalek, 2005; Gagne, 2011; Malkawi, 2004). Meta-heuristic optimization algorithms e.g. genetic algorithms and particle swarm optimization are the most commonly used techniques implemented to performance-based design of buildings (Nguyen et al., 2014).

Although meta-heuristic search techniques gained a relative popularity in the field of building design research, they have certain drawbacks. Meta-heuristics are generally black-box algorithms that does not inform designer about the nature of the problem at hand. Furthermore, they have the risk of stacking to a local solution than finding global optimum solutions (Nguyen et al., 2014). In computationally expensive design problems, simulation-based optimization run short in order to find solutions in a feasible time. This is partially caused by long simulation times of the simulation engines, and partially by the way, that meta-heuristic algorithm conducts the search. Chatzikonstantinou and Sariyildiz, (2016) demostrated that surrogate-based optimization models are much more faster than simulation-based optimization. Furthermore, as Wortmann et al. (2015)suggested, surrogate-based optimization finds better performing design alternatives compared to the ones that are found by meta-heuristic techniques such as genetic algorithm.

One of the most complex problems in architectural design is conceptual design of responsive-kinetic shading devices. When compared to design of a static system, level of complexity increases due to the dynamic nature of the design problem. For this reason, most of the studies in the literature on kinetic shading devices either reduced the complexity of the problem in a deterministic manner, or used search techniques such as parametric search or meta-heuristics such as genetic algorithm. Nevertheless, use of advanced design computation techniques in conceptual design of kinetic shading devices is far from being satisfactory. A few works tackled daylight or energy performance by taking them as a single objective optimization problem (El Sheikh and Gerber, 2011; Lee et al., 2016; Sharaidin et al., 2012; Wagdy et al., 2016). None of the studies in the literature handled the design problem from a multi-dimensional perspective and employed an optimization method for daylight, thermal and visual performance in the same problem in order to investigate the influence of dynamic shading devices on energy consumption and improve visual comfort of the interior space.

A responsive-kinetic shading device should optimize its movement for a smaller time basis, in order to respond its movement due to the change in the environment. If an hourly time interval is chosen for its design investigation, approximately 4400 different optimization problem should be conducted for each daylight hours in a year. Because simulation-based optimization needs a long time to come up with satisfactory solutions, it is not an efficient approach. On the other hand, surrogate model based optimization methods decrease the necessary amount of simulations. Although the nature of the problem is very suitable for using surrogate models, use of the technique in conceptual design of complex kinetic shading devices is quite limited in the literature. Two studies made use of surrogate models for the design of control for responsive-kinetic shading devices. Hu and Olbina (2011) utilized surrogate models for predicting the influence interior split-blinds on illuminance levels and achieved very low prediction errors. They focused only to daylight performance, by neglecting thermal and other visual comfort aspects such as view to the outside environment. Moreover, it is a fact that interior shading performs poorly with regard to thermal control when compared to exterior shading. In another study, Skavara (2009) implemented artificial neural networks for controlling the emergent behavior of an exterior shading system that is driven by cellular automata for daylight performance. Her focus was more on the training techniques of the network, than the comfort and energy related influence of the responsive-kinetic shading devices.

The review of the literature revealed that technical incompetency of the existing methods is leading to limitation in the design of responsive-kinetic shading devices. Furthermore, use of surrogate-model based optimization methods in the conceptual design of performance-based responsive-kinetic shading devices is still unexplored. The nature of the design problem necessitates a reduction in computational cost, without sacrificing the accuracy. With this motivation, a surrogate-based optimization method is proposed and tested in the case studies, which will be explained in detail in the following chapter.

3CHAPTER THREE
METHODOLOGY

The current research employed a quantitative approach for assessing the performance of shading devices in conceptual design stages. A novel computational framework was proposed for investigation of responsive-kinetic shading devices. The framework was implemented in a comparative study between annually optimized-static and hourly optimized responsive-kinetic shading devices. It was hypothesized that responsive-kinetic shading devices would outperform optimized-static shading devices in Izmir climate with regard to the given performance criteria. To test the hypothesis, an experiment was designed using the computational tools and measured the effect of quantitative independent variables on dependent performance variables.

This study was based on computational tools and techniques for the aim of establishing a novel framework for predicting and optimizing the working of performance-driven, responsive-kinetic shading devices in the real world. Parametric modeling, environmental simulation and computational decision-support tools were incorporated in an automated workflow for generating and exploring the design space of the kinetic shading devices (Figure 12).

At first, the parameter initialization process was conducted for the base case. Then, parametric models were established for the shading devices, which are mounted on the south-facing fully glazed façade of the base case. Same design parameters controlled both observations, optimized-static and responsive-kinetic, that are rotation angles of horizontal slats in six different zones of the shading systems. The variable randomization process updated the simulation model iteratively by generating random values for shading control and time of year parameters. The impact of the diverse types of shadings on indoor temperature, daylight intensity and view to outside were selected as performance indicators, which were the response variables in the study. The values for the shading control and the response parameters of the design alternatives were stored in spreadsheets by coupling parametric models with thermal, daylighting and view simulation engines in an automated manner.

Exploration for the optimum set of responses of kinetic shading devices to environmental conditions for a given time interval is a computationally expensive task, due to the requirement of excessive number of simulations. For this reason, artificial neural networks were utilized for function approximation, which were subsequently used in the multi-objective optimization problems. This allowed significant reduction in computational costs. The computational approach, which is a surrogate model based optimization, was implemented in the comparative study between two dependent observations. One of them was a static shading device that was optimized for average annual performance. The other was a responsive-kinetic shading device, whose performance was optimized on an hourly basis. Both observation had the same shading control parameters that was rotation angles of horizontal slats in six different zones of the shading systems. The static shading was searched for an annually optimized configuration regarding to the performance criteria, while the responsive shading searched for responding hourly fluctuations of the weather.

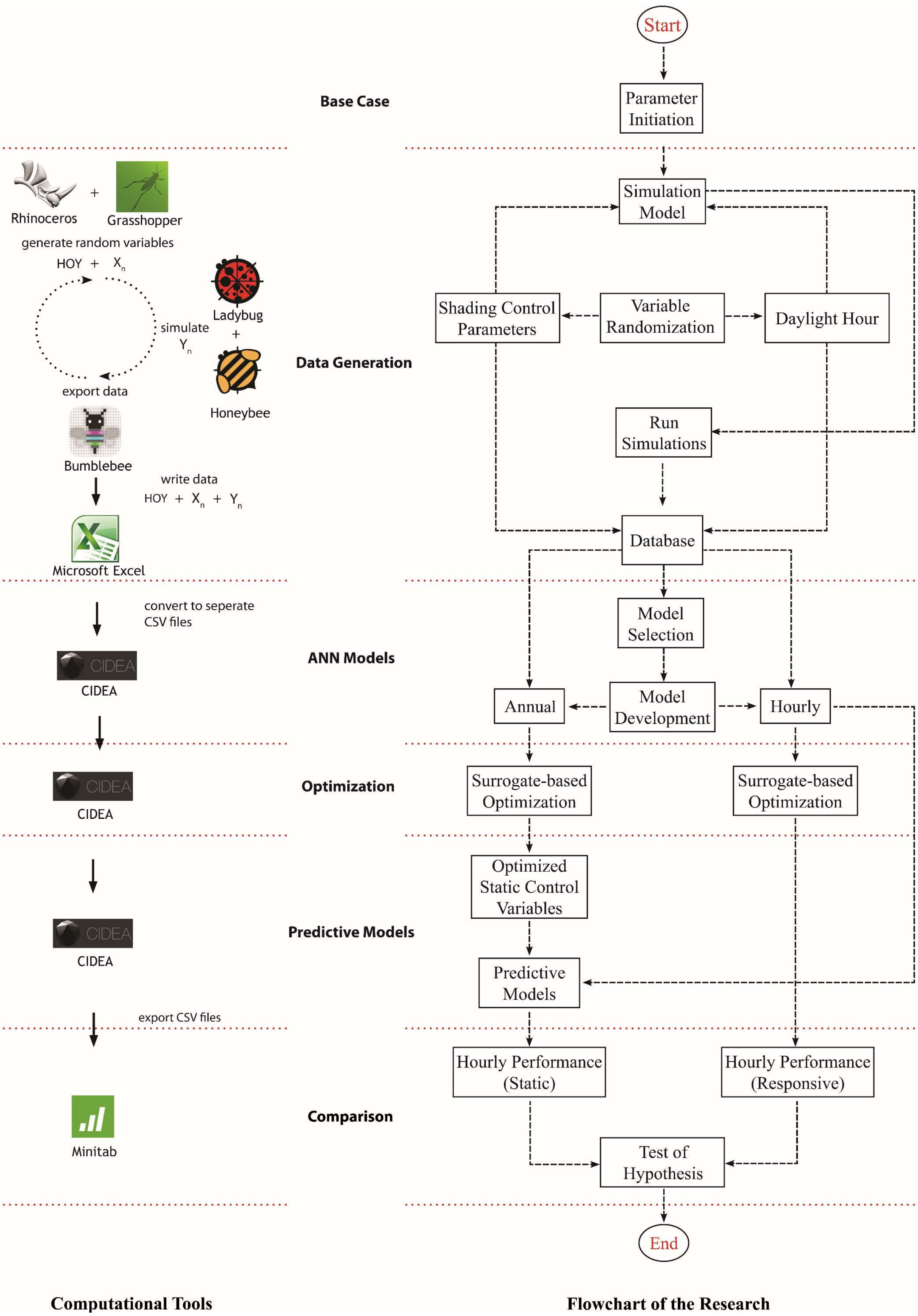

Figure 12. The computational tools used and the flow-chart of the research process

3.1. PARAMETER INITIALIZATION FOR THE BASE CASE

A test box was defined for the study of the exterior shading devices. At each of the cases, the parameters that describe the hypothetical building were kept constant. The dependent variables of annually-optimized and responsive-kinetic shading systems on the base building were examined by assuming that it is located in Izmir, Turkey. For measuring the sole impact of shading device, heat transfer was allowed only from the south-facing façade. Furthermore, it was assumed that there were no internal heat loads. Other assumptions can be seen at Table 1.

Table 1. Parameter initiation of the base case

Parameters		Values
Location		Izmir /Turkey
Dimensions	Width	3 m
	Depth	6 m
	Height	3 m
Reflectance	Floor	30 %
	Ceiling	80 %
	Walls	50 %
	Shading (exterior)	40 %
U Values	Walls (except South)	Adiabatic
	Roof	Adiabatic
	Floor	Adiabatic
	Window	2.39 $W/m^2.K$
	South Wall	0.49 $W/m^2.K$
Internal Loads	Equipments	0 W/m^2
	Infiltration Rate	0.003 $m^3/s\text{-}m^2$
	Lighting Density	0 W/m^2
	People Density	0 ppl/m^2
Window	Orientation	South
	Glazed Area	7.84 m^2
	Window to Wall Ratio	0.87
	Window Construction	Double Pane with Low E
Glass Material	Type	Clear glass
	Visible Transmittance	0.79
	Refraction Index	1.52

3.2. PARAMETERIZATION OF SHADING DEVICE

The research is based on parametric modeling and change of variables for performance explorations in an automated manner in order to predict the influence of shading geometry on indoor environment. The first step was defining the building geometry and its materiality. In the next phase, shading device's parameterization was conducted by using Grasshopper, an algorithmic modeling platform. The geometry of the shading was generated by subdividing a surface that was 5 cm away from the south façade into six parts. This would allow controlling of the conceptual shading system with zones. Subsequently, each of these parts was subdivided again into 30 parts. These operations generated a data tree with six lists each having 30 items. Each of the surfaces would form horizontal slats of the shading devices with a dimension of 0.03 m X 1.49 m. An axial rotation operation was defined for all the surfaces in six different lists. Shading surfaces in separate lists were controlled by independent rotation parameters, which could have a value within the range of 0.00 to 180.00 degree (Figure 13).

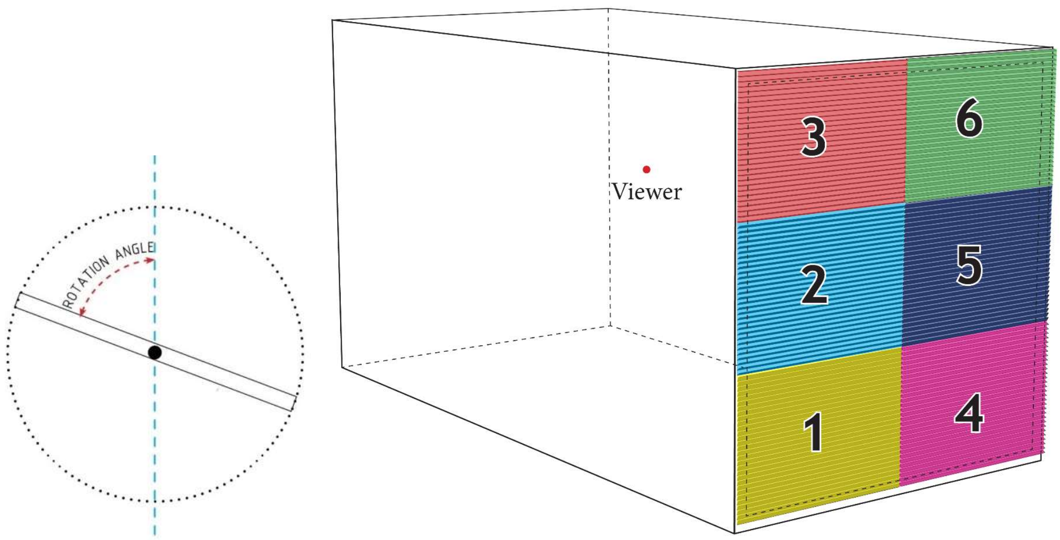

Figure 13. Exterior shading system with six control zones and the diagram of a single shading control parameter

3.3. PERFORMANCE METRICS

Mathematical combination of measurements, dimensions and conditions, which may not be directly measurable in the field, represented in a continuous scale is called a metric (Mardaljevic et al., 2009). Building performance metrics are used to measure 'quality' of spaces with respect to comfort, energy, and safety and so on. Performance metrics are quantitative tools, which can be used for comparative studies in building design (Glassman and Reinhart, 2015). Choosing the right metric is crucial when assessing the performance of a system, because it ensures that performance is measured accurately. In this study, instantaneous metrics will be used for performance evaluation, because one of the shading devices in question is a kinetic system that responds to continuous environmental changes. It is assumed that at each hour, the kinetic shading device is steady. The simulations will be run for each hour in order to assess the performance.

As defined by Mardaljevic, climate-based daylight modeling predicts radiant and luminous quantities such as irradiance, illuminance and so on, based on annual meteorological datasets. Locale climate data, which includes various climatic conditions, is considered along with fenestration orientation, geometry and material properties in order to predict absolute quantities that are likely to occur in the space. These datasets are derived from recorded measures at the field over a period of years and are freely available for download from the internet (Mardaljevic et al., 2009).

For the current study, we used Izmir weather dataset, which can be accessed from EnergyPlus webpage. Coordinates of the location is North 38° 30' and East 27° 1' GMT +2.0 Hours. The weather dataset is composed of a data collection from the years of 1982, 1984, 1986 and 1988.

3.4. COMPUTATIONAL TOOLS AND TECHNIQUES

Moloney (2007) proposed a concept for design software to meet the particular requirements for the design of a kinetic facade. He examined particular requirements of a digital prototype for the early design stages of a kinetic facade. His general model for the design of a kinetic facade is based on two principles: evaluation of performance and the calibration of performance. He refined this general approach by adapting a method from the discipline of information systems in order to pave the way for a software module for the design and simulation of kinetic facades.

Fotiadou (2007) made a research on existing animation and 3D modeling programs in order to evaluate their suitability for animating kinetic structures. She pointed out that there is a lack of software dedicated for design of kinetic structures. She concluded her thesis with a vision of software that will facilitate the detailed design, performance analysis and documentation for kinetic architecture. Although there are softwares, such as Solidworks, Inventor, etc., for mechanical design and analysis today, these tools are not peculiar for architectural design. They are rather used for engineering purposes in much smaller scales of design. The lack of design and analysis tools for kinetic architecture is, mostly likely, because of the dominance of static buildings in the market. However, there is an increasing necessity to employ dynamic components in the buildings in order to improve energy efficiency and inhabitants' comfort.

Because there is a lack of software package, particular to the design of kinetic facade components, researchers are developing custom methodologies by coupling various software platforms for the design and analysis of kinetic architectural components.

In this study, Grasshopper platform were used for generating a custom automated workflow, which produce database that contain randomly selected variables and the associative performance data. A parametric model of a kinetic shading device that operates on a hypothetical box model was created at the first step. Then, Ladybug and Honeybee programs were utilized for performing daylight, thermal and view to the outside analyses for the model. The simulations were run for each hour by using the EPW file for Izmir. The EPW file for Izmir is available on EnergyPlus webpage. A custom script is implemented for giving random values iteratively for the independent variables of the kinetic shading device. The independent variables and the three associative performance variables for each of the example shading configurations were stored in a Microsoft Excel file with help of Bumblebee plug-in. The database was used for subsequent training of Artificial Neural Networks, which will be explained in detail in the following sections.

3.4.1. PARAMETRIC MODELING

One of the advances of latest years within the context of algorithmic modeling was the release of Grasshopper; a graphical algorithm editor operates on Rhinoceros. It was developed by David Rutten at Robert McNeel & Associates. It is a node-based editor, which allows visual programming by means of data flow within a network of encapsulated functions. One of the main advantages of this platform that it is possible to develop and add new plug-ins to Grasshopper. These plugins extend the capacity of the program. It is possible to make environmental, structural or physics simulations by means of these plug-ins. These capabilities of Grasshopper make it be suitable for form-making as well as form-finding. Furthermore, it is possible two couple it with different software and hardware (Tedeschi, 2014). The use of grasshopper opened a new perspective in computational design. It has been accepted by both practice and academia for their studies. One of the main reasons of this application's popularity in the domain architectural design is that it does not require advanced syntaxical knowledge for generating parametric models as well as interoperability that it offers by means of useful plugins that are freely shared by the community.

In this study, virtual test box and a parametric model of a shading system that was composed of 6 zones, was developed by using Rhino/Grasshopper algorithmic modeling platform. Using parametric modeling tools helped controling and exploring movement of the shading systems. In the next step, the parametric model was coupled with environmental simulation engines for exploration of the performances.

3.4.2. PERFORMANCE INTEGRATION TO THE PARAMETRIC MODEL

Ladybug and Honeybee are open source plug-ins for Grasshopper, developed for aiding the designers to explore and evaluate environmental performance of any design alternative at the conceptual design phases. With help of the programs within Ladybug toolset, it is possible to import EnergyPlus weather data files (EPW) into Grasshopper, make various environmental analyses that rely on previously recorded local time-series data. Honeybee toolset contains programs that connects visual programming environment of Grasshopper with various validated simulation engines such as EnergyPlus, Radiance, Daysim and OpenStudio (Roudsari and Pak., 2013). An integrated and flexible design approach can easily be utilized in the design process by means of these plugins and the visual scripting environment that Grasshopper platform provides. By generating a definition on Grasshopper various design variables and associative performance data can be created for further research.

Daylight Performance

In this study, hourly daylight metric of illuminance was used for assessing daylight performance. (Littlefair, 1988) defined the illuminance (lumens/ meter^2) as the visual part of the radiant energy that is derived from a luminous efficacy model (Mardaljevic, 1999). Luminous efficacy is the ratio of the total luminous flux (lumens) to the total power (watts). Luminous flux can be defined as the quantity radiant flux falling on a unit area of the hypothetical non-reflective sphere's surface that surrounds the point source of radiation. The unit of luminous flux is lumen (lm). Flux density decreases as distance from the source increases. Illuminance is the incident luminous flux per unit area (lm/m^2) of any surface in space (Figure 14). 1 lm/m^2 is called 1 lux (lx) (IESNA, 2000).

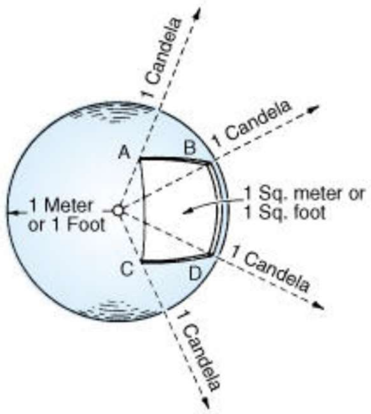

Figure 14. The sphere model that shows the relationship between luminous intensity (candela), luminous flux (lumen), illuminance (lux or footcandle), (IESNA Lighting Handbook (9th Edition), 2010)

Radiance is a free daylight simulation tool that is validated and accurate (Mardaljevic, 1999). It performs advanced simulations for calculating luminance and illuminance levels in non-empty spaces. It makes use of ray-tracing, a technique originally developed for realistic display of geometric models on computer screen, for calculating the lighting levels at a point. Radiance relies on both finite element analysis and Monte Carlo technique for lighting calculations (Ward & Rubinstein, 1988). Standard Radiance release has two sky generator programs called *gensky* and *gendaylit.* Gensky creates sky models based on CIE (International Commission on Illuminance) standards, which are clear or intermediate skies. Gendaylit generates sky models based on the Perez All-Weather model. It determines different types of sky conditions based on the input parameters, which make it a good choice to be used with time series measurements of weather data (Mardaljevic, 1999).

Air Temperature

Air temperature is a dominant environmental factor, since it is directly related with thermal comfort. ASHRAE (2009) defines thermal comfort as: "*that condition of mind that express satisfaction with the thermal environment.*" Air temperature is one of the environmental conditions that have an impact on metabolic activity of human body, along with relative humidity, air movement and mean radiant temperature. The comfort range extends from 20 °C in winter to 25 °C in summer depending on metabolic rate and clothing of the person (Lechner, 2015). Conditioning of a space aims at keeping the inside temperature at a level so that the occupants feel pleasant. The load calculations are conducted by using design temperatures and sizing of air conditioning devices and the energy needed to regulate air temperature is a function of the difference between the actual and desired air temperature (ASHRAE, 2009).

Shading strategies are one of the ways to regulate solar heat gain of an indoor space. By shading, excessive heat gain can be prevented, especially in summer. Shading devices that are placed on the exterior of a glazing is a more efficient way to control solar gain. Because, the directly transmitted solar radiation is blocked before entering the space.

In this study, air temperature inside the test box was used as a response variable to assess the performance of shading devices. Therefore, a relationship was established between shading device control parameters and their impact on air temperature parameter. From the offset temperature value, contribution to energy savings can easily be calculated.

EnergyPlus is an integrated simulation program that performs energy analysis and calculates thermal load demands of a building model. Based on a user's selection of the building's physical setup, it solves building, system and plant parts of the model simultaneously, in order to obtain physically realistic simulations. By using EnergyPlus, it is possible to study thermal performance of a building, calculate energy loads such as heating, cooling and lighting, necessary sizing of plant equipments, etc., for buildings in question for a given location. The program relies on the legacy of LAST and DOE-2 programs, which are predecessor energy and load simulation tools (Energyplus, 2016).

View to Outside and View Analysis

View is deemed to be one of the most important aspects in building design. The main reason for using glazing in buildings depends mainly on the need to connect the indoors to the outside. Excessive use of glassware, however, causes adverse effects on comfort and energy consumption. Reinhart et al. (2006) argues that, merely quantitative approach to view to the outside considerations does not bring quality to a space. In addition, when the shading device is movable, view to the outside parameter was said to be less meaningful; because, the shading devices will be frequently lowered due to glare. On the other hand, it is a fact that view is a psychological factor that influences the occupants in a positive way. Although people like to see a nature view rather than a built environment, having a view in an indoor space is important for psychological and physical well-being (Farley & Veitch, 2001). This is even more important when a room has only one opening. A shading device capable of responding to its environment can incorporate view to the outside, as a parameter to be maximized, in accordance with other daylight parameters.

Ladybug has a view analysis component that allows evaluating the visibility of an input geometry from a set of viewing points. The component outputs a percentage of view rays, which are not blocked by surrounding geometry. For the current study, a point is defined in the center of the interior space at the eye level for evaluating view performance of the shading geometry as a barrier that blocks view to the outside.

3.4.3. DATABASE GENERATION

For the current research, a performance integrated parametric model was generated for exploring the alternatives in the design space and the response variables of the static and responsive kinetic shading devices. The previously established parametric model had six independent variables, and three response variables that are performance indicators (Table 2 & Table 3). The next step was automating the process of generating and recording random independent variables for the control of shading zones and their associative performance variables in a database. For this purpose, a custom script was integrated to the parametric model.

Nabil and Mardaljevic (2005) stated that sub-sampling the meteorological dataset, such as picking only one day from each month, will naturally bring biases because different sky and conditions would be excluded. However, in the research presented here, the aim is not making an annual inference, but examining the point in time situation. For this reason, a random sampling of 50 hours was made from total daylight hours of a year, provided that the selected hours were between 9.00 am and 17.00 pm.

Table 2. Range of the decision variables

Variable	Description	Unit	Range
X_1	Rotation angle 1	degree	0.00 – 180.00
X_2	Rotation angle 2	degree	0.00 – 180.00
.	.	.	.
.	.	.	.
.	.	.	.
X_6	Rotation angle 6	degree	0.00 – 180.00

Simulations were run on an hourly basis for the randomly sampled times in a year. By assigning random values for the decision variables within the range, 500 simulations were performed for each of the 50 randomly sampled hour. For the static shading, a randomly generated set that contains 500 examples were performed on an annual basis. A total of 25500 runs were performed in an automated workflow in order to generate 51 datasets for further ANN models' development. At each run, the independent variables and their associative variables that contain performance indicator values for each hour and a year were stored in separate spreadsheets.

Table 3. The response variables

Variable	Description	Unit
Y_1	Δ Temperature	Celsius degree
Y_2	Δ Illuminance	Lux
Y_3	View to outside	Percentage

Three response variables were defined for performance evaluation, as can be seen at Table 2. Variable Y1 is the difference between the simulated air temperature inside and 23 °C threshold. Variable Y2 is the difference between the average illuminance what was simulated inside and 500 lx thresholds. Finally, Y3 is the average of the view percentage from a given point inside to the view frame at the outside.

The database generation loop for responsive shading followed the steps that are listed below:

- Step 1: Generate 6 random values within the range for shading control parameters
- Step 2: Run daylight, energy and view simulations

- Step 3: Write shading independent design variables and dependent response variables to spreadsheets
- Step 4: Iterate the above process for 500 times for each hour
- Step 5: Change the hour of the year.
- Step 6: Iterate for 50 times

With help of the iterative database generation process, 500 variations were written for each hour, for 50 random sample hours of year. The data generated for each hour was stored in separate spreadsheets. After finishing the database generation procedure, each spreadsheet was converted to comma-separated values (CSV) file with help of scripting that can be accessed from the reference[1].

3.4.4. DEVELOPMENT OF OBJECTIVE FUNCTIONS

In this research, three objective functions were defined for the performance optimization of responsive-kinetic shading device. These are minimization of the difference between average illuminance inside and 500 lx, minimization of the difference air temperature inside and 23 °C and maximization of view to the outside. The quantities were generated by validated simulation tools and used for developing surrogate models for the subsequent use in multi-objective optimization. Feed-forward Artificial Neural Networks (FAAN) was used for function approximation of the objective functions. The functions were trained by Resilient Back-propagation (RProp) algorithm. Root mean square error (RMSE) is the indicator that we used for measuring performances of the neural networks.

Artificial Neural Networks

Fausett (1994) defined an artificial neural network as an information-processing system that has similarities with biological neural networks. Mathematical models of human cognition and neural biology have been generalized for developing artificial neural networks. The basic assumptions that they both have in common are:

- Neurons are the simplest elements where information processing happens
- Signals are transmitted through connection links between neurons

[1] https://www.extendoffice.com/documents/excel/2972-excel-save-export-convert-multiple-all-sheets-to-csv-text.html Retrieved at 13 March 2017.NE

• There is an associated weight on each connection link, which multiplies the signal transmitted.

• An activation function is applied by each neuron to sum of weighted input signals in order to determine its output signal.

A collection of simple processing elements called neurons, units, cells or nodes make up a neural net. Each neuron has an activation function of the inputs it has received. The output of activation function becomes the signal for the other neurons. Thus, the input signal propagates until it reaches the output. Each neuron can only send one signal at a time to other neurons that it is connected to and each signal is scaled by a weight factor. Finding optimal values for the weights is called *training,* which is done by certain methods. The architecture of the network, training algorithm and activation function defines a neural network (Fausett, 1994).

In feedforward neural networks, a connection is allowed only from a node in a layer to nodes in the next forward layer. Multi-layer feedforward networks are very popular and long-established structures of artificial neural networks, which have been used in many applications such as forecasting and function approximation (Zhang, Patuwo, & Hu, 1998). This class of neural networks is identified by presence of hidden layers between the input and output of the network. Hidden layer contains hidden neurons, which are not directly seen from either input or output (Haykin, 2009).

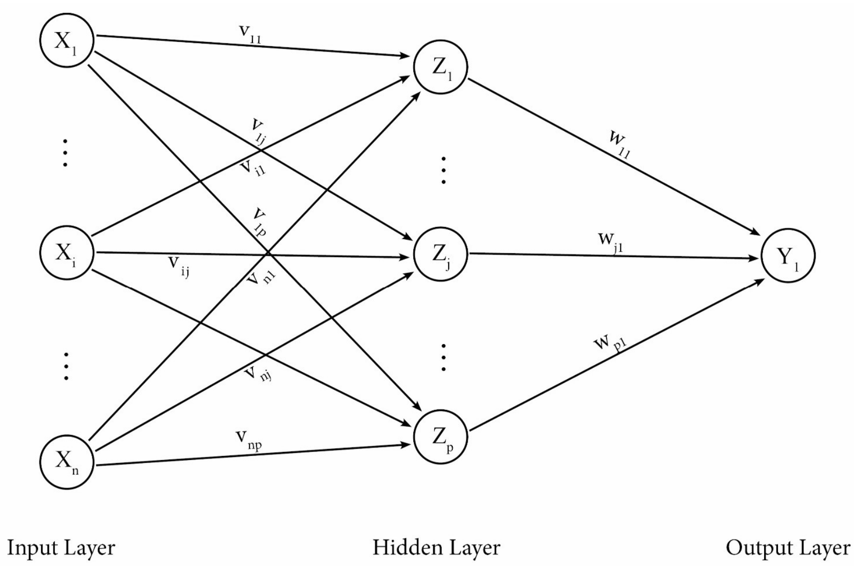

Figure 15. Diagram of a multilayer perceptron

Multi-layer perceptrons (MLPs) are one of the most effective artificial neural network models. It is capable of solving many problems such as forecasting, pattern recognition and function approximation. An MLP comprises o layers of neurons (or nodes). External information is received in the input layer and the problem solution is obtained in an output layer. Between the input layer and layers there are one or more layers that are called hidden layer. Acyclic arcs connect nodes in the lower layer to the adjacent higher layer (see Figure 15). Inputs are usually independent variables and outputs are dependent variables. The functional relation between them can be shown as follows:

$$y_n = f(x_1, x_2, \ldots, x_n)$$

One of the essential features of ANNs is the training, which is the process that determines weights on each arc that connect the nodes. ANNs should be trained in order to perform a desired task. An ANN performs complex non-linear mappings between the input and output neurons by means of the linking arcs. Training of multilayer perceptron is a supervised learning, which means that target value for each input pattern is always known. In the training process, free parameters of the neural network are calculated.

Training process starts with entering examples of the training set into the input nodes. In the first hidden layer, activation values are weighted and summed at each node. The sum is then transferred by an activation function into a value in order to be an input into the nodes in the next layer. An activation function determines the relationship between input and output of a node and a network (Zhang et al., 1998). In this study, sigmoid function was used as activation function. The sigmoid function is shown below:

$$f(x) = (1 + exp(-x))^{-1}$$

The training algorithm finds the weights that minimize an overall error metric such as the root mean square errors (RMSE). In this metric, the square root of all of the mean difference between the actual and predicted values is calculated by the following formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2}$$

One of the most important processes in developing a MLP, which is class of ANNs, is model selection. According to Haykin (2009) learning process of a multilayer perceptron is to encrypt an input-output mapping into the synaptic weights and thresholds with the desire that the network becomes well trained for learning from the past to generalize the future. The concept of cross-validation, which is a standard tool in statistics, is a key principle in model selection and assessing predictive ability of neural networks. In this technique, the dataset is randomly split into training sample and test sample. The training sample is further divided into separate subsets. Those are estimation subset that is used to select the model and validation subset that is used to validate the model. In order to avoid overfitting, the performance of the selected model is measured on the test sample, which is a diverse dataset from the validation subset.

More information about artificial neural networks can be found in Haykin (2009), Zhang et al. (1998) and Fausett (1994).

Development of ANNs

Three performance criteria were selected for the evaluation of exterior shading devices. The first one was the absolute difference between the simulated air temperature inside and comfort threshold of 23°C (ΔT). The second one was the absolute difference between simulated mean illuminance inside and the threshold value of 500 lx (ΔL). The last one was the percentage of view to the outside (V).

In the database generation process, a total of 500 examples of design variables of $\{X_{1,\ldots,}X_6\}$ and the response variables Y_1 (ΔT), Y_2(ΔL) and Y_3 (V) were quantified and stored in tables, for further use as data for developing ANN models.

For creating neural network models, a new tool called CIDEA[2] was utilized. CIDEA is a computational decision-support environment that was developed by Chatzikonstantinou (2016). The program consists of such modules as data analysis, predictive model training, optimization, etc. which can be coupled to make surrogate-based optimization.

The models that were prepared for the study are in the class of multilayer perceptrons (MLP), since they have one hidden layer, other than just having an input and output layer. According to the extensive review conducted by Zhang et al. (1998) ANNs with

[2] http://www.cidea.io

a single hidden layer are sufficient to approximate any complex non-linear function at any degree of accuracy. Therefore, number of hidden layers was not a parameter to search for in the model selection process that was conducted for finding best performing network models and avoiding over-training of the networks.

Prior to generating MLPs, three model selection operations were executed for three objectives to determine the network architectures (see Table 4. Search space, evaluation criteria and CV method for the model selection). The operation was performed by using datasets of annually optimized static model and hourly responsive kinetic model. For network architectures that would be used for responsive kinetic shading models, a dataset from a single hour was selected for testing network model, other than performing it to all the 50 datasets. The network architectures that outperformed remainders for the selected hour were used for developing the networks for the rest of hours for kinetic-responsive shading. For annually optimized static shading, this was not an issue because the network models used one dataset for annual performance. The results of the parameter tuning process are shown in Section 4.2.

For cross validation, Monte Carlo technique was implemented for both model selection and neural network training processes. Using Monte-Carlo, the randomly generated data sample was split into two random sub-samples by a factor of 0.1. That is, 450 random observations (corresponds to 0.9) in the datasets were used for neural network training purposes. To assess predictive ability of trained network on the unseen data, remaining 50 observations, namely test sample was used. This process was then iterated 10 times, generating new training and test partitions at random each time. The performance evaluation criteria for cross-validation is root mean square error that is subject to minimization.

Table 4. Search space, evaluation criteria and CV method for the model selection

No. Nodes in Hidden Layers	No. Iterations	Performance Criteria	Cross Validation
[4,20]	[500,10000]	Root Mean Square Error	Monte Carlo

Once the network architectures and number of iterations were determined for the models, the networks were trained using the data that contain simulation-derived examples. The multilayer perceptrons (MLP) were trained by Resilient Back-Propagation (RProp) algorithm. RProp is a fast learning algorithm for multilayer perceptrons that performs local adaptation of the weight-updates due to the act of the error function. More information on training algorithm used in the current study can be found elsewhere (Riedmiller & Braun, 1993).

In order for developing neural network models, we implemented a procedure, which can also be seen at Table 3. For each types of shading devices, diverse ANN models were developed for each of the three objectives. For responsive-kinetic shading type, we established 50 ANNs for each of the three objectives that aggregated 150 models in total. For static shading type, on the other hand, three network models were established for each of the three objectives. All the datasets were containing 500 randomly generated observations. However, 50 of the datasets, used for developing hourly ANNs for responsive shading, consisted observations from the 50 randomly sampled daylight hours of a year. A single dataset, used for developing annual ANNs for static shading, was a collection of 500 random observations over the course of a year (Table 5). The ANNs were used for the following purposes:

- Surrogate-based optimization: Hourly performance of responsive-kinetic shading device and annual performance of static shading device were optimized by using the related ANNs.
- Predictive models: Hourly performances of static shading devices were predicted by entering decision variables of annually optimized static shading as inputs to the predictive models that were generated for 50 sampled hours.

Table 5. Objectives and neural network models developed for the shading types

Shading Type	**Objective**	**Model**
	ΔT_R	$NN_{\Delta T1}$, $NN_{\Delta T2}$, $NN_{\Delta T3}$, … , $NN_{\Delta T50}$
Responsive-Kinetic	ΔL_R	$NN_{\Delta L1}$, $NN_{\Delta L2}$, $NN_{\Delta L3}$, … , $NN_{\Delta L50}$
	V_R	NN_{V1}, NN_{V2}, NN_{V3}, … , NN_{V50}
	ΔTs	$NN_{\Delta Ts}$
Static	ΔLs	$NN_{\Delta Ls}$
	Vs	NN_{Vs}

3.4.5. SURROGATE-BASED OPTIMIZATION

In the research, a surrogate method was employed in order to determine the three objective functions for each case. The surrogate models interpolated mathematical functions that relate design parameters to performance criteria. CIDEA tool allows referencing an ANN models as an objective function by turning it into a surrogate model.

HypE algorithm was employed for deriving optimal solutions with respect to Y_1 (ΔT), Y_2(ΔL) and Y_3(V). Bader and Zitzler (2008) proposed HypE as an evolutionary multi-objective optimization algorithm that is based on quality measure of hypervolume indicator. In their study, they compared the algorithm with other evolutionary optimization algorithms such as NSGA-II, SPEA2 and so on. Their results showed that HypE outperformed all the others, in multi-objective optimization problems with a dimension more than two (Figure 16). Therefore, HypE algorithm was the choice for the three-dimensional optimization problem that was formulated for the study of exterior shading devices.

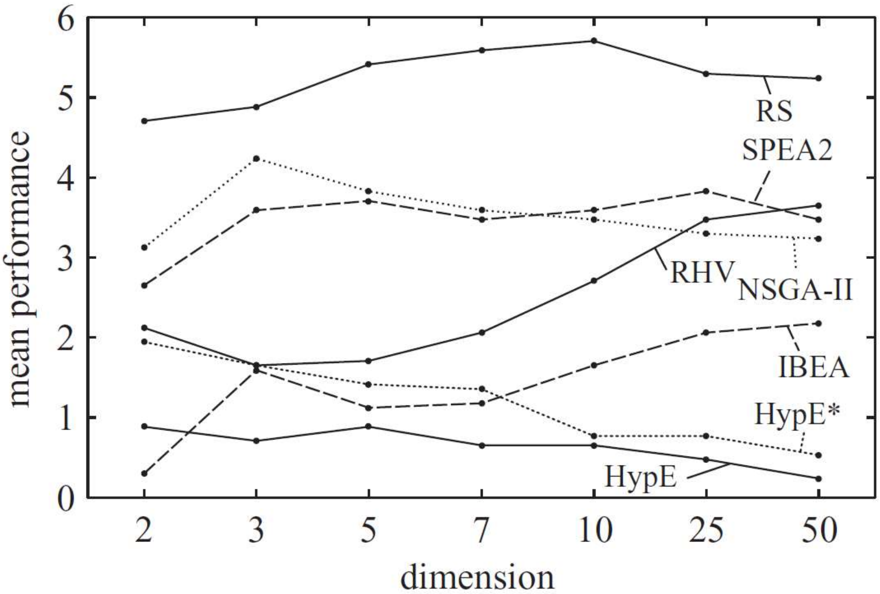

Figure 16. Comparison of various optimization algorithms with respect to number of objectives (Bader and Zitzler, 2008)

The objective functions that were used in the optimization problem are listed in Table 6. According to the problem formulation, while |T_{in}- 25 °C| and |Avg.Lux -500| was being minimized, (V) should be maximized, which formed an obvious conflicting situation (see Table 6). In the optimization phase, HypE algorithm was referenced to the neural networks for each objective functions.

Table 6. Objective functions for optimization problem

ID	Description
Objective 1	Minimize (Δ Temperature)
Objective 2	Minimize (Δ Lux)
Objective 3	Maximize (View to outside)

We used the default settings for optimization in order to generate 100 generations each having 100 populations. The settings that were used for optimization algorithm are listed in Table 7.

Surrogate-based optimization method was implemented for both types of conceptual shading devices in order to find best performing design alternatives. For responsive-kinetic shading 50 optimization operations were run for each randomly sampled daylight hours. For the static shading, only one optimization operation was performed to find best performing alternatives on an annual basis. At the end of the process, we extracted 100^{th} generation from each of the 51 optimization processes in total, for further operations.

Table 7. Optimization settings for HypE algorithm

Optimization parameter	Value
Population Size	100
Iterations	100
Hypervolume Samples	5000
Mutation Probability	0.1

3.4.6. PREDICTIVE MODELS

In order to study hourly performance of responsive-kinetic shading devices, 50 different ANN models were developed for each of the three objective functions. The models were created for 50 randomly selected hours of a year, between 9:00 am to 17:00 pm. Datasets for each hour were consisting of 500 examples which are produced by assigning random values to design parameters within the range of [0.00,180.00] and running simulations for the associative performances. For making comparison between annually optimized-static and hourly responsive-kinetic shading devices, we needed to find out the hourly performance of the static shading. For this purpose, we extracted 100^{th} generation of optimized design variables (rotation angles) of static shading. Subsequently, we used them as inputs to the hourly predictive models that we had generated for the responsive-kinetic shading. Because the neural networks already generated approximation functions between the same input and output parameters, we would use these functions for predicting hourly performance of static shading. Thus, we obtained the hourly performances of the static shading devices that were optimized for annual performance objectives.

3.4.7. HYPOTHESIS TEST

First, the selection of the type of hypothesis test was made. The data types that we generated are continuous. It was aimed to compare the means of the two processes, whether one of them is larger. The same set of items was measured under two different conditions (responsive-kinetic and optimized-static). Pair-T Test is the type of hypothesis test for our case, because it examines the mean difference between dependent observations whether they are significantly different (Minitab, 2016).

Paired t-tests were carried out for conducting a formal comparison among the performance of responsive-kinetic and optimized static shading devices. Initially, it was hypothesized that responsive-kinetic shading device would outperform optimized-static one for each of the three performance criteria. Three hypotheses were considered, which are as follows:

- $H_1 : \Delta T_R - \Delta T_S \leq 0$
- $H_2 : \Delta L_R - \Delta L_S \leq 0$
- $H_3 : V_R - V_S \geq 0$

4CHAPTER FOUR
RESULTS

The chapter introduces the results of the processes described at Chapter 3. The first section overviews the result of the data generation process. The second section demonstrates model selection process, which helped us selecting parameters for developing the neural network models. At the end of the process, we decided on number of hidden layers for concluding the network architecture and number of iterations for avoiding over-training of the neural network. The second section outlines the performances of each neural network models that were established by using the selected values from the previous section. In the following section, comparisons between static and responsive-kinetic shading devices for Izmir climate were demonstrated with respect to the given performance criteria. The final section outlines the test results for the null hypothesis of responsive-kinetic shading outperforms optimized-static shading.

4.1. DESCRIPTIVE STATISTICS OF THE GENERATED DATA

An automated process generated the data, as it was explained in section 3.4.3. At the end of the database generation process, 51 datasets were obtained for the consequent neural network development. This section demonstrates the descriptive statistics of the generated data.

Table 8 shows the descriptive statistics of decision variables (X_n) for shading control parameters. The generated data showed a normal distribution around the mean of approx. 90 with a standard deviation approx. fifty-two.

Table 8. Descriptive statistics of the decision variables

Date / Hours	X_1		X_2		X_3		X_4		X_5		X_6	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
24 JUNE 11:00	90,24	51,91	90,23	52,06	90,27	51,95	90,03	52,06	89,59	52,00	89,35	51,98
12 FEB. 11:00	90,00	52,08	89,74	51,97	89,91	52,02	89,94	51,86	90,11	51,99	90,59	51,96
19 DEC. 12:00	89,76	51,89	89,98	51,89	90,27	51,90	89,84	51,98	89,90	52,02	90,04	51,91
21 MAR. 10:00	90,24	52,07	89,86	52,00	89,91	52,02	90,10	52,04	90,06	51,89	89,84	51,98

Table 8 (cont'd). Descriptive statistics of the decision variables

Date / Hours	X_1		X_2		X_3		X_4		X_5		X_6	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
15 JULY 10:00	90,00	51,86	90,09	52,00	89,91	51,89	90,37	51,94	89,86	51,97	90,36	51,92
4 JULY 16:00	90,48	51,93	89,97	51,90	89,91	52,03	89,55	51,89	90,37	51,96	89,44	51,94
17 MAY 11:00	89,51	52,03	89,84	51,96	89,91	51,89	90,17	52,01	89,91	52,02	90,33	51,97
3 JAN. 11:00	90,11	52,06	89,95	51,96	89,91	51,89	90,34	51,90	89,76	51,99	89,93	52,01
26 FEB. 9:00	89,75	51,99	90,30	52,05	90,27	52,10	90,05	52,03	90,23	51,92	90,78	52,05
23 DEC.11:00	89,75	51,99	90,30	52,05	90,27	52,10	90,05	52,03	90,23	51,92	90,78	52,05
19 JAN. 15:00	90,58	52,03	90,18	51,93	89,90	51,94	90,32	51,91	90,03	52,06	89,50	52,03
13 MAY 14:00	89,62	52,04	90,05	52,03	90,26	52,09	89,86	52,06	89,83	52,01	90,38	52,07
30 OCT. 10:00	90,10	51,89	89,93	52,07	89,90	51,94	90,12	52,06	89,98	52,06	90,19	52,00
2 SEP. 12:00	89,86	52,13	90,16	52,00	89,90	52,08	90,03	51,97	89,78	51,91	89,63	52,05
20 APR. 15:00	89,98	51,95	90,04	51,98	89,90	51,94	89,93	51,97	89,94	52,07	90,51	52,00
13 DEC. 16:00	90,10	52,11	89,91	52,06	90,26	52,08	89,83	52,07	90,09	52,01	89,59	51,99
15 APR. 10:00	89,49	51,94	90,15	52,04	89,90	51,95	90,10	52,06	90,25	52,05	90,48	52,03
19 FEB. 15:00	90,33	51,95	90,02	51,91	90,26	52,07	90,00	51,91	89,69	51,93	89,92	51,96
27 SEP. 13:00	89,73	52,10	90,26	52,04	89,90	51,95	89,55	52,04	89,84	52,07	90,08	52,02
25 APR. 12:00	90,21	51,96	89,78	52,06	89,90	52,07	90,17	52,08	90,00	52,00	90,24	51,98
15 MAR. 15:00	89,61	52,12	90,37	51,98	89,90	51,95	90,43	51,98	90,16	52,04	89,33	51,98
9 OCT. 14:00	90,09	51,89	89,89	52,00	90,26	52,07	89,98	51,95	89,95	51,94	90,57	52,02
4 AUG. 14:00	90,56	52,06	90,12	52,06	89,89	51,96	89,88	52,06	90,11	52,07	89,65	51,96
31 OCT. 16:00	89,60	52,02	90,00	52,03	89,89	52,06	90,14	52,06	89,91	52,02	89,81	52,03
8 JULY 15:00	90,08	52,01	89,87	51,93	89,89	51,97	90,05	51,94	90,06	52,02	90,34	51,98
15 MAY 11:00	89,48	52,07	90,11	52,05	89,89	52,07	89,95	52,00	89,86	51,94	89,42	52,01
22 JAN. 10:00	90,32	51,88	89,99	52,06	90,25	51,97	89,86	52,09	90,01	52,06	90,30	52,04
28 MAR. 17:00	90,07	52,12	90,22	51,96	89,89	52,06	90,12	52,03	89,81	52,04	89,75	52,00
12 APR. 10:00	89,83	51,96	89,74	52,01	90,25	51,96	89,66	51,92	90,33	51,99	89,91	52,08
26 SEP. 13:00	90,31	52,09	90,33	52,06	89,89	52,07	89,93	52,06	89,76	51,97	90,07	52,03
14 NOV. 16:00	89,71	51,97	89,85	52,02	90,25	51,96	90,19	52,05	90,28	52,05	89,87	52,07
9 AUG. 12:00	90,55	51,92	90,08	51,95	89,89	52,07	90,09	51,97	90,08	52,06	90,40	52,03
6 APR. 16:00	89,59	52,12	89,60	52,05	90,25	51,95	90,00	51,97	90,23	51,96	89,84	52,00
28 AUG. 12:00	90,06	51,95	90,19	52,05	89,88	52,07	89,90	52,08	89,67	52,00	90,36	52,05
8 DEC. 11:00	90,18	52,13	90,07	51,94	90,24	51,95	90,17	52,05	90,19	52,04	90,16	51,98
4 OCT. 13:00	89,94	51,90	89,95	52,02	89,88	52,07	90,07	51,91	89,98	52,07	89,61	52,03
4 JUNE 16:00	90,42	52,02	90,18	52,06	89,88	51,94	89,97	52,05	90,14	51,94	90,49	51,99
17 SEP. 13:00	89,46	52,05	90,06	52,00	89,88	52,08	89,88	52,08	89,94	52,02	89,93	51,98
4 AUG. 11:00	90,66	51,98	89,93	51,97	90,24	51,94	90,14	51,97	90,09	52,02	90,09	52,02
18 APR. 9:00	89,69	52,10	89,81	52,06	89,88	52,08	89,68	51,96	89,89	52,07	89,90	51,96
3 OCT. 10:00	89,81	51,88	90,40	52,04	89,88	51,94	90,31	52,05	90,05	51,94	89,70	52,02
9 OCT 16:00	90,29	52,10	89,92	51,93	89,88	52,09	89,85	52,06	89,84	52,04	90,22	51,98
21 JAN. 12:00	89,69	51,97	90,15	52,03	89,88	51,94	90,48	51,93	90,00	52,00	89,66	51,98
30 MAR. 9:00	89,21	52,00	90,27	51,99	89,88	51,94	89,92	52,09	90,31	51,92	89,99	51,98
30 JUNE 17:00	90,04	51,91	89,78	51,99	90,23	52,09	90,19	52,01	89,75	52,06	89,79	52,05
24 SEP. 13:00	90,16	52,13	90,02	52,06	89,87	51,94	89,73	51,93	89,91	52,01	90,31	52,01
21 DEC. 10:00	89,92	51,95	89,89	52,04	90,23	52,08	89,99	52,06	90,06	52,06	89,40	52,02
6 JUNE 17:00	90,04	52,12	89,77	51,91	89,87	51,94	89,90	52,05	89,86	51,91	90,28	52,07
15 JAN. 15:00	89,80	51,92	90,00	52,04	90,23	52,08	90,16	51,96	90,02	52,07	90,08	52,03
ANNUAL (static)	89,59	52,01	90,27	51,96	90,10	52,01	89,85	51,95	90,04	52,00	89,64	52,05

Table 9 demonstrates the descriptive statistics of the response variables (Y_n) of shading control parameters of X_n. Among the response variables, Y_1 and Y_2 are dynamic objectives, air temperature and mean illuminance, respectively; which does not present a normal distribution around the means. In addition, simulated air temperatures inside are irresponsive to the outside temperatures. Recall that, the base case described at Section 3.1 was an adiabatic construction. That is, the heat transfer was only allowed from the south façade through glazing. The data generated for Y_3 (view to outside) showed a normal distribution around the mean of approx. 36.5 with a standard deviation approx. thirteen.

Table 9. Descriptive statistics of the response variables

Date / Hours	Y_1		Y_2		Y_3	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
24 JUNE. 11:00	13,92	0,86	635,68	622,19	36,59	13,06
12 FEB. 11:00	12,71	0,31	706,20	470,34	36,56	12,92
19 DEC. 12:00	5,76	0,02	1722,60	913,58	36,58	13,06
21 MAR. 10:00	2,32	0,18	471,35	351,41	36,53	13,01
15 JULY 10:00	14,61	0,61	225,35	226,42	36,64	13,30
4 JULY 16:00	15,78	0,64	115,41	80,61	36,56	12,89
17 MAY 11:00	13,94	0,31	385,55	288,16	36,59	13,06
3 JAN. 11:00	26,28	0,32	3706,70	2001,00	36,59	13,23
27 FEB. 11:00	6,49	0,29	1468,19	846,42	36,57	13,10
26 FEB. 9:00	3,30	0,16	159,77	113,69	36,55	12,97
23 DEC.11:00	3,30	0,16	159,77	113,69	36,55	12,97
19 JAN. 15:00	33,11	0,48	2209,39	1367,18	36,61	13,19
13 MAY 14:00	14,22	0,53	120,21	88,24	36,53	13,03
30 OCT. 10:00	0,79	0,12	160,58	109,48	36,55	13,26
2 SEP. 12:00	28,42	0,58	2574,17	1970,13	36,57	12,99
20 APR. 15:00	14,59	0,51	468,10	336,04	36,60	12,96
13 DEC. 16:00	2,92	0,08	336,21	71,18	36,49	13,11
15 APR. 10:00	3,00	0,13	159,62	114,46	36,60	13,19
19 FEB. 15:00	0,66	0,16	492,50	357,27	36,59	12,89
27 SEP. 13:00	36,33	0,62	3044,82	2309,73	36,59	13,02
25 APR. 12:00	13,07	0,58	1483,56	1138,10	36,51	12,92
15 MAR. 15:00	29,32	0,78	2453,53	1945,80	36,62	13,06
9 OCT. 14:00	32,52	0,50	1765,35	1148,91	36,59	13,16
4 AUG. 14:00	22,36	0,52	825,41	767,83	36,56	13,06
31 OCT. 16:00	23,12	0,35	302,99	233,27	36,59	12,88
8 JULY 15:00	10,86	0,73	263,95	198,86	36,60	12,77
15 MAY 11:00	13,01	0,50	636,29	624,36	36,58	13,12
22 JAN. 10:00	0,58	0,13	778,66	523,41	36,53	13,08
28 MAR. 17:00	12,73	0,45	146,02	102,18	36,63	13,28
12 APR. 10:00	18,79	0,56	1639,48	1258,15	36,58	12,81
26 SEP. 13:00	39,92	0,60	3897,65	2758,78	36,52	13,04
14 NOV. 16:00	20,73	0,34	163,49	116,18	36,60	12,92
9 AUG. 12:00	21,78	0,52	1612,70	1529,40	36,54	13,33
6 APR. 16:00	18,36	0,56	313,44	266,18	36,62	13,13
28 AUG. 12:00	27,91	0,56	2666,55	1817,70	36,49	13,10
8 DEC. 11:00	22,38	0,40	4502,90	1986,44	36,61	12,86
4 OCT. 13:00	37,95	0,63	3349,92	2228,83	36,60	13,21
4 JUNE 16:00	9,83	0,31	201,13	154,68	36,55	13,15
17 SEP. 13:00	25,73	0,45	2336,26	1693,17	36,60	13,26
4 AUG. 11:00	20,22	0,49	1026,54	920,89	36,56	13,03
18 APR. 9:00	9,30	0,44	257,96	198,14	36,59	13,08
3 OCT. 10:00	31,30	0,56	1355,85	1315,58	36,57	13,13
9 OCT 16:00	28,90	0,46	251,64	198,67	36,58	13,26
21 JAN. 12:00	0,77	0,13	355,72	266,33	36,62	13,03
30 MAR. 9:00	17,40	0,59	225,03	179,82	36,62	13,10
30 JUNE 17:00	13,36	0,65	152,43	96,31	36,57	13,09

Table 9 (cont'd). Descriptive statistics of the response variables

Date / Hours	Y_1		Y_2		Y_3	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
24 SEP. 13:00	32,36	0,52	3326,64	2139,35	36,56	13,10
21 DEC. 10:00	18,75	0,30	2031,19	1142,30	36,58	13,05
6 JUNE 17:00	11,24	0,65	142,41	95,47	36,52	12,94
15 JAN. 15:00	22,99	0,37	1005,50	745,91	36,63	12,89
ANNUAL (static)	14,23	0,33	206,24	151,68	36,52	13,08

4.2. MODEL SELECTION PROCESS FOR ARTIFICIAL NEURAL NETWORKS

The model selection process was conducted in order to determine the optimum number of training iterations and the number of neurons in the hidden layers. This process is referred to as parameter tuning. The dataset used for the parameter tuning, were randomly generated on annual and hourly basis for the static and responsive kinetic shadings, respectively. Monte Carlo technique was implemented for cross validation purpose. Using Monte-Carlo, the randomly generated sample data was separated into two random sub-samples by a factor of 0.1. That is, 450 random observations (corresponds to 0.9) in the datasets were used for neural network training purposes. To assess predictive ability of trained network on the unseen data, remaining 50 observations, namely test sample was used. This process was iterated for 10 times and cross validation RMSE value of the test sample is stored. Fifteen Neural Network alternatives, each housing random number of neurons in hidden layers and training iterations, were considered for each objective. The models with minimum RMSE values were selected as the final ANN models, which subsequently form objective functions.

4.2.1. MODEL SELECTION FOR HOURLY OBJECTIVE FUNCTIONS

An hourly set of observations was used in the model selection process for hourly objective functions. According to the results that is shown at Table 10, Table 11 and Table 12, neural network models with the IDs of NN_H-ΔT_{13}, NN_H-ΔL_8 and NN_H-V_{10} outperformed other options. Therefore, these network models were selected for training the datasets in order to develop the hourly objective functions.

Table 10. Results of the model selection for hourly ΔT objective for responsive-kinetic shading

ID	No. Training Iterations	No. Nodes in Hidden Layer	RMSE
NN_H-ΔT_1	3078	7	0.10
NN_H-ΔT_2	6507	9	0.08
NN_H-ΔT_3	5943	6	0.11
NN_H-ΔT_4	7559	4	0.15
NN_H-ΔT_5	4320	10	0.09
NN_H-ΔT_6	3676	7	0.10
NN_H-ΔT_7	4204	6	0.11
NN_H-ΔT_8	5431	4	0.15
NN_H-ΔT_9	9030	11	0.08
NN_H-ΔT_{10}	7941	11	0.08
NN_H-ΔT_{11}	1840	9	0.11
NN_H-ΔT_{12}	6855	4	0.17
NN_H-ΔT_{13}	8142	11	0.07
NN_H-ΔT_{14}	4731	5	0.10
NN_H-ΔT_{15}	9128	11	0.08

Table 11. Results of the model selection process for hourly ΔL objective for responsive-kinetic shading

ID	No. Training Iterations	No. Nodes in Hidden Layer	RMSE
NN_H-ΔL_1	1132	7	207.04
NN_H-ΔL_2	1797	7	202.06
NN_H-ΔL_3	7552	4	254.40
NN_H-ΔL_4	2930	6	210.44
NN_H-ΔL_5	6542	8	188.97
NN_H-ΔL_6	6195	8	197.28
NN_H-ΔL_7	5720	9	175.29
NN_H-ΔL_8	8994	11	134.19
NN_H-ΔL_9	8880	4	244.48
NN_H-ΔL_{10}	2337	7	203.12
NN_H-ΔL_{11}	2006	9	183.29
NN_H-ΔL_{12}	4036	5	251.06
NN_H-ΔL_{13}	1686	6	214.26
NN_H-ΔL_{14}	9546	10	186.47
NN_H-ΔL_{15}	2734	4	254.02

Table 12. Results of the model selection process for hourly V objective for responsive shading

ID	No. Training Iterations	No. Nodes in Hidden Layer	RMSE
NN_H-V_1	9598	8	5.19
NN_H-V_2	6297	7	7.22
NN_H- V_3	8757	9	4.19
NN_H-V_4	7891	5	9.64
NN_H-V_5	6877	4	10.52
NN_H-V_6	5958	10	4.31
NN_H-V_7	6314	6	8.55
NN_H-V_8	5993	4	10.70
NN_H-V_9	7331	7	7.26
NN_H-V_{10}	5018	10	3.72
NN_H-V_{11}	5013	5	9.10
NN_H-V_{12}	5140	6	7.67
NN_H-V_{13}	9827	10	3.89
NN_H-V_{14}	984	5	10.22
NN_H-V_{15}	7336	8	5.01

4.2.2. MODEL SELECTION FOR ANNUAL OBJECTIVE FUNCTIONS

The annual objective functions were developed for assessing the performance of static shading device. For these objectives, a randomly collected dataset over the course of the year were used for parameter-tuning process. According to the results that is shown at Table 13, Table 14 and Table 15, neural network models with the IDs of NN_A-ΔT_2, NN_A-ΔL_{14} and NN_A-V_3 outperformed other options. Therefore, these network models were selected for training the datasets in order to develop the annual objective functions.

Table 13. Results of the model selection for the annual mean ΔT objective for static shading

ID	No. Training Iterations	No. Nodes in Hidden Layer	RMSE
NN_A-ΔT_1	8764	6	0.16
NN_A-ΔT_2	6563	10	0.13
NN_A-ΔT_3	9174	11	0.14
NN_A-ΔT_4	1616	11	0.16
NN_A-ΔT_5	6372	6	0.16
NN_A-ΔT_6	8317	8	0.16

Table 13 (cont'd). Results of the model selection for the annual mean ΔT objective for static shading

ID	No. Training Iterations	No. Nodes in Hidden Layer	RMSE
NN_A-ΔT_7	7635	6	0.15
NN_A-ΔT_8	3388	4	0.21
NN_A-ΔT_9	7280	5	0.18
NN_A-ΔT_{10}	5186	5	0.19
NN_A-ΔT_{11}	7873	9	0.15
NN_A-ΔT_{12}	5253	7	0.15
NN_A-ΔT_{13}	5747	4	0.21
NN_A-ΔT_{14}	3492	7	0.16
NN_A-ΔT_{15}	7893	8	0.14

Table 14. Results of the model selection for annual mean ΔL objective for static shading

ID	No. Training Iterations	No. Nodes in Hidden Layer	RMSE
NN_A-ΔL_1	3244	11	108.88
NN_A-ΔL_2	5288	9	105.00
NN_A-ΔL_3	2351	4	125.76
NN_A-ΔL_4	4149	4	114.43
NN_A-ΔL_5	6179	6	118.53
NN_A-ΔL_6	5807	8	106.56
NN_A-ΔL_7	3988	6	113.87
NN_A-ΔL_8	6247	5	105.48
NN_A-ΔL_9	1301	6	113.79
NN_A-ΔL_{10}	4675	8	107.89
NN_A-ΔL_{11}	892	8	104.79
NN_A-ΔL_{12}	3919	6	110.92
NN_A-ΔL_{13}	5493	4	117.86
NN_A-ΔL_{14}	2947	11	100.16
NN_A-ΔL_{15}	9061	8	109.98

Table 15. Results of the model selection for annual mean V objective for static shading

ID	No. Training Iterations	No. Nodes in Hidden Layer	RMSE
$NN_A\text{-}V_1$	9657	9	5.59
$NN_A\text{-}V_2$	5495	10	4.78
$NN_A\text{-}V_3$	9746	11	3.88
$NN_A\text{-}V_4$	6417	8	5.55
$NN_A\text{-}V_5$	3568	6	8.18
$NN_A\text{-}V_6$	2596	6	8.54
$NN_A\text{-}V_7$	2627	9	6.84
$NN_A\text{-}V_8$	2868	8	6.56
$NN_A\text{-}V_9$	2130	8	6.75
$NN_A\text{-}V_{10}$	2993	9	5.91
$NN_A\text{-}V_{11}$	6058	9	5.86
$NN_A\text{-}V_{12}$	6265	4	9.84
$NN_A\text{-}V_{13}$	3197	9	5.77
$NN_A\text{-}V_{14}$	4072	6	8.52
$NN_A\text{-}V_{15}$	821	9	8.23

4.3. TRAINING RESULTS FOR HOURLY AND ANNUAL OBJECTIVE FUNCTIONS

The selected model parameters in Section 4.2 were used for training hourly and annual datasets for establishing artificial neural network models (ANNs). The performance statistics of hourly based and annually based ANNs are demonstrated respectively at Table 16 and Table 17. Training and cross-validation results are given in the same table in order to outline the predictive strength of the models.

Table 16. Performance of the neural networks for responsive kinetic shading

ID	ΔT (°C)		ΔL(Lux)		V(%)	
	RMSE (Training)	RMSE (CV)	RMSE (Training)	RMSE (CV)	RMSE (Training)	RMSE (CV)
NN-01	0.08	0.09	108.72	177.65	3.09	4.26
NN-02	0.07	0.08	117.30	127.32	3.17	3.75
NN-03	0.03	0.05	220.15	174.11	4.48	4.96
NN-04	0.04	0.06	85.07	137.42	5.79	5.58
NN-05	0.31	0.42	100.46	202.54	5.10	4.59

Table 16 (cont'd). Performance of the neural networks for responsive kinetic shading

ID	ΔT (°C)		ΔL(Lux)		V (%)	
	RMSE (Training)	**RMSE (CV)**	**RMSE (Training)**	**RMSE (CV)**	**RMSE (Training)**	**RMSE (CV)**
NN-06	0.32	0.44	47.99	77.07	2.94	5.69
NN-07	0.10	0.14	99.27	134.11	2.89	4.93
NN-08	0.06	0.09	268.50	381.63	3.12	5.15
NN-09	0.09	0.12	179.67	277.30	2.86	4.64
NN-10	0.02	0.03	10.74	13.92	4.69	4.89
NN-11	0.05	0.06	62.32	96.64	3.07	5.64
NN-12	0.07	0.11	351.41	451.16	4.48	4.49
NN-13	0.29	0.37	49.61	72.09	3.42	4.80
NN-14	0.03	0.04	63.71	95.01	3.86	4.77
NN-15	0.15	0.19	404.90	744.74	6.57	4.79
NN-16	0.16	0.22	84.35	137.00	3.32	5.04
NN-17	0.02	0.03	15.07	10.20	3.13	3.91
NN-18	0.04	0.05	62.81	94.55	5.34	4.31
NN-19	0.04	0.06	109.34	166.63	4.66	5.41
NN-20	0.11	0.15	691.99	780.94	4.05	5.60
NN-21	0.19	0.26	411.94	520.35	3.25	6.38
NN-22	0.16	0.22	296.06	464.95	4.28	5.13
NN-23	0.11	0.15	386.04	485.67	3.02	5.18
NN-24	0.19	0.27	279.17	487.76	4.34	4.27
NN-25	0.08	0.10	97.80	146.79	4.38	5.60
NN-26	0.36	0.53	84.30	131.36	3.30	4.42
NN-27	0.24	0.33	347.25	387.87	3.28	4.51
NN-28	0.03	0.04	131.68	187.61	3.38	7.09
NN-29	0.11	0.15	53.22	73.48	4.56	5.99
NN-30	0.14	0.19	295.58	531.87	3.05	5.06
NN-31	0.11	0.14	469.29	654.62	4.01	4.19
NN-32	0.06	0.08	76.25	106.18	3.01	5.05
NN-33	0.21	0.27	382.91	768.77	2.81	4.94
NN-34	0.14	0.17	106.98	155.75	2.89	5.30
NN-35	0.16	0.20	415.13	632.68	3.21	5.33
NN-36	0.05	0.08	425.33	509.40	4.95	6.17
NN-37	0.10	0.14	469.56	707.46	4.76	5.37

Table 16 (cont'd). Performance of the neural networks for responsive kinetic shading

ID	ΔT (°C)		ΔL(Lux)		V(%)	
	RMSE (Training)	RMSE (CV)	RMSE (Training)	RMSE (CV)	RMSE (Training)	RMSE (CV)
NN-38	0.16	0.21	76.17	111.30	3.39	5.04
NN-39	0.11	0.12	258.92	392.58	3.84	5.79
NN-40	0.21	0.36	355.21	564.56	4.74	4.91
NN-41	0.13	0.19	88.83	136.89	5.02	5.13
NN-42	0.11	0.13	329.78	770.06	3.28	6.51
NN-43	0.11	0.14	92.21	144.46	3.15	5.47
NN-44	0.03	0.04	109.27	138.94	3.17	4.30
NN-45	0.15	0.20	82.58	147.22	3.24	5.09
NN-46	0.35	0.44	29.93	50.98	4.45	5.21
NN-47	0.11	0.13	477.74	659.09	4.62	4.83
NN-48	0.08	0.07	157.08	246.23	3.01	6.47
NN-49	0.07	0.07	226.39	355.04	3.09	5.36
NN-50	0.07	0.08	193.45	286.04	3.04	5.16

Table 17. Performance of the neural networks for static shading

ID	ΔT (°C)		ΔL(Lux)		V (%)	
	RMSE (Training)	RMSE (CV)	RMSE (Training)	RMSE (CV)	RMSE (Training)	RMSE (CV)
NN_s-01	0.10	0.14	72.35	105.35	3.04	3.85

4.4. OPTIMIZATION OF SHADING CONTROL PARAMETERS

Performance optimization process for both types of shading devices were performed as it was explained Section 3.4.5. Objective functions developed by training the related datasets, were used as surrogates for optimization process for both static and responsive-kinetic shading types. For the responsive-kinetic shading type, 50 surrogate-based optimizations were performed for the three objectives, in order to find best-performing shading control parameters for the randomly sampled hours. On the other hand, the static shading was optimized by using objective functions that were developed on an annual basis.

At the end of the process, we obtained 50 sets of optimized decision variables for 50 randomly selected daylight hours for the responsive shading and one set of optimized decision variables for the static shading. Each of the 51 decision variable sets is consisted of 100 optimized design alternatives. Samples of the optimized shading configurations for both type of shadings are displayed in Figure 17 and Figure 18.

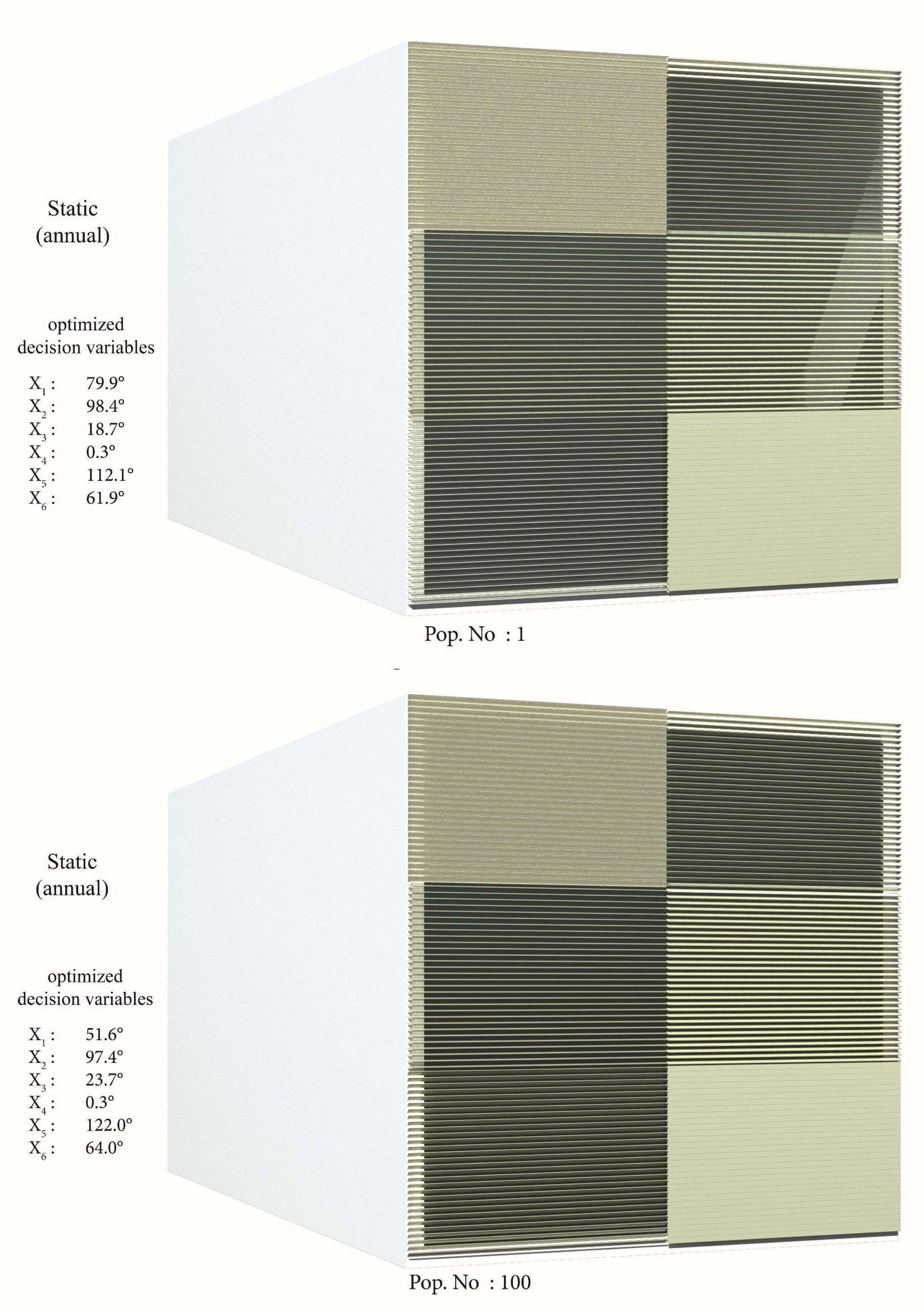

Figure 17. Visualizations of some optimized static shading configurations

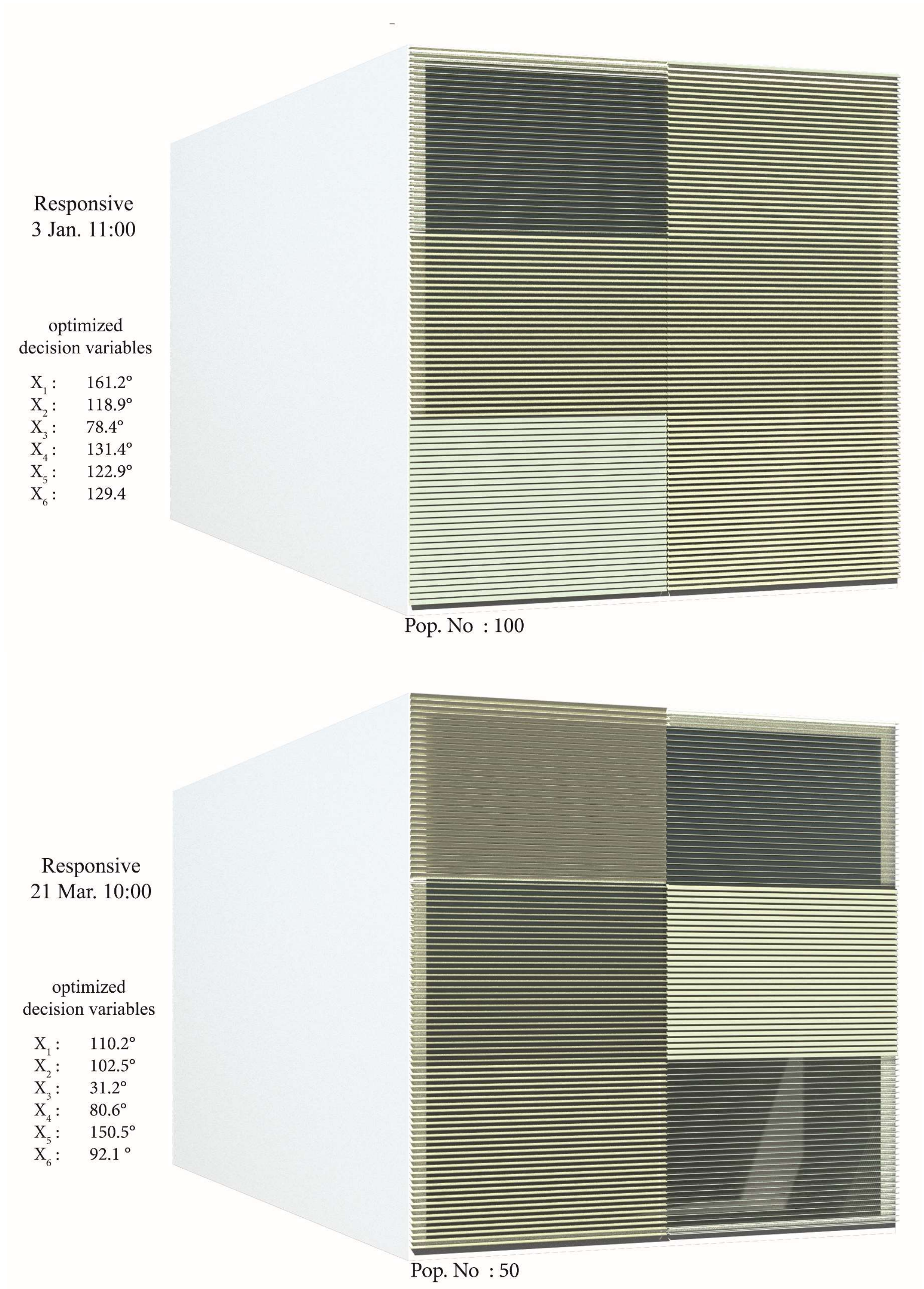

Figure 18. Visualizations of some responsive kinetic shading configurations

4.5. COMPARISON OF STATIC AND RESPONSIVE-KINETIC SHADING DEVICES

One of the aims of the research was making a formal comparison of the performances between an annually optimized static shading device, and a kinetic shading device whose movement was optimized on an hourly basis. So far, we obtained hourly performance values of the responsive shading and annual performance values of the static shading. For performing a comparison between the two types of shadings, it was required to find out how the annually optimized shading type performs at each of the hours. For this purpose the ANNs, developed for hourly objective functions, were used as predictive models. In order for making a prediction of hourly performances of the static shadings, the sets of decision variables that were obtained from the optimization process of the static shading device were used as inputs for the hourly predictive models. Thus, hourly performance values of the static shading device alternatives, which were actually optimized on an annual basis, were obtained.

Finally, the comparison was performed between the means of the identical performance values that belong to the two types of shading systems for the randomly sampled daylight hours. The comparisons of the optimized-static and responsive-kinetic shading devices with regard to performance criteria of temperature difference (ΔT), mean illuminance difference (ΔL) and percentage of view to outside (V) are reported in Figure 19, Figure 20 and Figure 21, respectively. The lower the ΔT and ΔL values the better, since the objective was minimizing these values. That is, the difference between the simulated performances and the threshold values of 23°C and 500lx, respectively, should converge to zero. On the other hand, the third objective was maximizing view to outside (V) from the given point placed at the center of the indoor space. Therefore, higher V values are meaning a better performance for this objective.

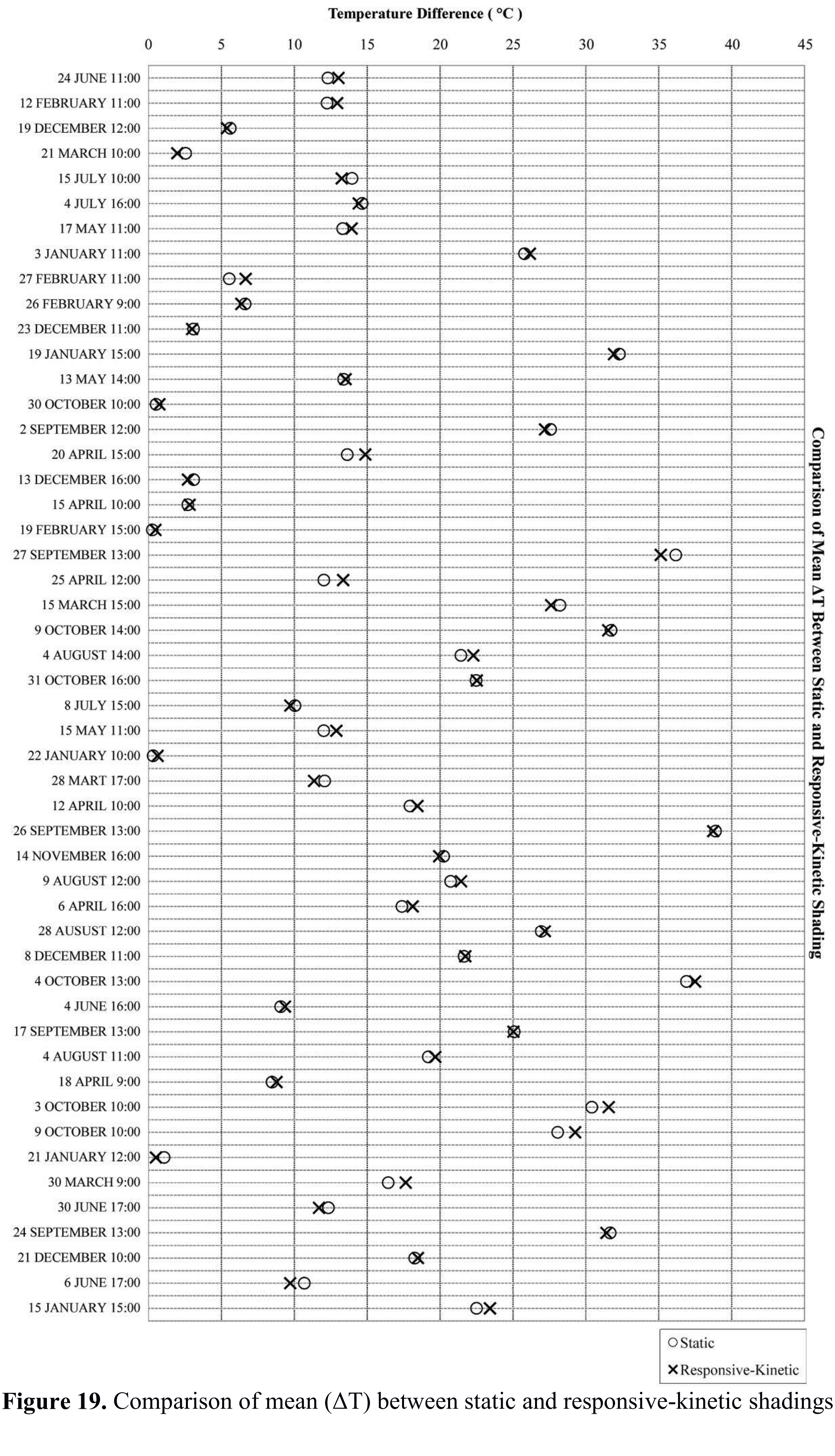

Figure 19. Comparison of mean (ΔT) between static and responsive-kinetic shadings

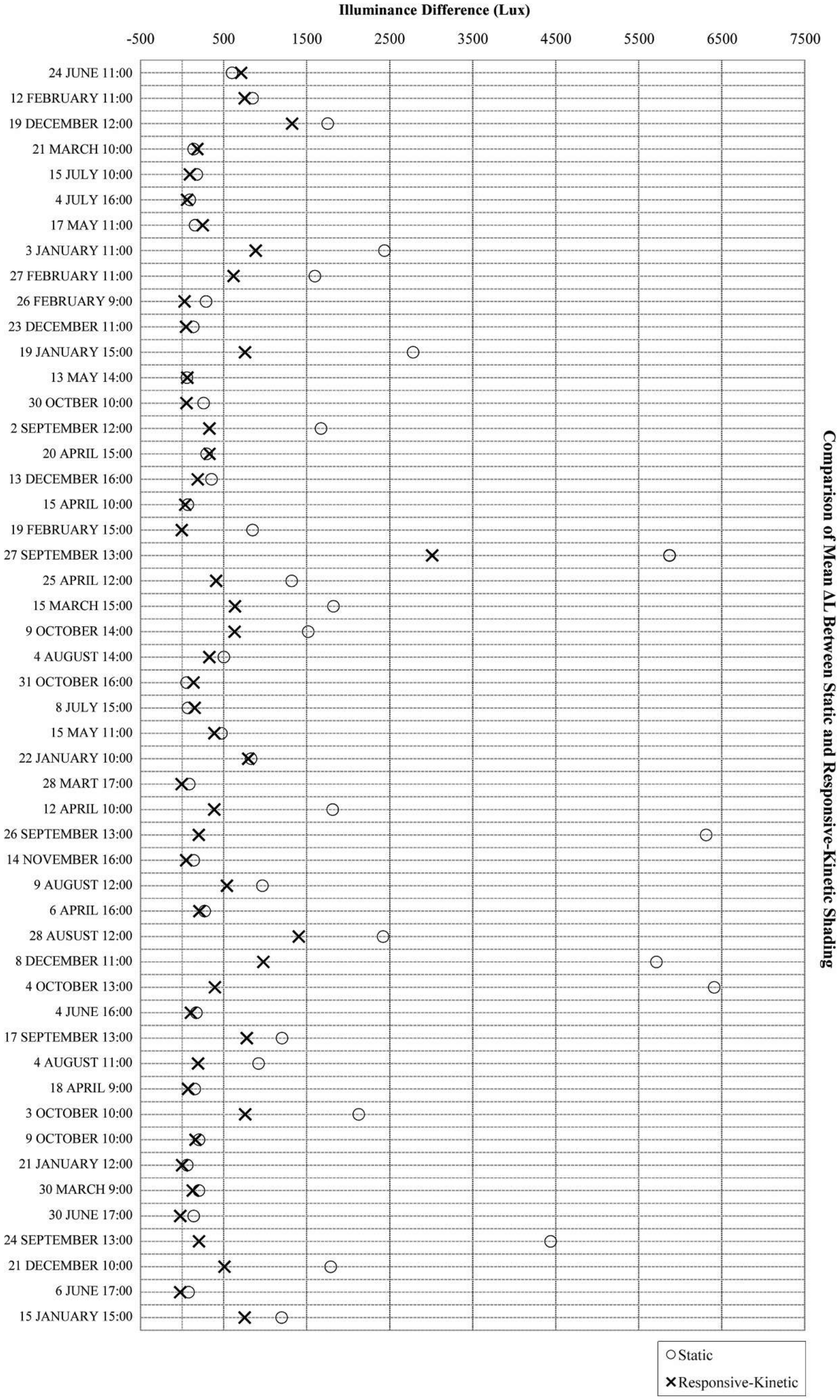

Figure 20. Comparison of mean (ΔL) between static and responsive-kinetic shadings

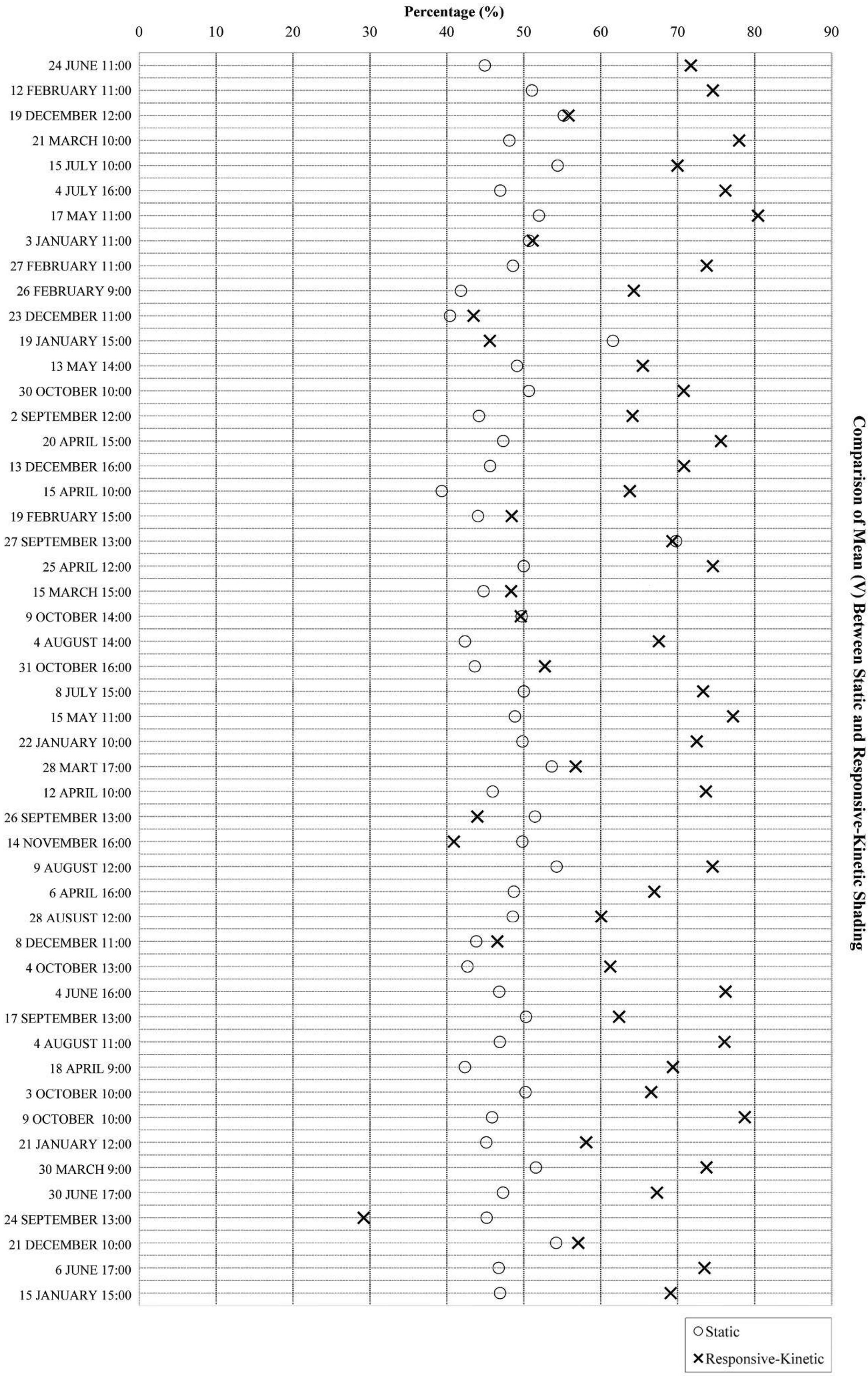

Figure 21. Comparison of mean (V) between static and responsive-kinetic shadings

4.6. TEST OF HYPOTHESES

In order to conduct a formal comparison among the performance criteria, we implemented Paired-T Tests. Initially, we hypothesized that responsive-kinetic shading device would outperform optimized static one for each of the three performance criteria. Three hypotheses were considered which were as follows:

- $H_1 : \Delta T_R - \Delta T_S \leq 0$
- $H_2 : \Delta L_R - \Delta L_S \leq 0$
- $H_3 : V_R - V_S \geq 0$

4.6.1. RESULTS FOR (ΔT) PERFORMANCE OBJECTIVE

According to the paired t- test for ΔT criteria, there is not enough evidence to conclude that the mean of responsive-kinetic shading is less than static shading at the 0.05 level of significance (Table 18). The distribution of differences can see seen at Figure 22.

Table 18. Pair t-test statistics for ΔT

	N	Mean	St. Dev.	SE Mean
ΔT_R	50	16,77	10,58	1,50
ΔT_S	50	16,60	10,61	1,50
Difference	50	-0,1698	0,6237	0,0882
mean difference = 0 (vs > 0):		*t*-Value = -1,93		P(*t*) = 0,970

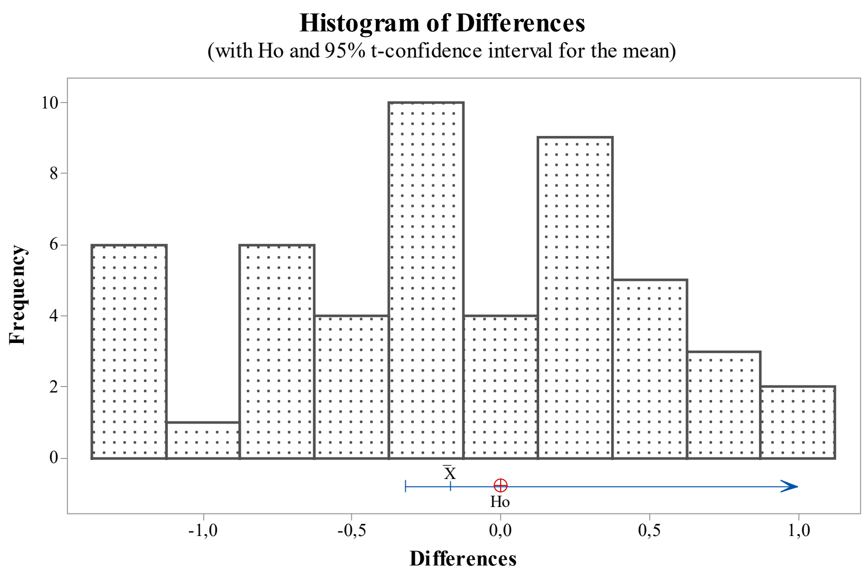

Figure 22. Distribution of differences for $H_1 : \Delta T_R - \Delta T_S \leq 0$

4.6.2. RESULTS FOR (ΔL) PERFORMANCE OBJECTIVE

Paired t-test for ΔL criteria suggests that at the 0.05 level of significance, we can conclude that the mean of responsive-kinetic shading is less than static shading (Table 19). The distribution of differences can see seen on the histogram at Figure 23.

Table 19. Pair t-test statistics for ΔL

	N	Mean	St. Dev.	SE Mean
ΔL_R	50	420	513	73
ΔL_S	50	1277	1696	240
Difference	50	857	1474	208
mean difference = 0 (vs > 0):		*t*-Value = 4.11		P(*t*) = 0.000

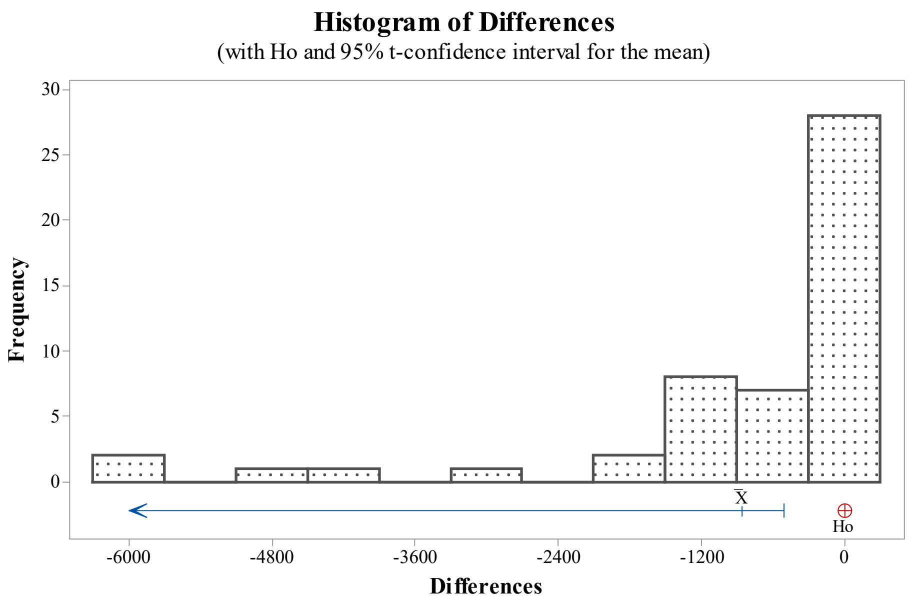

Figure 23. Distribution of differences for $H_1: \Delta L_R - \Delta L_S \leq 0$

4.6.3. RESULTS FOR (V) PERFORMANCE OBJECTIVE

According to the results of the paired t-test for (V) objective, we can conclude that the mean of V_R is significantly greater than the mean of V_S. That is responsive-kinetic shading performs better than the static shading (Table 20, Figure 24).

Table 20. Pair t-test statistics for V

	N	Mean	St. Dev.	SE Mean
$\mathbf{V_R}$	50	64.22	11.98	1.69
$\mathbf{V_S}$	50	48.45	5.22	0.74
Difference	50	15.76	12.77	1.81
mean difference = 0 (vs > 0):		*t*-Value = 8.73		P(*t*) = 0.000

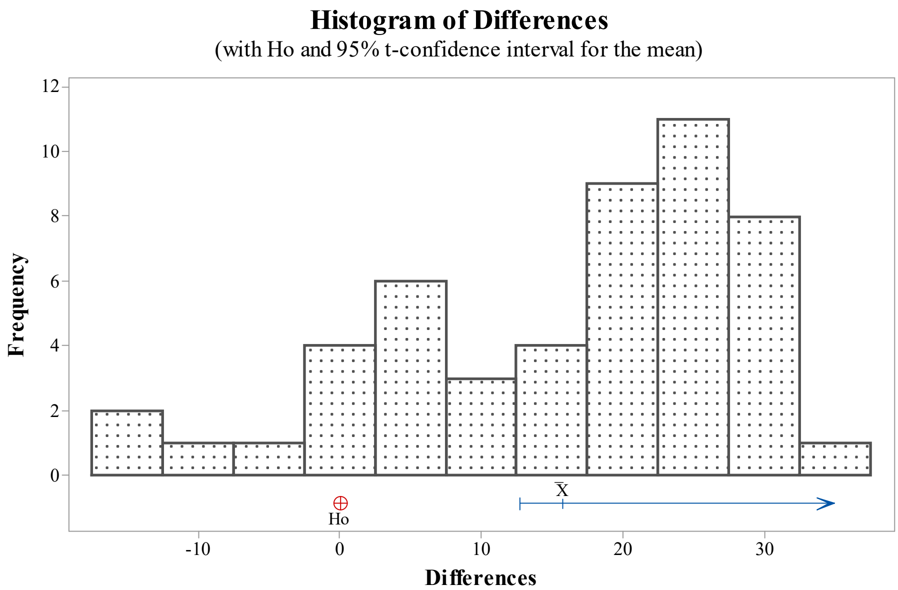

Figure 24. Distribution of differences for $H_1: V_R - V_S \geq 0$

5CHAPTER FIVE
DISCUSSION

The current research initially introduced the aim of reducing computational costs of the performance-based investigation of responsive kinetic shading devices. We achieved this goal by integrating surrogate models to the design process. Prior to implementing surrogate-based optimization, several tests were conducted by using multi-criteria optimization method for the conceptual design of responsive shadings for arbitrarily selected daylight hours. In these tests, satisfactory solutions for a single hour of a year emerged only after a process that last for more than 24 hours. On the other hand, when utilizing surrogate models the computational costs reduced significantly. The investigation of the performance for the responsive kinetic shading device, at 50 randomly sampled daylight hours lasted for about 105 hours. The computer conducted most of the process in an automated fashion.

The research established a novel framework for adequately exploring design alternatives and optimizing performance of control parameters of responsive-kinetic shading devices with respect to the proposed objectives. The urge for developing a framework stemmed from the absence of an efficient method for exploring and evaluating the performance of responsive-kinetic shading devices in the early design phases. Furthermore, a formal comparison of annually optimized static and hourly responsive-kinetic shading devices was presented. To our knowledge, there is no formal comparison in the literature between static and responsive-kinetic shadings whose performances are optimized with consideration of thermal, daylight and view objectives in the same design problem.

Parametric design approach offers a great potential for investigating variations in design process. When coupled with performance simulation tools, the approach becomes even more powerful. Although the nature of performance-based parametric design approach is very suitable for kinetic design of façade components, after a comprehensive review of the literature, we had the opinion that there is a lack in utilizing the full potential of the approach in conceptual design of responsive-kinetic shading devices. Some of the studies regarding the conceptual design of responsive-kinetic shading devices in literature run short at utilizing these powerful techniques for their purpose, mainly because of technical inadequacies in dealing with the complexity of the problem at hand. Therefore, they needed to over-simplify the design problem. For instance, Kensek and Hansanuwat (2011), Nielsen et al. (2011), Du Montier et al., (2013), Lee et al. (2016) and Grobman et al., (2016) examined performances of the responsive kinetic shading devices with a limited number of shading control variations that they previously determined. Thus, they had better control over their investigations. What they found out was best performing alternatives within the set of limited options within the ranges. However, they would have a much broader design space to operate on, if they had enhanced the parametric approach with computation.

In 2006, Beesley et al. anticipated the challenge for future researchers about how to explore design space of parametric models. Today, this challenge is still valid in the field of design research, more particularly in the conceptual design of responsive-kinetic shading devices. In order to achieve a better exploration of design space, researchers have implemented computational problem-solving techniques in the design problems.

Utilization of computational problem-solving techniques in the research of responsive kinetic shading systems is far from satisfactory. There are very few studies in the literature that made use of computational decision support techniques. El Sheikh and Gerber (2011) and Sharaidin et al. (2012) offered simulation-based optimization approaches for the design exploration of shading configurations, which would respond to dynamic conditions. They both used of a genetic algorithm for daylight performance exploration. However, they could only investigate limited number of weather conditions that they previously determined. This must have been due to the longer simulation times, which constitutes a bottleneck effect in the search process, and the nature of the search algorithm they used, which requires longer time for converging to satisfactory solutions. Furthermore, in another type of architectural design problem about daylighting, Wortmann et al. (2016) showed that surrogate-based optimization outperforms genetic algorithms.

Using artificial neural networks as surrogate models offers a time-efficient way for performance assessment of shading systems. The reason for this is not just because surrogate-based optimization provides better results, but also the technique has a much lower computational cost. Solutions can be obtained in a much faster manner. Therefore, surrogate-based optimization techniques can offer an even broader exploration potential in the conceptual design of responsive-kinetic shading devices. However, there is a gap in the literature about the use of surrogate-based optimization technique in the conceptual design of responsive-kinetic shading devices.

The current research utilized a surrogate-based optimization technique for investigating performance of the proposed responsive-kinetic shading device. By doing this, we were able to explore the performance of the shading at the design hours in an efficient manner. Most notable, this is the first study to our knowledge that investigates thermal, daylight and view objectives in the same optimization problem for the conceptual design of responsive-kinetic shading devices. The approach that was used for this purpose consisted of the following main phases for each hour:

1. Parameter initialization
2. Database generation
3. Neural network development
4. Surrogate-based optimization

Within the scope the research, we examined 50 daylight hours of a year. However, the method can easily be applied to all of the daylight hours over the course of a year. In this way, the annual performance of a responsive-kinetic shading device can be observed.

Some studies in the literature, aimed at obtaining annual performance of the responsive shadings by using Useful Daylight Illuminance (UDI) metric (Hu and Oblina, 2011; Grobman et al., 2016). However, UDI is a metric to assess daylight performance on an annual basis. It is calculated by averaging the occurrence of daylight illuminance at each daylight hours within a year. In order to use this metric, one should have all of the illuminance values at each hour. The studies that presented annual reports with inadequate sampling are prone to big errors, since most of the weather conditions will be out of consideration. We believe that the performance of a kinetic shading device that can respond to environmental changes requires to be examined for each single time point, because of the dynamic character of weather conditions. For this reason, working with smaller time steps such as hours, seemed appropriate for our purpose. Therefore, such point in time performance metrics as illuminance and hourly air temperature were employed for the dynamic metrics. Another performance metric that we used was the percentage of view to the outside, which is not a dynamic metric as the others. Reinhart et al. (2006) mentioned that view to outside consideration is less meaningful for movable shading devices, because it will lower itself to avoid glare. However, in an optimization problem that aims at maximizing view for psychological and physical well-being, this objective becomes an issue for trade-off.

The second aim of the research was conducting a formal comparison of performances between optimized-static and responsive-kinetic shading devices in a controlled experiment. The performance criteria were examined for the responsive-kinetic shading and optimized static shading types at 50 randomly sampled daylight hours with this motivation. The means of the two conditions were compared to find out whether the responsive-kinetic option has a better contribution to the performance objectives. The same base was measured under the influence of two different conditions. With the paired t-test, mean differences between the dependent observations were compared if they are significantly different. The tests were conducted for each of the three performance objectives.

The first performance objective function was minimization of ΔT. Therefore, we expected lower ΔT values for responsive-kinetic shading type. However, our findings suggested the opposite, that there was not enough evidence to conclude that the mean of responsive-kinetic shading is less than static shading at the 0.05 level of significance. We found out that the mean of ΔT_R is 16.77 °C, while the mean of ΔT_S is 16.60 °C. In an indoor space with a solely southern-exposure to the sun in Izmir climate, responsive-shading devices may not contribute to thermal comfort and energy efficiency better than an optimized static shading device. It is important to notice that we had other objective functions in the optimization problems for both observations. The function of view to outside maximization might have influenced this result, since it is an obviously conflicting objective in most of the weather conditions.

The second performance objective function was minimization of ΔL, that is, the difference of simulated mean illuminance inside and the threshold value of 500 lx. As in the first objective we aimed at minimizing it in order to make the average daylight intensity as close to 500 lx as possible. In the comparison test for ΔL objective, we found that, the responsive-kinetic shading performs significantly better than optimized the static shading at the 0.05 level of significance. We found out that the mean of ΔL_R

is 420 lx, while the mean of ΔL_S is 1277 lx. The daylight performance of responsive-kinetic shading is almost three times better than the optimized static shading according to the findings. However, it must be noticed that five of the paired differences were unusual, that is the difference between the pair is much more than the trend (see Figure 20). This situation contributed to the increase in the total mean difference. Nonetheless, we can be 95 % confident that the true mean difference is less than 507 lx and 90 % percent confident that it is between 507 and 1206 lx.

The final objective function for the performance evaluation was percentage of view to outside (V). Maximization was intended for this function, therefore the more the V values, the better for our purpose. The findings suggest that the mean of V_R and V_S is 64.2 and 48.4, respectively. As reported in the results, we can conclude that the mean of responsive-kinetic shading is significantly greater than the mean of optimized static shading at the 0.05 level of significance. We can be 95% confident that true mean difference is greater than 12.7, and 90% confident that it is between 12.7 and 18.7.

In the experiment, three hypotheses were put forward, that were H_1, H_2 and H_3. At each of these, it was hypothesized that the responsive-kinetic shading type would outperform the optimized static one. However, the results of Paired-T Tests showed that, while H_2 and H_3 are true, H_1 is false. That is, while responsive kinetic shading outperformed optimized static with respect to daylight intensity and view to outside, there was no significant difference in the comparison of the impacts of the two types of shadings on indoor air temperature. The reason for this result may be related with the formulation of the experiment. The controlled experiment was designed for investigation of sole impact of sunlight on the interior environment. The solar beams has two diverse but related aspects, namely thermal and daylight. Heat energy cannot reflect but radiate. Both of the shading devices intercepted the heat energy of solar beams on the outside in a similar manner. However, daylight aspect of solar beams were managed much better by responsive kinetic shading type. Performance objective about view in the design problem statement, which is not a dynamic measure that conflicts with the other objectives, must have contributed to this situation.

Our results provide compelling evidence in the comparison of the two types of shading devices with respect to the given performance objectives that are based on air temperature, illuminance and percentage of view. However, more experiments should be conducted in order to have a grasp of the true nature of the problem. Future work, therefore, may be designed to evaluate temperature & view and daylight & view objectives paired with each other.

6CHAPTER SIX
CONCLUSIONS

The research examined the problem of exploring and evaluating the performance of responsive-kinetic shading devices, and comparing the performance with the optimized static version of the same shading system that uses identical shading control parameters. For this purpose, a framework was developed for aiding the decision-making in a time-efficient way. The framework consisted of a computational workflow with several main phases. In the first phase, a database was generated by simulating and recording the input and output values of 500 examples in an automated manner for each of the 50 randomly selected daylight hours for responsive shading. For the static shading 500 random examples were generated over the course of a year. In the second step, artificial neural network models were developed by using the database. In the last step, the neural networks were used as surrogates for the multi-objective optimization process. The optimizations were run for 100 times for each case and 100th generations were extracted for further investigation. Thus obtained the optimized sets of input and output values for each of the 50 randomly sampled daylight hours (responsive) and a year (static). Using surrogate-based optimization approach in the workflow provided us to conduct a broader design exploration in a time-efficient manner. Most notably, this is the first study to our knowledge to investigate a multi-dimensional design problem of responsive-kinetic shading devices by utilizing a surrogate-based optimization approach.

The current study employed the proposed framework in an experimental case that was designed for comparing the performance of optimized static and responsive-kinetic shading types. It was hypothesized that responsive kinetic shading would outperform optimized static shading at all of the performance objectives. Hourly optimum responses for the kinetic shading were found by using hourly data in the surrogate models, which were used in the subsequent multi-objective optimization process. In order to optimize rotation angles for static shading, we made use of surrogate-based optimization technique again with the same objectives; but this time, it was based on the data consisting of 500 random examples generated for the course of a year. Thus, we generated optimum decision variables for the static shading. However, for the comparison between the two types of shadings, it was required to find out hourly performance of the static type as well. For making the comparison with hourly responsive-kinetic shading device, we extracted 100th generation of optimized design variables (rotation angles) of the static shading, and used them as inputs to the predictive models that we had generated for the responsive-kinetic shading type. Because the neural networks already generated functions between the same input and output parameters, we would use these functions for predicting hourly performance of static shading. Thus, we obtained hourly performances of optimized set of static shading control variables. After having hourly performance values of both types of shading systems, we conducted hypothesis tests for each of the performance objectives.

A surprising outcome of the comparative study was the result that the optimized static shading outperformed the responsive-kinetic one in the objective of ΔT (simulated air temperature – 23°C) with a small mean difference. In ΔL (simulated mean daylight intensity – 500 lx) and V (view to outside) objectives, the responsive-kinetic shading significantly outperformed the optimized-static shading. Thereby, we presented a novel approach for comparison of performances between optimized static and responsive kinetic shading devices in the conceptual design phase.

The thesis examined conceptual design of shading devices from the perspective of solar control and comfort. It employed parametric modeling and simulation engines for quantifying the performance of the two types of exterior shading devices. The impact of the two examples on a hypothetical indoor space was observed for 50 randomly sampled daylight hours in a year. The study presented an approach for hourly comparison for the sampled hours. In order to drive an annual inference, all of the weather conditions in daylight hours should be examined. For the study, structural aspects were neglected. Influence of wind on shading devices were out of the scope of the thesis. The proposed framework was tested by using EnergyPlus weather data (EPW) of Izmir, Turkey. However, it can easily applied for diverse climates by using related EPW files.

In the future works, the relationships between weather conditions, design variables and performance objectives should further be examined. Certain weather parameters, such as global illuminance, global radiation, are required to be extracted from the weather file and match with the design and response parameters, to picture the relationships between them. Along with that, ANN models may be developed for various weather scenarios. Therefore, the problem will not be dependent on time parameter and responsive-kinetic shading device will not need to be optimized on the time basis; but it will be based on the response to various environmental conditions. In addition, optimization may be run with hard constraints, and with fewer objectives. Most importantly, physical prototypes may be developed in order to validate the results. Real-time prediction and optimization for the prototype is on the agenda as well.

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