

An Adaptive Intelligent Integrated Lighting Control Approach  
for High-Performance Office Buildings

by

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## ABSTRACT

An acute and crucial societal problem is the energy consumed in existing commercial buildings. There are 1.5 million commercial buildings in the U.S. with only about 3% being built each year. Hence, existing buildings need to be properly operated and maintained for several decades. Application of integrated centralized control systems in buildings could lead to more than 50% energy savings.

This research work demonstrates an innovative adaptive integrated lighting control approach which could achieve significant energy savings and increase indoor comfort in high performance office buildings. In the first phase of the study, a predictive algorithm was developed and validated through experiments in an actual test room. The objective was to regulate daylight on a specified work plane by controlling the blind slat angles. Furthermore, a sensor-based integrated adaptive lighting controller was designed in Simulink which included an innovative sensor optimization approach based on genetic algorithm to minimize the number of sensors and efficiently place them in the office. The controller was designed based on simple integral controllers. The objective of developed control algorithm was to improve the illuminance situation in the office through controlling the daylight and electrical lighting. To evaluate the performance of the system, the controller was applied on experimental office model in Lee et al.'s research study in 1998. The result of the developed control approach indicate a significantly improvement in lighting situation and 1-23% and 50-78% monthly electrical energy savings in the office model, compared to two static strategies when the blinds were left open and closed during the whole year respectively.

## DEDICATION

To my husband Behnam for being supportive, loving, patient and understanding. There is no doubt in my mind that without his continued support and counsel I could not have completed this work. He stood by me during the most difficult time of completion and consistently helped me keep perspective on what is important in life.

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# 1 INTRODUCTION

## 1.1 Background

A high performance green building is defined as one which is at least 50% more energy efficient than the current standard energy efficiency requirements in building codes and, in addition, meets certain other criteria regarding indoor air quality, water use, recyclable material and landscape design (ASHRAE Standards, 2010). These building are also known as sustainable buildings, green buildings or low-energy buildings.

In addition to the use of high levels of insulation, energy efficient windows, low levels of air infiltration and heat recovery ventilation, the design of such buildings involves a number of advanced elements and sub-systems that require dynamic control during operation such as advanced fenestration systems, shading elements, internal lighting system dimming, daylight harvesting, demand ventilation control, under-floor air distribution, advanced HVAC system control, heat recovery systems, ground-source heat pumps, integration with solar thermal and photovoltaic (PV) systems and so on.

Furthermore, various decision-making capabilities at the Energy Management and Control System (EMCS) level are being developed involving energy performance monitoring, fault detection, supervisory control, load shedding in response to real-time electricity pricing, indoor air quality monitoring and mitigation, electricity management from building integrated PV systems which greatly enhance the “value” of such buildings. Current methods of management and control rely on static fixed algorithmic programs which are expensive to deploy, maintain, re-program and do not dynamically change with varying physical conditions and operating criteria.

An acute and crucial societal problem is the energy consumed in existing commercial buildings. There are 114 million homes and about 1.5 million commercial buildings in the U.S. with only about 3% being built each year. Hence, existing buildings will have to be properly operated and maintained for several decades, and overlooking their larger impact is extremely short-sighted. Studies have indicated that 10-30% of energy use can be reduced by existing and cost effective equipment and operational technology available today, while this savings fraction can double if cutting edge research ideas and transformational multidisciplinary research results can be implemented in actual buildings.

In addition, the need of light and especially daylight, is a basic need of human beings. It is generally known that daylight is able to affect physical, physiological and psychological conditions of occupants. During the last few years, architects and design professionals started to recognize the importance of introducing natural lighting into buildings and its positive impact on work environment.

Recent studies reveal a correlation between environmental lighting and human performance and health, with positive results, (Kroelinger, 2005). What is known, is that insufficient or inappropriate light exposure can disrupt standard human rhythms which may result in adverse consequences for performance, safety and health, (DAURAT et al., 1993; Leppämäki et al., 2002; Partonen & Lönnqvist, 2000; Eastman & Martin, 1999; Knez & Kers, 2000; Burgess et al., 2002).

To provide the perfect amount of daylight and increase indoor environment comfort, designing the proper daylighting systems and strategies, such as windows, overhangs and shading devices play a very important role. A coordinated control strategy which integrates

daylighting with electric lighting systems leads to substantial lighting energy savings in existing as well as new buildings. Results of one of the first studies demonstrate the impacts of manual control of window blinds on annual energy consumption. They confirm that a blind system by itself, without a proper control, will not contribute to any energy savings, (Newsham, 1994, Lee 1998).

Furthermore, application of dimmable electric lighting along with the integrated window-shade control strategies can lead to significant energy savings. In a typical building, where over 70% of its energy use is for electric lighting, heating and cooling (U.S. Department of Energy, 2011), significant energy cost savings may be achieved by reduction of electric lighting and cooling/ heating loads, as well as by lowering peak electric demand (Athienitis and Tzempelikos, 2002; Guillemin and Morel, 2001).

In order to link the daylighting and artificial lighting systems in one controller, artificial intelligence techniques have been applied, (Guillemin et al., 2001; Guillemin, 2003; Chang, 2000; Bauer et al., 1996). These research studies show that soft computing techniques (SCTs) are a promising technology with respect to complex integrated and adaptive control problems encountered in building lighting management systems. A fuzzy logic-based control algorithm to minimize thermal and electric lighting energy demand in a building was first developed by the Technical University of Vienna, (Bauer et al. 1996).

To integrate the self-adaptation property into the controller, an artificial neural network and genetic algorithms were employed (Guillemin & Morel, 2001), where the control system was capable of adapting to user behavior and the room characteristics. Such

research demonstrate that through application of such controllers, high amount of energy savings could be achieved.

The problem with these highly complicated systems is that firstly, they all have very complicated structure which make them difficult to apply and maintain. Secondly, in most cases these energy savings are only achieved in specific climate conditions or for one significant building. There is still a need for more adjustments in the controller in order to be easier to apply, maintain and operate especially when physical changes are applied to the building. They also need adjustments in order to increase the level of comfort by controlling different/more dynamic elements as a one centralized control unit.

This research work demonstrates an innovative control approach which could achieve significant energy savings and increase indoor comfort in an office building. The developed controller integrates daylighting and electrical lighting systems. It is adaptive, robust, low-cost and easy to deploy. It has the capability of being applied on any building with different shape, size, function and climatic conditions. The control algorithm can adapt to the changes in the building infrastructure and component failures without the need for costly experts to re-program it.

## 1.2 Problem Statement

Though there is ongoing research into decentralized control systems, the current industry solution is to develop centralized building energy information systems (C-BEIS), which provide some degree of automation along with intelligent assistance and decision-making information to human decision-makers who operate and maintain these buildings. The current systems are statically programmed (with some manual overrides) and have to be customized for each building. Other difficulties being faced with C-BEIS are that these are proprietary, narrowly focused on one specific system of the facility, and require lengthy set-up times. Any changes or even troubleshooting involves the need for costly experts, and hence adaptation of the embedded control system is not feasible.

Furthermore, deployment of intelligent control systems in a legacy building is often prohibitively expensive due to installation of wiring, sensors and digital controls. In addition, the building industry lacks trained professionals with the ability to modify these software programs and perform programming tweaks on a continual basis in tune with temporal changes in how these buildings are operated and with changes in equipment over time. Finally, the underlying analysis methods are largely manual though many of the functions are better achieved via data-centric and automatic heuristic-based methods. The cause for this gap is the reluctance as well as lack of knowledge and proper understanding of such adaptive intelligent learning algorithms and methods by C-BEIS developers who are mostly control companies.

Based on some cutting edge research ideas in the last decades, there has been a notable increase in the number of innovative building elements and systems that lead to a better application of solar energy inside the buildings. These elements such as dynamic shading devices, integrated building control algorithms, efficient electrical lighting systems and many others, make it possible to achieve higher rates of energy savings and comfort for the occupants. However, one of the crucial problems found by most of these control algorithms is their highly complicated mathematical structures, which leads to difficulties in system deployment and maintenance by building operators. Moreover, many of current control algorithms vary with different factors such as climatic conditions, location and adjacent buildings on site. Many research studies demonstrate specific saving numbers that do not apply for different climatic regions, different sky conditions or different shape/type of buildings (Tzempelikos and Athienitis, 2007; Hammad and Abu-Hijleh, 2010). These control algorithms often need to be re-programmed or refined in order to be applicable on other buildings or in other climatic conditions.

### **1.3 Objectives and Scopes**

Based on the gaps in the current stage of research, there remains a need to improve the current control algorithms to address the issues and problems as mentioned above. As a result, the developed adaptive controller should be able to apply the best settings for the buildings' dynamic elements and systems based on immediate conditions of weather, interior settings or occupants' needs while at the same time maintaining a simple structure for easy application and implementation.

Further, the outcome of this research should greatly reduce the adverse impacts without compromising the health, comfort, and productivity of building occupants, thereby leading to more sustainable buildings.

Unlike most of the current systems which are customized and run on fixed control programs, the proposed control strategy should be adaptive, robust, low-cost and easy to deploy and customize. It should enable building control systems to be plugged into existing/legacy as well as in new buildings. Hence, the developed approach should have the ability to handle automatic expandability, local sensor or sub-system failures and other dynamic demands of the physical and operating environment.

In order to achieve these goals, this study demonstrates an innovative approach to implement and dynamically control advanced building elements and systems which will be increasingly used in the next generation of high performance or green/sustainable buildings. It demonstrates four development, validation and refinement steps of the adaptive control algorithm which relies on information provided by an optimized number of sensors distributed in the building.

This algorithm allows for the robust control of various dynamic elements in a building under different multi-objective minimization scenarios along with automatic adaptation when physical and operational changes are made to the building over time. It would result in minimizing manual customizations and provide a much higher level of flexibility, additional features and evolution of needs. The basic idea behind this concept is that the entire system is “generic”, expandable and not preprogrammed for a particular building.

## **1.4 Research Questions**

In order to achieve the intended objectives, some specific research questions need to be addressed. One of these questions is the type of building, daylight system and dynamic shading devices initially needed for the study. Another is, how should the process be optimized and automated in different design phases without sacrificing the accuracy of system, while simplifying the process and shorten the time. For example, what types of simulation software are most proper for the purpose of this study and how to minimize the number of simulation-runs and how to select specific days or hours. Also, in order to automate and optimize the whole process, the determination of the optimal number sensors which are responsible for delivering illuminance data to the controller and their distribution in the building is another question that needs to be investigated.

Another important issue is the structure of the proper control algorithm for the control system. Based on previous discussion in the last sections, there are many control algorithms applied in high performance buildings that require complex mathematical structure which raises the question of what type of algorithm would be the most efficient one to overcome this gap in the field. And finally, how the results of the system should be evaluated or validated in order to demonstrate the feasibility and applicability of the algorithm on real time buildings.



## 2 LITERATURE REVIEW

### 2.1 Energy Consumption in Buildings

Every facet of human society is affected by the operational costs of buildings. Offices, businesses, data centers and homes consume power and require manual attention. There are 1.5 million commercial buildings (and 114 million homes) in the US with a growth rate of about 3% a year, (U.S. Department of Energy, 2011). Hence, existing buildings will have to be properly operated and maintained for several decades, and overlooking their larger impact is extremely short-sighted. According to the U.S. Department of Energy data book, (2011), 41% of the U.S. primary energy was consumed by the buildings sector, compared to 30% by the industrial sector and 29% by the transportation sector.

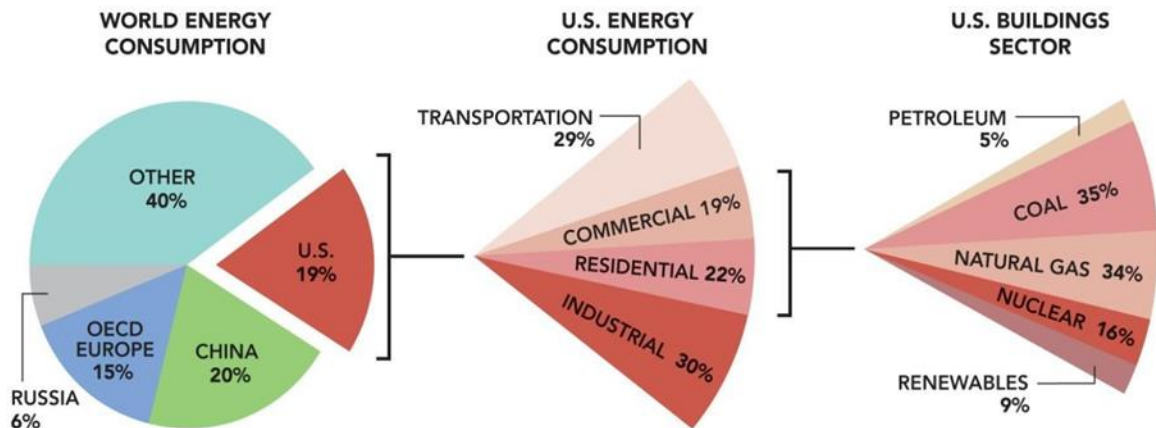


Figure 2. 1. World's energy consumption in 2009, (US Department of Energy, 2011).

As shown in Figure 2.1, of the 41 percent consumed energy in the building sector, homes accounted for 22% and commercial buildings accounted for 19% of the whole

delivered (site) energy. This doesn't include the lost energy during the production, transportation and distribution to the consumers, (U.S. Department of Energy, 2011).

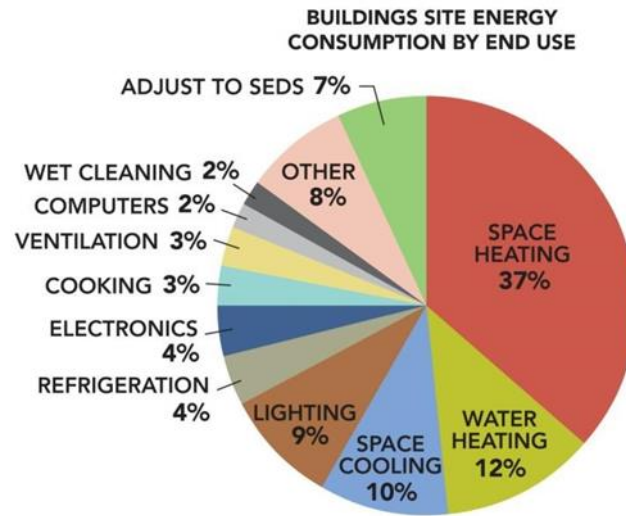


Figure 2. 2. Buildings' site energy consumption by end use, (The US Department of Energy, 2011).

Space heating with 37%, water heating with 12%, space cooling with 10% and lighting with 9% are the top four consumers of site energy consumption (Figure 2.2). Other end uses, such as consumer electronics, kitchen appliances, and ventilation, include the rest.

In commercial building sector, space heating consumed 27% of site energy in 2010, more than any other end use. Next major end-uses include lighting with 14% and space cooling with 10% (Figure 2.3), (U.S. Department of Energy, 2011).

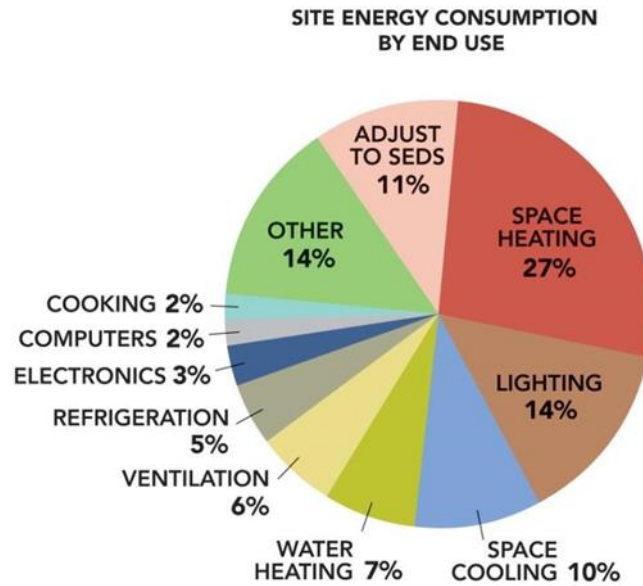


Figure 2. 3. Buildings site energy consumption by end use in commercial buildings.

On one hand, the annual growth in building energy consumption leads to increased amount of carbon dioxide emission in our environment. Again, according to U.S. Department of Energy data book (2011), the total amount of carbon dioxide equivalent emission for the U.S. commercial buildings has increased from 653 million metric tons in 1980 to 1036 MMT in 2010. It is documented that 20% percent of these produced emission in commercial buildings sector is caused by lighting energy. Clearly, the increased amount of CO<sub>2</sub> in atmosphere is destroying our environment by causing extreme climate changes and human health and related issues. Based on this fact, the importance of decreasing energy consumption in building sector in order to minimize carbon footprint is an enormous motivation for building designers and engineers.

On another hand, according to the U.S. office of Air and Radiation in 2009, ninety percent of American people spent their time indoors. As a result, designing for a thermally

and visually comfortable indoor environment is another challenge for building experts to overcome.

All these statistical facts point to importance of designing for more efficient buildings with effective concepts in order to reduce energy consumption and improve the level of comfort for occupants. Studies have indicated that 10-30% of energy use could be reduced by existing and cost effective equipment and operational technology available today, while this savings fraction can double if cutting edge research ideas and transformational multidisciplinary research results can be implemented in actual buildings.

In this context, efficient intelligent control strategies are design key elements and the main motivation and focus of this research study. Thus, the next sections include a background on intelligent buildings, their definition and some examples of control strategies in such buildings.

## **2.2 Definition of Smart Buildings**

There are many published definitions and descriptions of smart buildings, also known as intelligent buildings that to some extent maintain the same meaning and vision. For example, some contend that a smart building is an automated building, others believe they are where the building automation systems are integrated, while some others content that a smart building is one that provides flexibility in layout and operation. Carter Myers in his book “intelligent buildings” defines intelligent building as an integrated and automated tool that increases the occupant’s productivity, efficiency and effectiveness, (Myers, 1957). We believe that the use of networked technology, embedded within building to monitor and

control elements of the building for exchange of information between users, systems and buildings makes a building smart.

### **2.2.1 Elements of Smart Buildings**

Based on the smart building definition, the key elements of such buildings are optimized, energy efficient and environment friendly building automation and networking systems. These systems consists of sensors, controllers, actuators, software and an operator that interfaces with the system via central workstation or web browser to support the dynamic features in the building. There are different forms of control systems in a building to control HVAC, lighting (which is a combination of daylighting and artificial lighting), water/energy management, alarm and sprinkler systems. The focus of this research is on lighting control systems in commercial buildings.

### **2.2.2 Examples of Smart Buildings**

Pressure ring facade, “KFZ Westarkade” office building in Frankfurt, Germany. One of the recent applications of sensors to control the indoor environment is the “Westarkade Tower” in Frankfurt, Germany. The building is the first building equipped with “pressure ring” facade and sophisticated sensorich control scheme that consumes less than 100 kWh/m<sup>2</sup> per year. The control system manipulates the dynamic ventilation flaps installed on the outer layer of building facade, to maintain a ring of positive air pressure around the building. With this energy consumption, the Westarkade is a world class energy miser, using half as much energy as a conventional office building in Europe (Fairley, 2010). Figures 2.4 and 2.5 display views of this building in Frankfurt.



Figure 2. 4. View of KFZ-Westarkade in Frankfurt, the office building' facade is equipped with 180 flaps to control the wind pressure around the building and improve the natural ventilation in the office spaces, (Sobek et al., 2011).



Figure 2. 5. View of the flaps on the outer facade layer, (Sobek et al., 2011).

Solar Shutters, Biokatalyse Laboratory Building, Technical University of Graz, Austria. The outer skin of the south facade of the Biokatalyse laboratory (Figures 2.6 to 2.8) consists of solar shutters, and a cavity of one meter width. Moving and rotating the shutters allows for indoor daylight distribution to be altered, for instance by having lighter pass through the envelope onto specific room surfaces, (Wyckmans, 2005; Graz, 2004).





Figure 2. 6. View of Biokatalyse building in Austria, (Graz, 2004).



Figure 2. 7. View of the Biokatalyse laboratory building with adaptive solar shutter system, moveable and tiltable shutters, the shutters are located in the outer layer of a double skin facade, Graz, Austria, (Graz, 2004).



Figure 2. 8. The inside view (left) and the view of the solar shutters as part of facade system, (Graz, 2004).

As mentioned before, efficient intelligent control strategies are design key elements and the main motivation and focus of this research study. In more details, the main goal of

the thesis is to design an intelligent lighting controller for smart buildings. Hence, it is important to have a background on daylight and its significance on occupants' comfort, health, performance and productivity.

### **2.3 Daylighting in Buildings**

“...the history of architecture is the history of the struggle for light”, (Le Corbusier, 1989).

Quality of lighting in buildings, for most part of the human civilization, was determined by availability of daylight. By the end of 19th-century, daylight started to be supplemented, or in many cases, replaced by electric light which essentially required the consideration of good daylight strategy, (Kroelinger, 2005). At that time, there was a belief among architects that there is no definite relationship between natural light and work hygiene which was supported by different professional organizations such as congress of medicine professionals. In 1965, they officially concluded that humans do not need natural lighting in work environments stating that windowless work rooms, from work hygiene perspective, do not impair or negatively impact human health as long as the rooms provide optimal lighting condition (Batzel, 1989).

However, this belief started to change during the last quarter of 20th century, when researchers started to recognize the positive impacts of natural light on workers. Based on research' findings, daylight is not fundamentally better than electric light but it does have greater likelihood of maximizing visual performance than most forms of electric lighting. It is due to the fact that daylight has a large variation of visible spectrum, whereas electric



light sources cannot be constructed to closely match the daylight spectrum (Boyce et al., 2003).

In one of the first studies about daylight in buildings conducted by Heschong Mahone Group in 1999, the impacts of daylight in classrooms on students' performance was investigated (Heschong, 1999). The study analyzed the test scores of more than 21,000 students in three school districts in California, Washington, and Colorado (Heschong, 1999). In one school district, students with the most daylighting in their classrooms progressed 20% faster on math tests and 26% faster on reading tests in comparison to students in the least daylight classrooms.

In another research study conducted by Plympton in 2000, the impacts of daylight on school students was investigated. The study showed that daylighting in schools significantly increases students' test scores and promotes better health and physical development (Plympton et al., 2000; Hathaway, 1995).

Likewise, studies conducted on work environment had similar results; namely, that daylighting improves productivity and performance of the workers. Field surveys in a large number of offices indicate that daylighting in working spaces lead to high level of environmental satisfaction and self-rated productivity (Boyce et al., 2003; cuttle, 1983). Cuttle in 1983 conducted a questionnaire-based survey in England and New Zealand to explore the benefits of windows in working environments. Four hundred and seventy one office workers participated in his questionnaires. The survey included questions about having windows in their offices and why it was important to them. Ninety nine percent of participants answered that every office should have windows and 86% of them preferred

daylight as their light source in the office. They explained that working in a daylit space helps them feel more comfortable and have less stress.

In addition to these studies, Heerwagen (1986) conducted a survey in Seattle over two summer and winter seasons. The majority of participants stated the same belief. They all felt that daylight is better for their health, mental comfort, visual comfort, perception and pleasantness of their office space its colors and furnishing. These participants rated the daylight availability in their office space 19 out of 20 in importance among other features.

In another survey in Canada (Veitch et al., 1993; 1996), a mixed sample of students and office workers were asked about daylight and its importance and effects on productivity, comfort and health. Almost 80% of the participants strongly stated that daylight is their preferred light source. The average score of this statement was 2.94 on a scale from 0–4, where 4 shows a stronger belief. When we look at the questionnaire in more detail some interesting results stand out. For example, 52% of the mixed participants described that they have done their best work in places where natural light was available. Also a significant group of samples stated that they believe in harmfulness effects of fluorescent light on health including headache and eyestrain.

In addition to the research studies about daylight and productivity, Wells (1965) conducted an interview-based study to investigate the importance of window and view in the work environment. He interviewed office workers in the U.K who were located on an open, deep-plan office building with glass-curtain walls. The main goal of the study was to identify and investigate the correlation between participants' physical health conditions, view, natural lighting and artificial lighting situation in the office space. The majority of

the employees (89% out of 2500 participants) stated that they strongly prefer daylight as their light source and view in their working space.

The study discloses very interesting details about peoples' perception of daylight and electrical lighting. People overestimated the proportion of daylight that they had available on their working area proportionally with their distance from the windows. They perceived considerable amount of daylight on their desks, even when there was very little daylight available and most of the illumination was supplied by the electric lighting. Wells concluded that the amount of daylight and view that people believe they need depended on psychological considerations such as the judgment of apparent brightness distribution and the preference for a view to the outside, which were not related to the distance from the nearest window. Table 2.1 summarizes these studies and their results.

Table 2. 1 Summary table of research conducted on importance of daylight in buildings.

| Study           | Year | Research Method  | Results   |
|-----------------|------|--|---|
| Heschong et al. | 1999 | <ul style="list-style-type: none"> <li>Impacts of daylight in classrooms on students' performance</li> <li>21,000 students participated</li> <li>Schools were in California, Washington, and Colorado</li> </ul> | Students with the most daylighting in their classrooms in comparison to students in the least daylight classrooms progressed: <ul style="list-style-type: none"> <li>20% faster on math tests</li> <li>26% faster on reading tests</li> </ul> |
| Plympton et al. | 2000 | <ul style="list-style-type: none"> <li>Impacts of daylight on school students</li> </ul>   | <ul style="list-style-type: none"> <li>Promotes better health and physical development</li> </ul>   |

|               |             |   |   |
|---------------|-------------|---|---|
| Cuttle        | 1983        | <ul style="list-style-type: none"> <li>• Questionnaire-based survey to explore the benefits of windows in working environments</li> <li>• 471 workers participated</li> <li>• In England and New Zealand</li> </ul>   | <ul style="list-style-type: none"> <li>• 99% of participants stated every office should have windows</li> <li>• 86% of them preferred daylight as the main light source</li> <li>• They stated working in a daylit space helps them feel more comfortable and have less stress.</li> </ul>  |
| Heerwagen     | 1986        | <ul style="list-style-type: none"> <li>• Questionnaire-based survey with office workers</li> <li>• Seattle</li> <li>• For two summer and winter seasons</li> </ul>  | <ul style="list-style-type: none"> <li>• Participants felt that daylight is better for their health, mental comfort, and visual comfort.</li> <li>• They stated that the colors and furnishing in their office was more pleasant when daylit.</li> <li>• They rated daylight availability in their office space 19 out of 20.</li> </ul>        |
| Veitch et al. | 1993 & 1996 | <ul style="list-style-type: none"> <li>• Mixed sample of students and office workers</li> <li>• Questionnaire-based survey</li> <li>• They were asked about daylight and its importance and effects on productivity, comfort and health</li> </ul>                              | <ul style="list-style-type: none"> <li>• 80% of the participants strongly stated that daylight is their preferred light source</li> <li>• They stated that they believe in harmfulness effects of fluorescent light on health including headache and eyestrain.</li> </ul>  |
| Wells         | 1965        | <ul style="list-style-type: none"> <li>• Interview-based study</li> <li>• In UK</li> <li>• Main goal was to identify the correlation between participants' physical health conditions, view, natural lighting and artificial lighting situation in the office space.</li> </ul> | <ul style="list-style-type: none"> <li>• The amount of daylight and view that people believe they need depended on psychological considerations such as the judgment of apparent brightness distribution and the preference for a view out</li> <li>• These considerations were not related to the distance from the nearest window.</li> </ul> |

## **2.4 Daylight Systems**

One of the most important elements which provide the optimal daylight and view to the outside while avoid the heat gain and glare in buildings, are daylight systems including windows, glazing and shading devices. A proper combination of different systems could lead to significant amount of energy savings and at the same time it could improve the thermal and visual comfort situation.

There has been many research works about proper size of the windows and different glazing materials for the efficient daylighting design, however since the focus of this research are dynamically controlled shading devices, the literature review concentrates on these elements, their impacts on comfort performance, different control strategies for these elements and the investigation of energy savings based on different control strategies.

Roller shades and venetian blinds are the most common dynamic shading devices in office buildings which are simple to install, operate and maintain, but at the same time they need a dynamic movement control to respond to daylight situation inside the office. There are many research works all around the world that investigate blinds' settings and their impacts on occupants' comfort. These research work are very useful in order to understand the behavior of the occupants toward shading devices in long term scenarios.

One of these research works was conducted by Rubin in 1978. The methodology he applied included taking several photographs of 6 different office buildings in Maryland, USA to study the behavior of the occupants towards the shading devises. The photographed offices were in the perimeter of the building and they were equipped with venetian blinds. The photographs indicated that the preferred blinds' settings in the most offices had little

to do with the sun position or daily and seasonal climatic conditions. The researchers set all 700 blinds in either open or closed position during the night and observed the behavior of the office workers on following day when they came back to work. The experiment took place over 3 different time periods in February, July and October and each period lasted 10 days. The building facade was photographed twice in the morning and twice in the afternoon before and after the blinds' settings were changed by office workers.

Rubin's results demonstrated that 80% of the participants on south oriented offices closed the blinds whereas only 50% of the participants on north-oriented facade closed their blinds when they arrived at work. The office workers stated that they usually use their blinds to avoid direct sunlight penetration and overheating effects. Another interesting result of this study was that occupants did not change their blind position daily. They tend to have a preferred specific blind setting that was chosen over a long period of time.

In another research study in 1984, Rea guided a pilot study in Ottawa, Canada, in a 16-storey building. The goal of the study was to investigate the impacts of window orientation, time of the day and weather conditions on the blinds' setting in the offices. The methodology included again several photos from three different orientations of building's facades (southern, eastern and western side) three times a day (once in the morning, once at noon and once in the afternoon) on a cloudy day in April and a clear day in May.

Results indicated that occupants change the blinds' settings very irregularly. They rarely changed the setting for view or daylight, only when there was direct sunlight on their working area, they were most likely to change the setting by closing the blinds. Otherwise, there was no change in blinds' settings for a long period of time.

In context to Rea's study in 1984, she and her research group continued to observe the behavior of workers in 58 U.S. offices (1998). This time, the study lasted about seven weeks and the results confirmed her earlier findings in 1984. She stated that as soon as there was direct sun penetration on the working area, participants pulled the shades down and it stayed down for a long time even when the glare situation ended. However, they changed the blinds' setting 3 to 5 times per week more on south and west facades than on north and east facades. She also observed that sky conditions, sun position, type of the tasks done by the occupants and the location of the desk in the office actually influenced the blind position and the slat angle chosen by participants.

Moreover, in another interesting research study conducted by Inoue et al. (1988), the relationship between solar radiation through daylight on a working plane and blinds' setting was investigated. The study was done on facades of four high-rise buildings in Japan and included over 1000 windows with east, west, south-west and south-east orientations in winter, summer and fall. In this approach, research group photographed the blinds and surveyed over 800 occupants of the offices with a questionnaire. The researchers concluded that when the solar radiation exceeded  $60\text{W/m}^2$  on the work plane, the number of blinds being photographed in close position was proportional to the depth of the sunlight penetration into the office.

However, like results from previous research studies, this changed in different facade orientations and with different sky conditions. According to the photographs, on a clear day, when blinds on the east-facade were set to closed position in the morning, they stayed closed until the afternoon. The opposite situation happened for the west facade. On an

overcast sky, there was no change on the blinds' settings. This suggested that change in the blinds' settings was directly correlated with the sunlight penetration from the window to the office space. More than 60% of the blinds were not changed at all through the whole day, which is another confirmation of the previous studies about most people tend to operate the blinds based on perceptions formed over long periods of time, rather than primarily in response to current conditions.

In the questionnaire provided to the participants, 70% of them specified that they usually don't change the blinds' setting unless it is too bright or too hot, which points to the glare and heat gain problem. Based on Inoue's study, when the depth of sunlight penetration into the offices was over 2 meters, or when the solar radiation falling into the work area was about  $250 \text{ W/m}^2$ , the blinds' settings were changed most frequently. Similar conclusions to these studies were reached by many other researchers for example, Farber Associates in 1992 and Escuyer and Fontoynt in 2001.

Following the research studies about the occupants' habits in changing blinds' settings, some researchers developed predictive approaches to determine the optimal blind angle settings for the occupants based on climate and sky conditions (Sutter et al., 2001). Sutter introduced a model which was operating based on a specific illuminance level (8000 lux) on the window frame. If the illuminance exceeded that level, then the controller was activated to close the blinds in order to achieve the optimal visual and thermal comfort level. Sutter's model provided a more detailed guideline to optimize the view compared to other research studies (Hopkinson and Bradley, 1965; Moon & Spencer 1945).



The illuminance level of 8000 lux as the limitation point was developed based on study conducted by Hopkinson and Bradley in 1965 and it was based on 22 photographs of a daylight office in France. The photos were taken under different sky and climate conditions and were analyzed based on screen luminance values and measured illuminance on the window plane. The prediction model indicated that the blind settings have a direct relationship with the geographical latitude (Sutter et al. 2001). The probability of blinds left in a horizontal position in northern latitudes was shown to be about 65% while this probability in southern latitudes was only about 40%. All these research studies are summarized in Table 2.2.

Table 2. 2 The summary table of research about daylight shading devices.

| Study         | Year | Research Method   | Results  |
|---------------|------|---|--|
| Rubin         | 1978 | <ul style="list-style-type: none"> <li>• Main goal was to study the behavior of the occupants towards the shading devices in buildings</li> <li>• Methodology included photographs of 6 different office buildings in Maryland, USA</li> <li>• The offices were in the perimeter of the building</li> <li>• They were equipped with 700 venetian blinds</li> <li>• Blinds were left either open or closed during the night</li> </ul> | <ul style="list-style-type: none"> <li>• Results demonstrated that 80% of the participants on south oriented offices closed the blinds</li> <li>• Only 50% of the participants on north-oriented facade closed their blinds</li> <li>• The office workers stated that they usually use their blinds to avoid direct sunlight penetration and overheating effects.</li> </ul>   |
| Rea           | 1984 | <ul style="list-style-type: none"> <li>• Main goal was to investigate the impacts of window orientation, time of the day and weather conditions on the blinds' setting in the offices</li> <li>• Methodology included photographs of 58 different office buildings in Maryland, USA</li> <li>• For 7 weeks</li> </ul>   | <ul style="list-style-type: none"> <li>• Results showed that as soon as there was direct sun penetration on the working area, participants pulled the shades down and they stayed down for a long time.</li> <li>• Participants changed the blinds' setting 3 to 5 times per week more on south and west facades than on north and east facades.</li> <li>• Sky conditions, sun position, type of the tasks done by the occupants influenced the blind position chosen by participants.</li> </ul> |
| Inoue et al.  | 1988 | <ul style="list-style-type: none"> <li>• Main goal was to investigate the relationship between solar radiation through daylight on a working plane and blinds' setting</li> <li>• On 4 high-rise buildings in Japan</li> <li>• Methodology included photographs of over 1000 windows with east, west, south-west and south-east orientations in winter, summer and fall</li> <li>• Surveyed over 800 occupants</li> </ul>             | <ul style="list-style-type: none"> <li>• Result showed when the solar radiation exceeded the 60W/m<sup>2</sup> on the work plane, the number of blinds being closed was proportional with the depth of the sunlight penetration into the office.</li> <li>• This changed with different facade orientations and sky conditions.</li> <li>• 70% of participants specified that they usually don't change the blinds' setting unless it is too bright or too hot.</li> </ul>                         |
| Sutter et al. | 2001 | <ul style="list-style-type: none"> <li>• Developed a predictive approaches to determine the optimal blind angle settings for the occupants based on climate and sky conditions</li> <li>• A model introduced which was based on a specific illuminance level, (8000 lux) on the window frame.</li> </ul>  | <ul style="list-style-type: none"> <li>• It provided a detailed guideline to optimize the view in comparison to other research approaches.</li> <li>• The prediction model indicated that the blind settings have a direct relationship with the geographical latitude.</li> <li>• The probability of blinds left in a horizontal position in northern latitudes was 65%</li> <li>• This probability in southern latitudes was only about 40%.</li> </ul>  |

To summarize, all the above mentioned studies highlight the importance of an efficient daylight system and dynamic shading devices in office buildings in order to maximize the occupants' comfort and minimize the energy consumption through application of daylight. They provide a guide line for occupants' behavior towards shading in different conditions.

In most of these research studies, it has been shown that outside view is one of the important drives for occupants to change blind settings if the heat gain does not exceed their comfort level. Thus, to optimize the daylight in buildings, it is very crucial to plan for an optimal control of shading devices during the design process. To do so, choosing the proper daylight/lighting simulation tool to understand the daylight availability inside the space, especially in the first design steps is a key element to an optimal daylight design. Therefore, the next section of the literature review encloses a background about daylight simulation tools.

## **2.5 Daylight Simulation Tools**

In connection to the previous discussion about the importance of daylight availability in buildings and its relationship to occupants' productivity and health, this section is devoted to a background on daylight simulation tools, their calculation methods and their effectiveness, strength and weaknesses.

### **2.5.1 Historical Overview**

The first lighting calculation program which was able to calculate lighting levels in a simple rectangular room was developed by Plant and Archer in 1973. During 1990s, through further developments, the lighting software were enhanced by improved computer calculation methods and were also able to provide simple graphical outputs including images (Nakamae and Tadamura, 1995). Next, light transparency and material properties became important in calculations. The output became more versatile and included more lighting scenarios. They could provide users with numerical data as well as different images rendered closer to reality (Kiss et al., 2003). However, completely realistic and exact calculations were complicated to define and there were many limitations in lighting algorithms (Wilkie et al., 2009). That is why the early lighting simulation programs were limited to simple geometries, no daylight or energy estimations (Svendenius and Pertola, 1995).

Even though the current lighting programs available in the market don't have many of these limitations, there is still a need for more efficient calculation algorithms for solving complicated lighting problems, (Ulbricht et al. 2006; Moeck and Selkowitz, 1996; Ward and Shakespeare 1998).

### 2.5.2 Lighting Simulation Algorithms

Algorithms are processes or set of rules to be followed in calculations or other problem-solving operations, especially by a computer. They have been applied to solve lighting distribution problems through combination of different physical formulas in an effective way. According to Dutra et al. (2006), in general, most modern physical models that describe light transport in all types of media (such as quantum optics) are too complex for computer calculations and image generation. To deal with this problem, he developed and applied a very simple geometrical optics and energy conservation model which was able to solve illumination problems handling different light sources. However, his model was unable to adequately deal with some difficulties such as light calculation from diffusion or reflection in a space. Furthermore, since Dutra's model has a very simple structure and assumed light distribution was constant and in a steady-state form, significant differences between actual measured illuminance data and simulated data were reported.

In the next phases of lighting calculation algorithms' development, Hurdles models were introduced which found a method to calculate surface reflectivity of different opaque materials. Hurdles models were defined based on different simplified sub-models which require their own bidirectional reflection distribution functions (BRDFs), (Pineda, 1988). This was one of the first steps towards computer graphics, although the output of Hurdles models was limited to few colors and hard-shadow determination. Subsequently, ray tracing and radiosity illumination algorithms were developed, (Pineda, 1988; Ochoa et al., 2012). In some literature reviews, (Ochoa et al, 2012; Carroll, 1999) lighting simulation algorithms are classified into three main types:

Direct calculation algorithms: These algorithms are used to calculate the light emitting from a direct lighting source such as a lamp, sun or even the daylight from an opening. Direct calculation algorithms contain simplified specific physical formulas. A well-known example of direct calculation algorithm is the lumen method calculation which is applied to calculate the light on a specific object or task surface.

View-dependent algorithms: These calculation methods are based on heat transfer calculation formulas and was developed and investigated by Willmott and Heckbert in 1997. One of the application areas of this calculation method is radiosity where every scene is divided into smaller surfaces and the radiometric of these simple surfaces are calculated independently from the whole view. However, one of the limitations with the view-dependent algorithms is that they are not suitable for scenes including specular reflecting objects (Willmott and Heckbert 1997; Wang et al. 1992). Based on the complicated calculation formulas in this method, it is mainly used for lighting calculations with numerical output rather than image generation (Wang et al. 2009).

Scene-dependent algorithms: These calculation algorithms include formulas that are based on direction from which rays are computed by the model in each scene. One of the application examples of these kind of methods is Ray-tracing where rays are usually traced from the light source (forward tracing) or from the observer's eyes (backward tracing) or both ways (Lafortune and Willems, 1993). In some cases, both backward tracing and forward tracing are combined together which is defined as image-bound method. Image-bound method is the ideal method to calculate the light from a direct light source, diffused light and reflected light from specular surfaces. However, like the other methods there are

still limitations with scene-dependent algorithms as well. For example, if there are several diffused reflection light sources in the scene, they are not able to calculate the light accurately (Ochoa et al, 2012). An illustration of the basic principles of three main algorithms is shown in Figure 2.9.

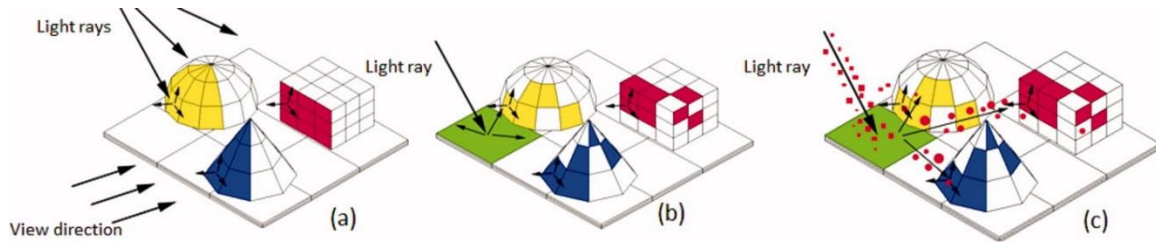


Figure 2. 9. Schematic principles of three commonly used lighting simulation algorithms: (a) ray tracing, (b) radiosity and (c) photon map, (Ochoa et al., 2012).

Although a combination of two or even three calculation methods is the best way to deal with complicated lighting scenes, there are however limitations with computing complex situations such as fog, special diffusing materials, etc. (Kniss et al. 2003; Dutre et al. 2006). In such cases, combinations of two or three different calculation methods are still the best solution approach to deal with complicated lighting scenes. One of the first integrative algorithms was developed by Kajiya in 1986. The radiance model developed by Ward and Shakespeare in 1998 also uses an integrated method of backward ray tracing and bidirectional distribution functions (scene-dependent).

The photon map calculation method developed by Jensen in 1996 is another integrative, scene-dependent model. It works by sending packets of energy (photons) to different surfaces in the scene. Results of photon map calculation are saved for each simulation

scenario and are combined with results from ray tracing and surface radiance applied on the surfaces.

Table 2. 3 Lighting simulation algorithms currently available.

| <b>Algorithm</b>   | <b>Calculation Method</b>  |
|--------------------|--|
| View-dependent     | Forward ray tracing<br>Backward ray tracing<br>Bi-directional ray tracing  |
| Scene-dependent    | Radiosity<br>Photon map<br>Integrative approaches<br>Multi-pass approaches |
| Direct calculation | For artificial lighting, follows national standards                        |
| Calculation aids   | Deterministic methods (classical approaches)                               |

### 2.5.3 Current Lighting Simulation Tools

Advanced lighting and energy simulation software could be powerful tools to predict the energy consumption and comfort in building environment. On average, green buildings use about 30% less energy than conventional buildings, although through the proper energy analysis software more energy savings could be achieved (Bhavani et al., 2009). The persistent research in daylighting and energy systems has paved the way for more sophisticated tools which predict the indoor conditions more accurately. In order to design effective and intelligent control systems which respond to user inputs and environmental conditions, the advanced computer simulation software need to be carefully chosen.

Nowadays, there are numerous design tools in the market and depending on their level of sophistication and type of analysis engine used, the accuracy level of their results changes. Also, given their generic nature, not all types of shading devices and/or shading



control algorithms can be evaluated. Furthermore, some of these software lack the ability to run an annual analysis and can only generate results for a specific day and time in a year.

The United States Department of Energy (USDOE) provides a list of simulation tools (USDOE 2014a), which includes a short description of their capabilities, strengths and their weaknesses. Some of these tools are specifically for lighting, while others integrate lighting calculation with the whole-building calculations. In addition, there are some extensive reviews which compare current lighting tools, their applications and limitations (Guglielmetti et al., 2010; Ochoa et al., 2012)

Based on the online list of lighting software provided by USDOE and based on Ward's and Shakespeare's book that has recorded 294 citations in the Scopus database, RADIANCE is the most efficient lighting tool especially for researchers and computer graphics communities (USDOE, 2014a; Ward 1994; Ward and Shakespeare, 1998; LBL, 2010a). Radiance was the first software to generate calculation results for a fixed viewpoint, using as input data three-dimensional geometrical description of a scene and physical properties of its materials. It has also advanced some of the current calculation techniques available in most lighting simulation models (Ward et al. 1988).

Furthermore, Radiance is the perfect tool for building research instead of only imaging, is flexible to solve a great majority of natural and electric lighting simulation problems, is freely available and is distributed under an open-source agreement (LBL, 2010a; Ward, 2002). Also, RADIANCE is one of the very few tools that has been validated by many research studies (Grynberg, 1989; Mardaljevic, 1995, 2001, 2004; Reinhart and Herkel, 2000; Ng, 2001; Reinhart and Walkenhorst, 2001; Reinhart and Andersen, 2006). In all

these research studies Radiance has shown consistency in results based on accuracy within acceptable limits, according to the test situation.

Besides the effectiveness and accuracy of this software there are some weaknesses to consider as well. For example, Radiance lacks a user interface of its own and needs considerable expertise to manipulate its variables (Reinhart and Fitz, 2006). Nevertheless, it continues to be favored by the lighting research community (Reinhart and Fitz 2006). This can be partly explained by features such as (i): it is intended for building research (instead of imaging only), (ii): is flexible to solve a great majority of natural and electric lighting simulation problems, (iii) is freely available, and is distributed under an open source agreement (LBL, 2010a). The open source nature allows contributions from researchers themselves and model continuity (Ward, 2002). It is also one of the few models validated extensively (e.g. Grynberg, 1989; Mardaljevic, 1995, 2001 and 2004; Ng, 2001; Reinhart and Herkel, 2000; Reinhart and Walkenhorst 2001; Reinhart and Andersen 2006).

Another extensively used product in the market is AGI32, (Lighting Analysts Inc., 2014). AGI32 is developed for commercial uses and is able to perform electric lighting and daylight performance analysis, (Reinhart et al., 2006). The software uses photometric data files and has many standard CIE sky models. Direct calculations is applied to calculate lighting from the light fixtures. Radiosity calculations are applied for daylight calculations. Limited ray tracing analysis is used for daylight and small surfaces.

Next widely used program especially in Germany is DIALux, (DIAL GmbH, 2014). It is usually applied for calculation of indoor and outdoor electric lighting systems. It follows different national standard lighting calculations and can import directly photometric

databases from manufacturers. There are some daylight calculation capabilities, using German standard DIN 5043 and CIE Publication 110. Geometrical input is limited to certain shapes. Sky choices are somewhat limited but acceptable for diverse range of weather conditions. There is an external radiosity and ray-tracing model, POV-Ray (Persistence of Vision Inc., 2014). It is used to produce images from calculation results and for presentation renderings. DIALux is available free of charge but is not open source. Some noteworthy scientific studies that used DIALux include determining criteria for energy-efficient lighting, (Ryckaert et al., 2010) or simulating luminaire arrangements for a study of patients suffering dementia, (van Hoof et al., 2009).

Relux, (Relux Informatik, 2014) is another European lighting software which calculates lighting arrays, daylighting and very simple electrical energy data. Calculation for each aspect can be made separately or in a combined mode. Aradiosity and a modified Radiance ray tracing algorithm are used in Relux light calculation engine and user can decide if he/she would like to incorporate all these methods into calculations. The ray tracing module is also used for rendering. Its accuracy has been validated by Maamari et al. (2006a). It has been used to evaluate comfort conditions of traditional architecture (Ruggiero et al., 2009) and to provide an electric lighting base case for comparison with daylighting systems (Linhart and Scartezzini, 2010). Relux is also free but does not provide an open source.

Another commercial model available is Inspirer (Integra, Inc 2014). Distributed mainly in Japan, it is used for architectural and industrial design analysis. It employs bidirectional ray tracing. Limited validation has been performed on its accuracy (Khodulev and Kopylov

1996; Drago and Myszkowski, 2001). These tests showed acceptable results. The program generates high-quality images.

Based on the literature review, Radiance remains the “general-purpose” lighting simulation tool. Other packages implement similarly advanced algorithms, such as radiosity or the photon map. Tools dedicated to artificial lighting layouts use advanced algorithms only as supplement to direct calculations when diffuse daylight is involved. Direct calculations are needed to demonstrate compliance with local building codes, and daylight has limited scope within them. A summary of characteristics discussed in this section is given in Table 2.4.

Table 2. 4 Summary table of current and common lighting simulation tools (Ochoa et al., 2012).

| <b>Tool</b>      | <b>Software Calculation Algorithms</b>                                  | <b>Application</b>                        |
|------------------|---|---|
| AGi32 (paid)     | Direct calculation<br>Radiosity<br>Limited ray tracing                  | Luminaire design                          |
| Radiance* (free) | Backward ray tracing<br>Scene radiance                                  | General purpose                           |
| Relux (free)     | Direct calculation<br>Radiosity and modified Radiance<br>ray tracing    | Luminaire design,<br>daylight integration |
| DIALux (free)    | Direct calculation<br>Daylight calculation<br>POV ray tracer for images | Luminaire design, daylight<br>integration |
| Inspirer (paid)  | Bidirectional ray tracing   | General purpose                           |

Since daylight entering a building also brings heat along with it, the thermal comfort of the occupants cannot be compromised. The visual comfort parameters such as illuminance, uniformity and glare need to be synergized with the thermal comfort parameters such as Solar Heat Gain Coefficient (SHGC), Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD) (Kreider, 1995). The energy consumption of the overall building should be designed in such a way that the daylight penetration does not increase the cooling load of the Heating, Ventilation and Air Conditioning (HVAC) systems during summer months and the heating load in the winter months. So the constraints for the integrated lighting controller are that it should contain a feedback mechanism and needs to be intelligent enough to adjust its parameters so as to operate in an optimal manner according to the environmental and user preferences (Bhavani, 2009).

Based on this fact, one of the crucial issues for choosing the proper lighting simulation software for a project is its ability to simulate the energy concepts along with lighting for

integrated control strategies. Further, in some complicated design projects with dynamic facade-elements, it is very crucial to find the suitable software package to simulate the energy consumption of the building including heating, cooling and lighting, based on such advanced control systems. EnergyPlus, eQuest and TRNSYS software that have been applied in recent research studies (Lee et al., 1998; Crawley et al., 2005), are all limited to fixed facade and shading elements and can only perform the simulation with few facade-element-parameters that cannot be changed based on the thermal and lighting conditions during a single run. This issue also appears in IES Virtual Environment. The options to change the facade-elements or parameters in these software packages are very limited.

## **2.6 Human Comfort and Control Strategies**

As discussed before, to design an efficient optimal control system for a building, many aspects have to be taken into consideration such as human comfort, energy efficiency of the system and the ease of maintenance and customization. One of the gaps in the current research is that many studies only focus on how control systems influence a single environmental condition (Galasiu & Veitch, 2006; Navai & Veitch, 2003; Veitch, 2001; Brager & de Dear, 1998; Nicol & Humphreys, 2002).

In addition, Frontczak and Wargocki (2011) conducted a literature review about the impacts of different environmental and non-environmental factors on human satisfaction and comfort, and categorized different field studies based on their procedures and methodologies. The paper is a great resource that describes how environmental aspects contribute to achieve occupants' comfort, and how these aspects rank to have high importance from building users' point of view.

Depending on the test environment (test chamber, school buildings, commercial or residential buildings) the applied methodology differs among these collected research studies. In all of them the basic information about comfort or discomfort level is gathered through interviews or surveys where building users respond to the questionnaires (Alm et al. 1999; Astolfi & Pellerey, 2008; Choi et al. 2009; Clausen et al. 1993; Humphreys, 2005; Lai et al. 2009; Lai & Yik, 2007, 2009; Wong et al. 2008).

The results of these studies indicate that these studies are very helpful in providing general ideas about occupants comfort and satisfaction level while designing the control strategies in a building especially in the early stages of design. However, information about relative importance of environmental conditions on overall satisfaction with IEQ, are not constant and differ depending on different building types, climatic conditions, experiment factors, the location of the building, occupants' cultural aspects and gender, purpose of stay, type and function of the building, duration of working or living in the building, occupants' location within the building, (core or perimeter zones) and many other factors. These influence the judgment of the participants very strongly. Based on this fact, the human comfort study in each research should be designed individually and customized based on different testing/working environment conditions and standards.

## **2.7 Daylight Responsive Control Strategies**

When speaking of daylight-responsive control, there are at least three key factors that need to be considered: the control of daylight input to the space, the control of the electric lighting output and control of comfort performance. The first is critical for providing adequate quantity and quality of natural light in interior spaces. The second saves energy

and improves the overall distribution of light when daylight is insufficient to fulfill all lighting needs and the third criteria improves user satisfaction. Annoyances caused by the system due to high contrast ratios resulting in glare, temporary reductions or sudden changes in brightness, or irritating mechanical noise, will reduce the system's effectiveness. Therefore, the objectives of predictive control of dynamic envelope and lighting systems are different. A study by Scheatzle (1990) claims that human control of motorized shading devices is not reliable and causes a constant disruption to the occupants. Also, when a microprocessor automatically operates the shading device as an occupant would if he/she were to constantly monitor interior and exterior conditions, psychological and physiological factors affecting human comfort are ignored. Another study by Vine et al. (1998) investigated worker response to an automated venetian blind and electric lighting system. The research showed that most office workers prefer higher light levels. However it raises questions as to how appropriate illuminance levels should be decided for a given setting. It also suggests that occupants must be trained prior to the installed of controlled shading devices to improve their overall experience.

An Automated Shading System is an efficient application of building shading as it allows the device(s) to operate independently based on a local solar clock combined with weather/climate sensors along with optional occupancy sensing. When shading control is used together with electric lighting control, it is a comprehensive solution for overall decrease in building energy consumption and occupant comfort (Lee et al., 1998; Kolokotsa et al., 2001). Consequently, integrated lighting/daylighting systems are gaining more popularity.



Control of dynamic shading devices has a twofold benefit. Firstly, as a result of actively controlling the device(s), solar heat gain through the facade is regulated to suit seasonal requirements by automatically allowing solar heat gain in the winter and cutting out the heat gain in the summer. This results in reduced instantaneous heating/cooling loads, thus reducing the peak and total energy demand for the space. A joint control strategy may also be designed to take advantage of thermal mass resulting in shifted peak load (Tzempelikos and Athienitis, 2007). Secondly, electric lighting usage can be remarkably reduced. Instead of using the thermal mass of the building to reduce peak loads, the operation of the dynamic envelope system can be coordinated with the daylighting control system to reduce envelope and light heat gains and to reduce the electric lighting power consumption on a short-term basis.

## **2.8 Control Algorithms in Buildings**

### **2.8.1 Classical Controllers**

Originally, the goal of the development of control systems for buildings was mainly to minimize the energy consumption. In the early phases of controllers' development, designers used Proportional–Integrate–Derivative (PID) controllers (Alm et al., 1999; Astolfi and Pellerey, 2008). Although these controllers improved the situation, improper choice of the gains in the PID controller was often a problem which was making the whole system unstable. This problem was the trigger for developing the optimal, predictive, or adaptive control techniques to solve the classical controllers' problems.

### **2.8.2 Optimal, Predictive and Adaptive Controllers**

Important research was conducted on optimum and predictive control strategies during the 1980s and 1990s. However, no industrial development has followed these scientific studies, especially due to implementation issues. In order to use optimal control (Choi et al., 2009; Clausen et al., 1993; Humphreys, 2005; Lai et al., 2007; Lai and Yik, 2007, 2009; Wong et al., 2009; Kummert et al., 2001; Burghes and Graham, 1980; Inoue et al., 1998), or adaptive control, (Curtis et al., 1996) a model of the building is necessary. Predictive control (Chen, 2001; Kummert et al., 2001; Morel et al., 2000; Nygard, 1990; Lam, 1993) is very important because it includes a model for future disturbances (e.g. solar gains, presence of humans, etc.). It improves thermal comfort mainly by reducing overheating (Lute and Paassen, 2000; Paassen et al., 1990; Milanic and Karba, 1996) but especially through night cooling. However, mathematical analysis of the thermal behavior of a building generally results in nonlinear models which are very complicated and require control engineer experts to deal with them. In addition and even more importantly, these models differ from one building to another.

Adaptive controllers have the ability to self-regulate and adapt to the climate conditions in the various buildings. More specifically, adaptive fuzzy controllers are regarded as the most promising adaptive control systems for buildings, (Clausen et al., 1993; Curtis et al., 1996; Lute and Paassen, 2000). Nesler, (1986) developed an adaptive controller for thermal processes in buildings. The standard PI control algorithm is adequate for the control of heating, ventilating, and air-conditioning (HVAC) processes. The Recursive Least squares (RLS) estimator provides estimates of the gain, time

constant and dead time of a process. RLS estimator diverges when the control loop is subjected to an un-modeled load disturbance. Actuator nonlinearity is also another problem and limitation of self-tuning controllers. Only a few authors have directly applied adaptive techniques that learn the characteristics of a building and its environment (Nesler, 1986; Teeter and Chow, 1998). These controllers are not often applicable in real-time buildings, since they have various constraints such as their need for a building model, or to make parameter estimation in real time with the algorithms being used sensitive to noise. Furthermore, their reliance on elements of bioclimatic architecture complicates their process of minimization of their cost functions and if such a minimization is obtained, the results are not applicable in practice. That is why, under real conditions, such techniques may give inaccurate results.

Additionally, such techniques do not deal with the problem of comfort. Nonlinear features that could determine some difficulties when monitoring and controlling HVAC equipment characterize the PMV index. The resulting control systems are not user friendly, since the user does not participate in the configuration of the climate of his/her environment (User preferences). Also, the classical control maximizes the energy conservation without giving priority to passive techniques (Dounis and Caraiscos, 2009).

### **2.8.3 Fuzzy Algorithms as Computational Intelligence**

Application of intelligent methods to the control systems of buildings essentially started in 1990s. Artificial Intelligence (AI) techniques were applied to the control of both conventional and bioclimatic buildings. Intelligent controllers, optimized by the use of evolutionary algorithms were developed for the control of the sub-systems of intelligent buildings (Lopez et al., 2004). The collaboration of the neural networks technology, with fuzzy logic, and evolutionary algorithms resulted in the Computational Intelligence (CI), which now has started to be applied in buildings. To overcome the nonlinear feature of PMV calculation (comfort evaluation), time delay, and system uncertainty, some advanced control algorithms have combined fuzzy adaptive control (Dounis and Manolakis, 2001; Calvino et al., 2004; Singh et al., 2006; Kolokotsa, 2001), optimal comfort control (Lai et al., 2009), and minimum-power comfort control (Federspiel and Asada, 1994).

Neural networks have been extensively used in Japan (Asakawa and Takagi, 1994) where they have been applied to commercial products such as air conditioners, electric fans etc. A system of two neural networks has been incorporated in an air conditioner to further fine-tune the equipment to the users' preferences. One of the neural networks applied in this controller is devoted to estimate the value of the PMV index by using sensor inputs. The other neural network further corrects this output. The user can train this neural network, however, this is not always optimal for a given user.

The need to obtain energy savings and to guarantee comfort conditions, taking into consideration the users' preferences, drove researchers to develop intelligent systems for energy management in buildings (Building Intelligent Energy Management Systems-

BIEMS), mainly for large buildings like office buildings, hotels, public and commercial buildings, etc. These systems are designed to monitor and control the environmental parameters of the building's microclimate and to minimize the energy consumption and operational costs (Dounis and Caraiscos, 2009).

The results of these intelligent controllers are superior when compared with classic control algorithms. The need for a complicated mathematical model to control different systems in high performance buildings makes it impossible to apply traditional control methods in buildings. But intelligent systems do not require such a model and can deal with different parts of a building model. This fact was the main motivation for development of automatic control systems. By incorporating new-type, higher-level variables that define comfort into the intelligent controllers (Dounis et al., 1992), it was possible to control comfort without going into the regulation of lower level variables like temperature, humidity and air speed. In such systems, users start to participate in the specification of the desired comfort.

Furthermore, genetic algorithms coming from the theory of adaptive control were used to optimize fuzzy controllers. Fuzzy logic control has been used in a new generation of furnace controllers that apply adaptive heating control in order to maximize both energy efficiency and comfort in a private home heating system (Altrock, 1994). The development of fuzzy controllers to control thermal comfort, visual comfort, and natural ventilation, with integration control of these sub-systems has led to remarkable results (Ardehali et al., 2004; Calvino et al., 2004; Humphreys, 2005; Dounis and Manolakis, 2001; Dounis et al., 1992; Dounis et al., 1994; Gouda et al., 2001; Guillemin, 2003; Guillemin and Morel, 2001;

Guillemin and Molteni, 2002; Kolokotsa et al., 2001, 2002, 2003, 2004, 2005; Rutishauser et al., 2005; Lah et al., 2005, 2006; Hamdi and Lachiever, 1998; Kolokotsa, 2001).

Synergistic neuro-fuzzy techniques: Neuro-fuzzy systems originated when neural network techniques were used in fuzzy technology. The technology of neural networks has found important applications not only to the control systems of buildings (Barnard, 1993; Kreider, 1995; Mozer, 1998; Ben-Nakhi and Mahmoud, 2001; Liang and Du, 2005; Egilegor et al., 1997) but also to more general problems regarding renewable energy sources. Egilegor and his research group in 1997, developed and tested a fuzzy-PI controller adapted by a neural network. However, it did not offer significant improvement. Later, Yamada et al. (1999) developed an air-conditioning control algorithm that combines neural networks, fuzzy systems, and predictive control. This system predicts weather parameters and the number of occupants. These predictions are then used to estimate building performance in order to achieve energy savings and to maintain the indoor conditions in a high comfort level.

Fuzzy P controllers: Many different methods exist to use fuzzy logic in closed-loop control systems. The simplest structure is to use the measurement signals from the process as the inputs to the fuzzy logic controller and the outputs of the fuzzy logic controller to drive the actuators of the process. This pure fuzzy logic system is called fuzzy P controller. The inputs of a global fuzzy P controller are PMV and outdoor temperature, CO<sub>2</sub> concentration, change of CO<sub>2</sub> concentration, Daylight Glare Index (DGI), and illuminance. The outputs of the system are Artificial Lighting and window opening angle settings (Dounis and Manolakis, 2001; Calvino et al., 2004; Singh et al., 2006; Kolokotsa, 2001;

Dounis et al., 1994; Ardehali et al., 2004; Altrock et al., 1994; Shepherd and Batty, 2003; Huang and Nelson, 1994; Liang and Du, 2005, Kolokotsa, 2001; Shepherd and Batty, 2003; Liang and Du, 2005; Ardehali et al., 2004; Goudaet al., 2001; Guillemain, 2003; Kolokotsa et al., 2004, 2005).

Passive techniques are one of the interesting design priorities in fuzzy P controllers. During moderate seasons, the fuzzy rules allow natural cooling through window openings in order to reach thermal comfort by using natural ventilation. During winter and summer, windows are kept closed to avoid thermal losses. The solar gains are controlled to allow passive heating during the winter and cut off unnecessary heat gain during the summer (Dounis & Caraiscos, 2009).

In addition to passive technologies built into the controller, illuminance rules are also designed to give priority to the natural lighting. The electric lighting is on when indoor illuminance is zero, during nighttime and during cloudy conditions. When indoor illuminance is increased, the electric lighting is immediately turned off and shading improves the indoor visual comfort. The performance index in the building control system is minimization of energy consumption (Kolokotsa et al., 2001).

Fuzzy PID controllers: Fuzzy PID controllers are classified into two major categories, according to their structure, (Hu et al., 2001; Xu et al., 2000). The first category of fuzzy PID controllers involves typical fuzzy logic controllers (FLCs) realized as a set of heuristic control rules. They are also called PID-like (PI-like or PD-like) FLCs. Most of the research on fuzzy logic control design refers to this category (Zhao Y, Collins, 2003; Pal, 2002; Chao and Teng, 1997; Carvajal et al., 2000; Woo et al., 2000).

The second category of fuzzy PID controllers is composed of the conventional PID controllers in conjunction with a set of fuzzy rules and a fuzzy reasoning mechanism to tune the PID gains online (Zhao et al., 1993). Controllers of this type can adapt to varying environments. The main disadvantage of PID controllers is that they are mainly model-dependent, since they require human experience with controlling the plant in order to define the range of the proportional gain.

PD-like FLCs are suitable for a limited class of systems. They are not suitable when measurement noise and sudden load disturbances accrue in the system. PID-like FLCs are rarely used because of the difficulties associated with the generation of an efficient rule base and the need for tuning its large number of parameters.

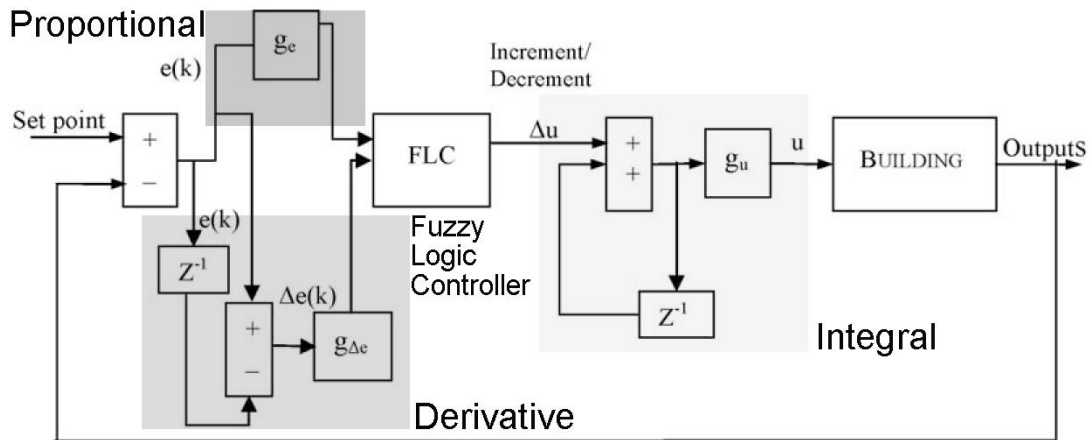


Figure 2. 10. Structure of fuzzy PI controller, (Dounis and Caraiscos, 2009).

The advantage of a fuzzy PI controller is that it does not have an operating point. The control strategy of rules evaluates the difference between the measured value and the set



point and also evaluates the change of this difference in order to decide whether to increment or decrement the control variables of the building. A fuzzy logic controller can implement nonlinear control strategies.

Adaptive fuzzy PD and fuzzy PID controller: The structure of the adaptive fuzzy PD controller is the same as for the fuzzy PD controller. The difference is that the adaptive fuzzy PD controller uses a second-order system as a reference model for the determination of the scaling factors of the controller. The objective is to design an adaptive fuzzy PD controller such that the behavior of the controlled building remains close to the behavior of a desired model. In order to improve the system's response, Calvino et al. (2004) added an adaptive network to a classical PID controller. Furthermore, they modified some control rules, aiming at determining a monotone “control surface” to guarantee better stability features of the system (Hwang and Lin, 1992). The addition of the adaptive network to the original model allows the users to vary the values of the parameters regarding the integrative and derivative blocks. Doing so, these parameters will depend on the peak of the “step response”, which improves the stability of the entire system.

Neural network controllers: In thermal comfort control (Liang and Du, 2005) and in the temperature control of hydronic heating systems (Kanarachos and Geramanis, 1998), direct neural network controllers (NNC) are used. These controllers are practical and contrary to the indirect neural network controllers and they do not require the identification model of the plant.

Table 2.5 illustrates a summary of the mentioned controllers, their applications, their structure and their technical issues based on the classical and advanced control methods.

In the column of energy consumption, the symbol H denotes that the advanced control strategies can achieve significant energy savings compared to the classical control systems. However, these potential energy savings percentages depend on weather conditions, building characteristics and user preferences (Dounis and Caraiscos, 2009).

Table 2. 5 Comparison of control algorithms based on a literature review work conducted by Dounis and Caraiscos in 2009.

| Control systems                 | Thermal comfort control (PMV) | IAQ control (CO <sub>2</sub> ) | Visual comfort control (illumination) | Energy consumption | Global control strategies | Priority to passive techniques | User preferences | Learning | Tuning: fuzzy systems or GA or neural adaptation | Temperature control | Adaptation | DCV ventilation control |
|---------------------------------|-------------------------------|--------------------------------|---------------------------------------|--------------------|---------------------------|--------------------------------|------------------|----------|--|---------------------|------------|-------------------------|
| ON/OFF                          | -                             | -                              | -                                     | -                  | -                         | -                              | -                | -        | -  | ✓                   | -          | -                       |
| PID                             | -                             | -                              | -                                     | ✓                  | -                         | -                              | -                | -        | -  | ✓                   | -          | ✓                       |
| Fuzzy P control                 | ✓                             | ✓                              | ✓                                     | ✓                  | ✓                         | ✓                              | -                | -        | -  | -                   | -          | ✓                       |
| Fuzzy PID control               | ✓                             | ✓                              | ✓                                     | ✓                  | ✓                         | ✓                              | -                | -        | -  | -                   | -          | ✓                       |
| Adaptive fuzzy PD               | ✓                             | ✓                              | ✓                                     | ✓                  | ✓                         | ✓                              | -                | -        | -  | -                   | ✓          | ✓                       |
| Fuzzy systems                   | ✓                             | ✓                              | ✓                                     | ✓                  | ✓                         | -                              | ✓                | -        | -  | -                   | -          | -                       |
| Fuzzy PI control                | ✓                             | ✓                              | ✓                                     | ✓                  | ✓                         | ✓                              | -                | -        | ✓  | -                   | -          | ✓                       |
| Adaptive fuzzy PI               | ✓                             | ✓                              | ✓                                     | ✓                  | ✓                         | -                              | -                | -        | ✓  | -                   | -          | ✓                       |
| Neural network control          | ✓                             | -                              | -                                     | ✓                  | -                         | -                              | -                | ✓        | -  | -                   | ✓          | ✓                       |
| Agent-based intelligent control | ✓                             | ✓                              | ✓                                     | ✓                  | ✓                         | ✓                              | ✓                | ✓        | ✓  | -                   | ✓          | ✓                       |
| Predictive control              | ✓                             | -                              | -                                     | ✓                  | ✓                         | ✓                              | ✓                | ✓        | ✓  | -                   | -          | ✓                       |
| Supervisory control             | ✓                             | ✓                              | ✓                                     | ✓                  | ✓                         | ✓                              | ✓                | ✓        | ✓  | -                   | -          | ✓                       |
| Reinforcement learning control  | ✓                             | ✓                              | ✓                                     | -                  | ✓                         | ✓                              | ✓                | ✓        | -  | -                   | -          | ✓                       |
| Ambient intelligent             | ✓                             | ✓                              | ✓                                     | ✓                  | ✓                         | -                              | ✓                | ✓        | -  | -                   | -          | ✓                       |
| Self-adaptive control system    | ✓                             | ✓                              | ✓                                     | ✓                  | ✓                         | ✓                              | ✓                | -        | ✓  | -                   | -          | ✓                       |
| Optimal control                 | -                             | -                              | -                                     | ✓                  | -                         | ✓                              | -                | -        | -  | ✓                   | ✓          | ✓                       |
| Optimal and robust control      | -                             | ✓                              | -                                     | ✓                  | -                         | -                              | ✓                | -        | -  | -                   | -          | ✓                       |

## **2.9 Integration of Daylight and Artificial Lighting Systems**

As mentioned before, integrating daylight and electrical lighting control systems in a building could lead to significant energy savings, improvement in performance of the system and level of comfort for the occupants. Studies conducted to assess the impacts of design and control of shading devices in buildings using exterior roller shades, clearly show that integrated shading and lighting control, designed to maximize daylight utilization, result in minimum collective lighting and cooling energy consumption (Tzempelikos and Athienitis, 2005, 2007; Roisin et al., 2007; Kapsis et al., 2010; Park et al., 2010).

Many research studies confirm that lighting control alone can result in a decrease in cooling energy demand, but the effect of integrated shading and lighting control is impressive. However, they also state that the shading type and control algorithm must be carefully chosen depending on various factors such as fenestration orientation, location, etc. In the next paragraphs, some of the significant studies in this field are reviewed.

One of the first studies in this field was conducted by Lee et al. (1998). She studied the potential energy saving of automated venetian blinds operating in combination with daylighting controls in Oakland, California. To measure the electric lighting power consumption and the cooling energy called for the window and lighting systems, the full-scale Oakland Federal Building demonstration facility was constructed. The facility consists of two adjacent identical rooms (4.57m (W) 3.71m (D) 2.68m (H)). For comparison, one room was equipped with a 'base case' system and the other one with a 'dynamic' system. For the base case system, the venetian blind was set to one of three static positions throughout the day to simulate manual control: horizontal (0°), partly closed (45°)

and nearly closed ( $68^\circ$ ). For the dynamic system, a prototype system was developed to activate the blind every 30 seconds for blocking direct solar radiation and maintaining a daylight illuminance of 540 lux–700 lux. The range of blind motion was restricted to  $8^\circ$  (Horizontal) to  $-68^\circ$  (partly closed) to limit sky view and glare. Data were collected for 14 months from June 1, 1996 to August 31, 1997. Lee concluded that an integrated system (or prototype system) could achieve energy savings of 13%–28% for cooling and 1%–22% lighting energy, respectively, compared to a static blind slat angle of  $45^\circ$ . However, because the automated blind system only blocked the solar radiation, similar to Newsham, (1994) it can be disadvantageous in places where the heating load is dominant.

In other words, the optimization of blind systems can only be achieved if a criterion for selecting control variables is performance-based (sum of cooling, heating and lighting energy use) rather than rule-based (threshold values of solar radiation and illuminance). According to Bauer et al. (1996) a fuzzy logic based control algorithm to minimize thermal and electric lighting energy demand in a building was first developed by the Technical University of Vienna. Because of the algorithm limitation, which focused only on energy conservation, Bauer proposed a modification of the TU-Wien controller for achieving energy efficiency, as well as thermal and visual comfort. The experiments were carried out in two south-facing facade offices with a floor area of  $15.6 \text{ m}^2$  and a window area of  $3.77 \text{ m}^2$ . Using the fuzzy logic-based smart blind controller, the experiments resulted in 11% lighting energy reduction, as well as 20%–50% heating/cooling energy savings.

Later, Guillemin and Morel, (2001) proposed an automated system for the regulation of solar gains, daylighting and ventilation based on fuzzy logic controllers optimized with

genetic algorithms. They developed a fuzzy logic-based system for integrated control of blinds, electric lighting and heating, ventilation and air conditioning (HVAC) systems. To achieve self-learning, an artificial neural network and genetic algorithms were employed. This technique meant that the system was capable of adapting to user behavior and the room characteristics. The adaptive controller in this study was split into two parts based on user presence: Visual comfort was optimized on detection of occupancy, otherwise energy saving was optimized. The method was tested in two rooms (4.75m by 3.6m by 2.8m with a south facing window covered with textile blinds) representing the integrated and a conventional system. The conventional system was examined without blind or dimming control, while in the integrated system the blinds were lowered or retracted by fuzzy logic rules without slat angle control. Owing to the predictive ability of the controller, the integrated system reduced energy consumption by 25% over 94 days compared to the conventional system. However, this approach does not reflect the momentary behavior of the system.

Other study by Lah et al. (2005) presented a daylight based control for automated roller blinds based on the fuzzy logic algorithm, designed to relate to human reasoning, while obtaining desired illuminance levels inside the room (Figure 2.11). A cascade type control algorithm consisting of a fuzzy controller and a PID auxiliary controller was developed.

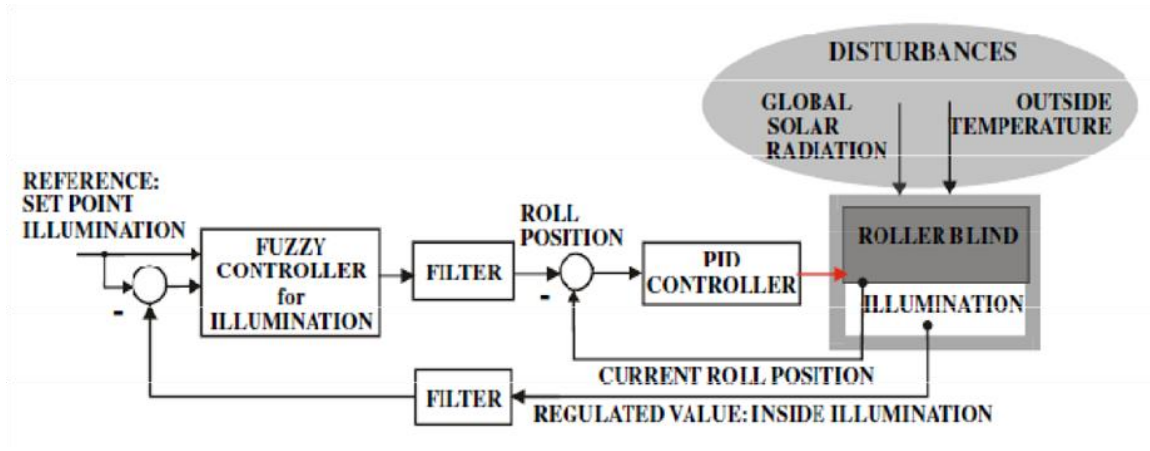


Figure 2. 11. Illuminance Control Loop (Lah et al., 2005).

The study showed that with moderate continuous movements of the blinds, the desired illuminance levels were maintained with an error of about 20 lux. However, it also restraints that results depend on the local site and weather conditions and the process of tuning the system may be a time consuming process based on human expertise.

In another research study conducted in University of Ljubljana, Slovenia (Kolokotsa et al. 2001), a system was designed and applied on an actual office space, as a hybrid cascade system incorporating fuzzy logic and conventional PI controllers. Regulation was performed with the use of sensors which monitor the environmental conditions and actuators. The main control objectives of the controller were aspects of thermal, illuminance and ventilation control and to maintain indoor environmental conditions in the desired range of the set-point values. However, there are no adequate data about the overall total energy consumption of the building or energy savings through this integrated system.

In another study by Mahdavi in 2008, a prototype daylight-responsive lighting and shading systems control was developed that was based on real-time sensing and lighting

simulations. This system was designed to control the position of window blinds and the status of the luminaires. At regular time intervals, the system considered a set of candidate control states for the subsequent time step. These alternatives were then virtually enacted via a lighting simulation application that receives input data from a self-updating model of sky (luminance distribution maps obtained via calibrated digital photography), room, and occupancy. The simulation results were compared and ranked according to the preferences (objective function) specified by the occupants and/or facility manager to identify the candidate control state with the most desirable performance.

The operation of the developed control system was documented in the course of fifteen days (in May and June 2005). To dynamically provide the context model (sky luminance distribution map) to the simulation engine of the lighting control system, a method was developed, whereby calibrated sky luminance maps are derived based on digital photography. The results suggested that calibrated sky luminance maps derived based on digital photography can provide a reliable basis for locally representative sky descriptions in daylight simulation tools. However, taking digital photos to calibrate the simulation software might not be an automated solution when it comes to reducing the amount of effort in operation and maintenance of the system. Moreover, the illustrated results of this predictive method show that some times during the day predicted blinds' positions are changing very often during only each hour. This shows that the system does not contain any aspects to improve the comfort level in the room.

In another study by Park (2010) a closed-loop proportional control algorithm was designed and relative performance of the integrated systems and single systems was



investigated. The concept of the improved closed-loop proportional control algorithm for the integrated systems was to predict the varying correlation of photo sensor signal to daylight work plane illuminance according to roller shade height and sky conditions for improvement of the system accuracy. As a result, the average maintenance percentage and the average discrepancies of the target illuminance, as well as the average time under 90% of target illuminance for the integrated systems, significantly improved in comparison with the current closed-loop proportional control algorithm for daylight responsive dimming systems as a single system. Although the system demonstrated improvements, many comfort based concepts such as view preference and the number of changes in roller shade settings during the day were neglected in the control strategy in this study.

Colaco et al. (2012) explored building energy savings using fuzzy-based blind and electric lighting control in Mangalore, South India. The position of the blinds was closed, opened or partially closed to reduce glare, and solar heat gain, and provide uniformity of daylighting (Figure 2.12). In this research, an adaptive neuro-fuzzy inference system (ANFIS) was applied to the daylight-electric lighting integrated scheme for adaptation to changing environments and room characteristics. Electric lighting was operated fully on, off or in between to satisfy the illuminance criteria which was 400 lux. The fuzzy-based blind controller was operated by three criteria: (i) visual comfort mode (user present), (ii) visual/thermal comfort mode (user present) and (iii) energy optimization mode (user absent). The integrated fuzzy blind controller with daylighting controls could achieve 20%–80% of annual energy savings compared to the base case of manual blind systems without daylighting control. Colaco and his group accomplished real-time control of

integrated systems (electric lighting and blinds) using ANFIS, but blind control was limited to position control (lowered or retracted) without any variation in slat angle.

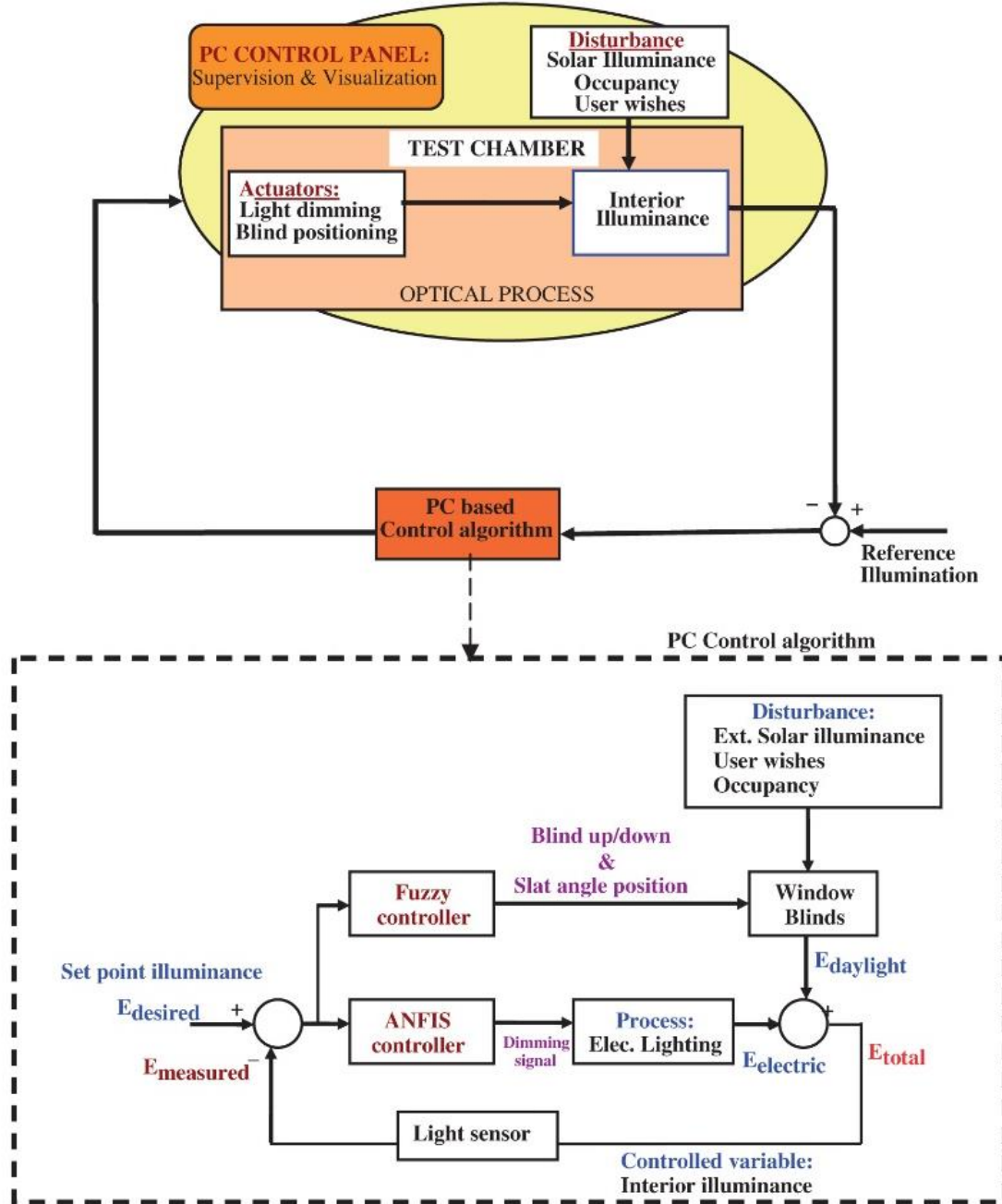


Figure 2. 12. Simplified functional block diagram illustrating the control scheme of integrated ANFIS light and fuzzy logic (Colaco et al., 2012).

Table 2. 6 Summarizes the research work in the field of integrated daylight and artificial lighting control systems.

| Study               | Year | Research Method  | Results  |
|---------------------|------|--|--|
| Lee et al.          | 1998 | <ul style="list-style-type: none"> <li>• Main goal was to study the potential energy saving through automated venetian blinds operating in combination with daylighting controls</li> <li>• In Oakland, California</li> <li>• 2 full-scale southeast-facing offices 4.57m by 3.71m by 2.68m</li> <li>• One based case and one room for dynamic control strategy</li> </ul>   | <ul style="list-style-type: none"> <li>• 1-22% lighting energy savings, 13-28% cooling load reductions, and 13-28% peak cooling load reductions through dynamic system</li> <li>• Control system met design objectives under all weather conditions to within 10% for at least 90% of the year.</li> </ul> |
| Bauer et al.        | 1996 | <ul style="list-style-type: none"> <li>• A fuzzy logic based control algorithm was developed to minimize thermal and electric lighting energy demand in a building</li> <li>• Main focus was on energy conservation</li> <li>• Two south-facing facade offices</li> </ul>  | <ul style="list-style-type: none"> <li>• Experiments resulted in 11% lighting energy reduction, and 20%–50% heating/cooling energy savings</li> </ul>  |
| Guillemin and Morel | 2001 | <ul style="list-style-type: none"> <li>• Integrated control of blinds, electric lighting and heating, ventilation and air conditioning (HVAC) systems</li> <li>• System was based on fuzzy logic controllers optimized with genetic algorithms</li> <li>• To achieve self-learning, an artificial neural network and genetic algorithms were employed</li> <li>• Tests for integrated and a conventional system</li> </ul> | <ul style="list-style-type: none"> <li>• Reduced energy consumption by 25% over 94 days compared to the conventional system</li> </ul>   |
| Lah et al.          | 2005 | <ul style="list-style-type: none"> <li>• Daylight based control for automated roller blinds based on the fuzzy logic algorithm and a PID auxiliary controller</li> </ul>   | <ul style="list-style-type: none"> <li>• Results showed that with moderate continuous movements of the blinds, the desired illuminance levels were maintained with an error of about 20 lux.</li> </ul>  |
| Kolokotsa et al.    | 2001 | <ul style="list-style-type: none"> <li>• Main controller objectives were aspects of thermal, illuminance and ventilation control and maintain indoor environmental conditions in the desired range of the set-point values.</li> </ul>   | <ul style="list-style-type: none"> <li>• No adequate data about the overall total energy consumption of the building or energy savings through this integrated system</li> </ul>   |
| Mahdavi             | 2008 | <ul style="list-style-type: none"> <li>• A prototype daylight-responsive lighting and shading systems control was developed</li> <li>• System was based on real-time sensing and lighting simulations</li> <li>• Fifteen days in May and June 2005</li> <li>• A method was developed, whereby calibrated sky luminance maps were derived based on digital photography</li> </ul>   | <ul style="list-style-type: none"> <li>• Result showed that developed methodology can provide a reliable basis for locally representative sky descriptions in daylight simulation tools</li> <li>• taking digital photos to calibrate the simulation software is not an automated solution</li> </ul>      |

|               |      |   |  |
|---------------|------|---|--|
| Park          | 2010 | <ul style="list-style-type: none"> <li>• A closed-loop proportional control algorithm for the integrated systems was developed</li> <li>• Main objective was to predict the varying correlation of photo sensor signal to daylight work plane illuminance according to roller shade height</li> </ul>   | <ul style="list-style-type: none"> <li>• The integrated system demonstrated improvements in comparison to current closed-loop proportional control algorithm for daylight responsive dimming systems as a single system</li> <li>• Many comfort based concepts were neglected in the system</li> <li>•</li> </ul>                        |
| Colaco et al. | 2012 | <ul style="list-style-type: none"> <li>• An adaptive neuro-fuzzy inference system (ANFIS) was applied to control blind and electric lighting control</li> <li>• Study done in Mangalore, South India</li> <li>• Main objective was to control the blinds to reduce glare, and solar heat gain, and provide uniformity of daylighting</li> <li>• Controller was operated by three criteria: (1) visual comfort mode (user present), (2) visual/thermal comfort mode (user present) and (3) energy optimization mode (user absent)</li> </ul> | <ul style="list-style-type: none"> <li>• Result show that controller could achieve 20%–80% of annual energy savings compared to the base case of manual blind systems without daylighting control.</li> <li>• Blind control was limited to position control (lowered or retracted) without any variation in blind slat angles</li> </ul> |

## 2.10 Summary and Gaps in Research

Although the majority of buildings already use some sort of automated control for the regulation of indoor environmental parameters (e.g. regulation of heating and cooling systems, daylight responsive artificial illumination, etc.), these systems do not address the complexity of the indoor environment since they regulate mainly discrete phenomena and neglect the holistic nature of the problem. Moreover, in some of control approaches where many design aspects such as daylighting, artificial lighting and comfort are integrated together, the nature of the control algorithm becomes very complicated which leads to complexity of the control system and difficulties in application, operation and maintenance of such systems in buildings and requires many experts and long delays of the system. In addition, many of these research works display integrated systems that are not responsive to different changes in the building shape and size and also in different climatic conditions.

Based on reviewed research studies, there is a need for applying an innovative control methodology to achieve a higher level of comfort and overall energy savings in the buildings which is based on a much simpler and manageable algorithm structures and is applicable on real-time buildings. A methodology is needed that combines the produced knowledge from past research studies, and at the same time fills the gaps in research and refines the current control methods.

In this research study, an innovative automated control methodology is developed and demonstrated that introduces an adaptive integrated control algorithm, with a simplified structure which makes it easy to implement and operate in buildings. The system is able to improve the visual comfort in the office space and at the same time significantly reduces the electrical energy consumption. It is adaptive and applicable on a broad variety of buildings with different geometry and climatic conditions. In addition, it is automated and requires simple input data, (light levels read by minimal number of sensors in the room) in order to regulate the dynamic movements of blinds' slat angle and electrical lights efficiently.

### **3 PHASE I: DEVELOPMENT OF A PREDICTING ALGORITHM TO OPTIMALLY CONTROL VENETIAN BLINDS**

#### **3.1 Introduction**

The reviewed research studies in the last chapter point to the need for an innovative lighting control approach to achieve a higher level of comfort and overall energy savings which is based on a much simpler algorithm structure and applicable on real-time buildings. A methodology is needed that combines the existing knowledge from the past research studies, and at the same time fills the gaps and refines the current control methods in order to provide an efficient lighting scenario inside the building and save more electrical, cooling and heating energy. More specifically, there is a need for a simplified control system that takes the comfort and energy efficiency aspects into account and at the same time is adaptable to all types of buildings and pays attention to the occupants' needs at all times.

In this research study, an innovative automated control methodology is developed and demonstrated that introduces an adaptive integrated lighting control algorithm, with a simplified structure which makes it easy to implement and operate in real-time buildings. The system is able to improve the visual comfort in the office space and at the same time significantly reduce the electrical energy consumption in the buildings. In addition, as mentioned before, it is automated and requires simple input data, (light levels read by minimal number of sensors in the room) in order to regulate the dynamic movements of blind's slat angles and electrical lights efficiently.

The first development step of such algorithm is represented in this chapter. The chapter focuses on a preliminary simulation-based study to establish a control baseline to predict the optimal blind slat angles inside an office space. This approach will be then validated and applied on adaptive controller in the next design steps.

The demonstrated prediction approach is based on using daylighting simulation software in the context of a small scaled test cell which represents a virtual office space. A startup baseline for the optimal blind slat angle settings for windows is developed with the objective of maintaining uniform lighting levels on a horizontal surface (work plane) inside the test cell. The lighting baseline simulations are limited to specific times and days of the year to reduce and automate the simulation process. These limited simulations are then applied to predict the optimal blind slat angles for other days of the year. The developed methodology is described, results of such approach are presented to predict the optimal blind slat angle setting during a year and during any chosen day.

As mentioned in the last chapter, some researchers investigated and developed different prediction methods to determine the optimal blind slat angle settings for the occupants (Hopkinson & Bradley, 1965; Moon & Spencer 1945; Sutter et al., 2001). Sutter in 2001 introduced a model which operated based on a specific illuminance level, (8000 lux) on the window frame. If the illuminance exceeded that level then the controller was activated to close the blinds in order to achieve the optimal visual and thermal comfort level.

Sutter's model also provided a detailed guideline to optimize the view and visual comfort which unlike many other research works that neglected the comfort concepts, was one of the strength points in his research study.

However, most of these studies are limited to specific solar latitude and geographical location. Based on the literature review in integrated lighting control section, if any of these designed controllers are applied on other locations the accuracy of the system decreases significantly. Since the proposed prediction approach is based on a limited set of simulations and simulated data, it could be applicable on different locations with the same level of accuracy.

### **3.2 Objective and Scope**

The prediction method is the first step of designing an adaptive integrated control strategy which provides a base-line for an automated start-up of blind settings with an optimal angle in order to provide sufficient daylight in the office space.

The strategy is developed on a small scaled virtual test cell that represents a small office space. A set of daylighting simulations inside the virtual model were applied as input for the prediction algorithm to predict the optimal blind angle settings for three venetian blinds inside the model. The main objective of this step was to suggest the optimal settings in order to achieve a uniform daylight level on the defined work plane.

### **3.3 Methodology**

The prediction approach is based on simulated data inside a small-scaled model which represents an office area. Then, software code was written in MATLAB in order to further analyze the daylight illuminance levels inside the virtual model. In the following sections, the simulation based approach is described in more detail.



### 3.3.1 Daylight Simulation

The test room model was built in ArchiCAD and then imported to Relux Professional lighting software for further analysis (Figure 3.1).

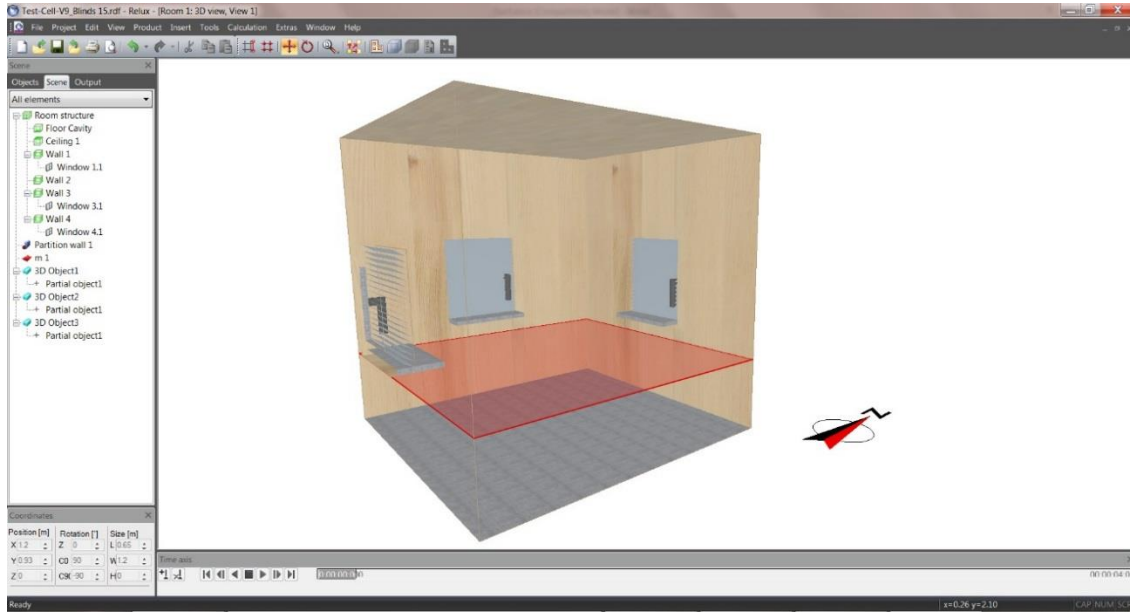


Figure 3. 1. The test cell model in Relux professional lighting software.

ArchiCAD is an architectural BIM CAD software for Macintosh and Windows developed by the Hungarian company GRAPHISOFT (GRAPHISOFT, 2014).

In addition, Relux is a European lighting software which calculates lighting arrays, daylighting and very simple electrical energy data. Calculation for each aspect can be made separately or in a combined mode (Relux Informatik, 2014). Aradiosity and a modified Radiance ray tracing algorithm are used in Relux light calculation engine and user can decide if they would like to incorporate all these methods into calculations.

The ray tracing module is also used for rendering. The accuracy of the software has been validated by Maamari et al. (2006a) and it has been used in several lighting studies (Ruggiero et al., 2009; Linhart & Scartezzini, 2010). Relux is also free but does not provide an open source.

The small- scaled virtual test bed model is built to investigate daylighting situation and pertains to a 4 by 4 by 4 feet office area with three 1 by 1.3 feet windows on the North, West and South walls (Figure 3.2). In addition, all interior walls and ceiling are from Birch wood and the floor is furnished with a grey carpet. All three windows have a clear glass with 80% transmittance and are equipped with matte aluminum blinds. The interior frames of the windows are also made of matte aluminum. The blinds slat angles are set on different degrees in order to control the amount of daylight penetrating to the test cell. Furthermore, to calculate and demonstrate the light level in virtual office, a measurement surface inside the test cell is defined which represents the working surface in an actual office (shown in red in Figure 3.3).

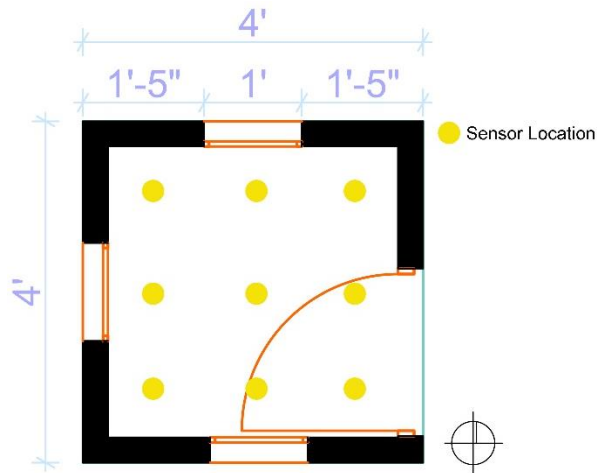


Figure 3. 2. Virtual test cell plan and sensor locations for phase I of the study, (Test cell size: 4×4×4 feet).

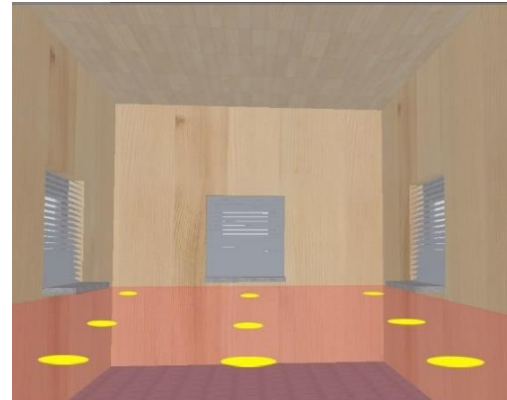


Figure 3. 3. Perspective of the virtual test cell model in Relux and sensor distribution.

The calculations were done for Phoenix, Arizona ( $33^{\circ} 27' 0''$  N,  $112^{\circ} 4' 0''$  W) for clear sky according to International Commission on Illumination, (CIE), which refers to less than 30 % cloud cover, or none. To measure the daylight levels on the work plane, there are 9 virtual light sensors placed in the test cell to read the illuminance. Figure 3.3 shows the sensor placement in the model.

As stated earlier, the intent of the simulated-based approach is to optimally regulate blind slat angles in order to achieve a unified light level on the defined work plane based on the desired-lux level which is 250 lux in this phase of study. At the same time, to reduce the simulation time and automate the approach, simulated data are limited to a minimum number of runs. These limited simulations include three different days that capture the variability of the solar movement over the year and day in summer, winter and fall, (summer and winter solstice and autumnal equinox days):

- June 21
- September 22
- December 21

In addition, the simulation was done for three hours each day including 10am, 12pm and 2pm, which catch the daily solar path inside the virtual office.

The daylight simulations ran with only one window open with different blinds' slat angles one at a time while other two windows closed. We assumed that illuminance level at a specific area is additive and the total lighting for the case whereas all three windows are open was calculated as the sum of the solar radiation contribution from separate simulation cases including window north, west or south open with different slat angles. All three windows were equipped with interior blinds (matte aluminum) which were movable from 0° (fully open) to 90° (fully closed) in 15° intervals (Figure 3.4). The reason for applying only downward slat angles was that in most of downward settings there is view availability, even if it is only a view of the sky. This will improve the level of visual comfort in the prediction algorithm.

Different Settings of Blind Slat Angles

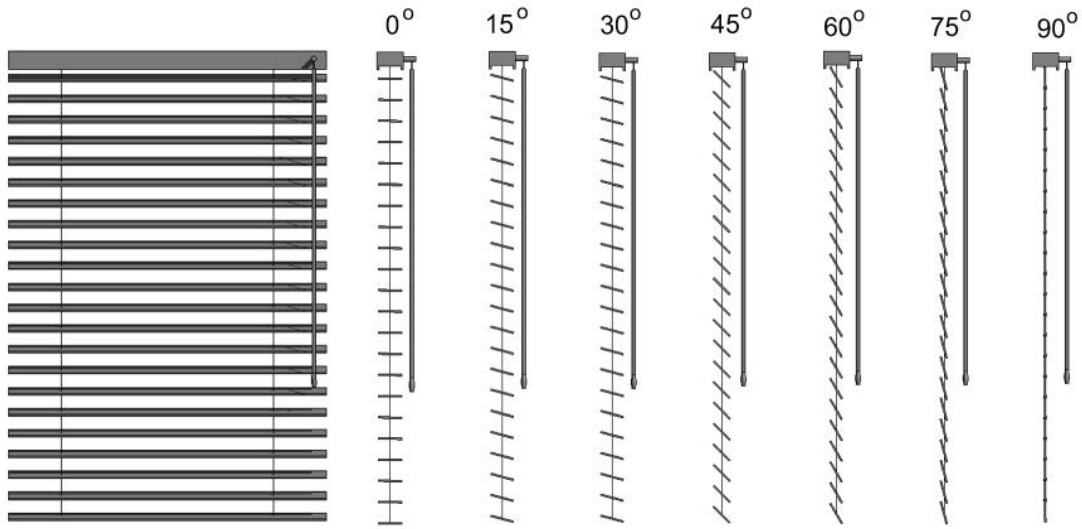


Figure 3. 4. Different blind slat angle settings applied in this study.

### 3.3.2 Analysis

To analyze the output results of Relux daylight simulations for three chosen days which were in text format, a MATLAB code was written to firstly combine the simulated daylighting data read by each sensor in order to establish all possible combinations that include all three window settings which are  $7^3=343$  (seven different angle positions and three windows) different combinations. Secondly, another MATLAB code was programmed to investigate the optimal blind slat settings based on uniformed light level on work plane. The following section describes the calculation method for this step.

Calculation of “Total Error” values for all blinds’ setting combinations. The control objective was to find the best blind slat settings for three windows that prove the most uniform illuminance level the work plane. A target of 250 Lux was defined to compare all simulated data provided by 9 sensors on the work plane for each combination. To achieve

this goal, a Total Error (TE) value was calculated for each setting combination as following:

Mean Square Error (MSE) Calculation:

$$MSE = \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n - 1} \quad (1)$$

Total Error (TE) Calculation:

$$TE = \sqrt{(y_{desired} - \bar{y})^2 + MSE} \quad (2)$$

Where:

$y_i$ : measured light level in lux by 9 sensors installed on the work plane

$\bar{y}$ : average illuminance level of all sensors in lux

n: number of sensors

$y_{desired}$ : desired illuminance level in test cell model in lux

The total error values were calculated for all possible blind setting combinations inside the test cell model which are  $7^3 = 343$  combinations, (3 windows and 7 blind stat settings for each window, (0°, 15°, 30°, 45°, 60°, 75°, 90°)) on June 21<sup>st</sup>, September 22<sup>nd</sup> and December 21<sup>st</sup>. The fitness function was set to find the optimal combination for blind settings with smallest total error. The results are shown in following graphs.

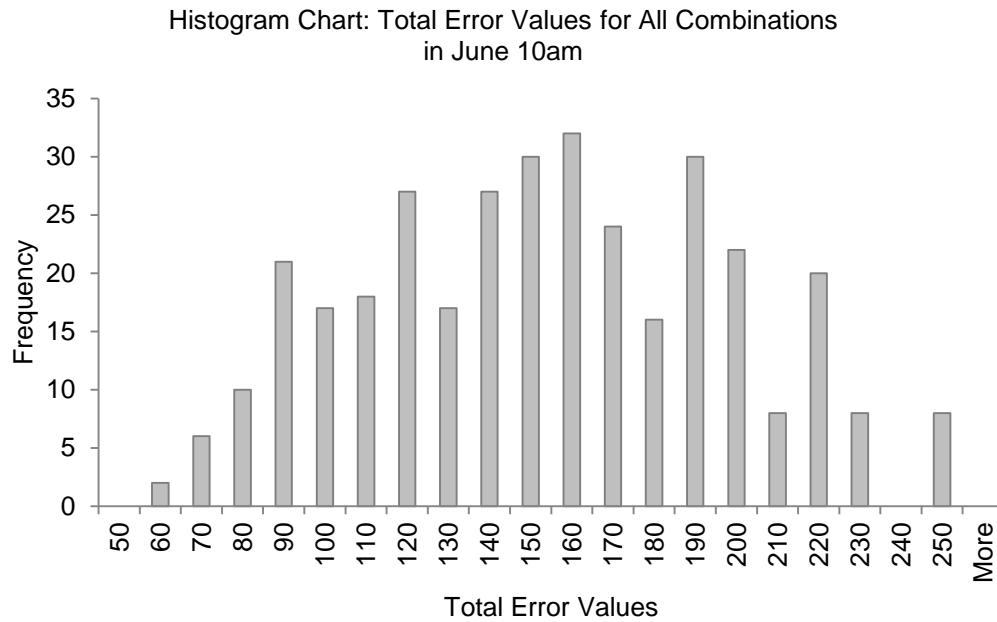


Figure 3. 5. Histogram Charts of total error values for all combinations in June 10am.

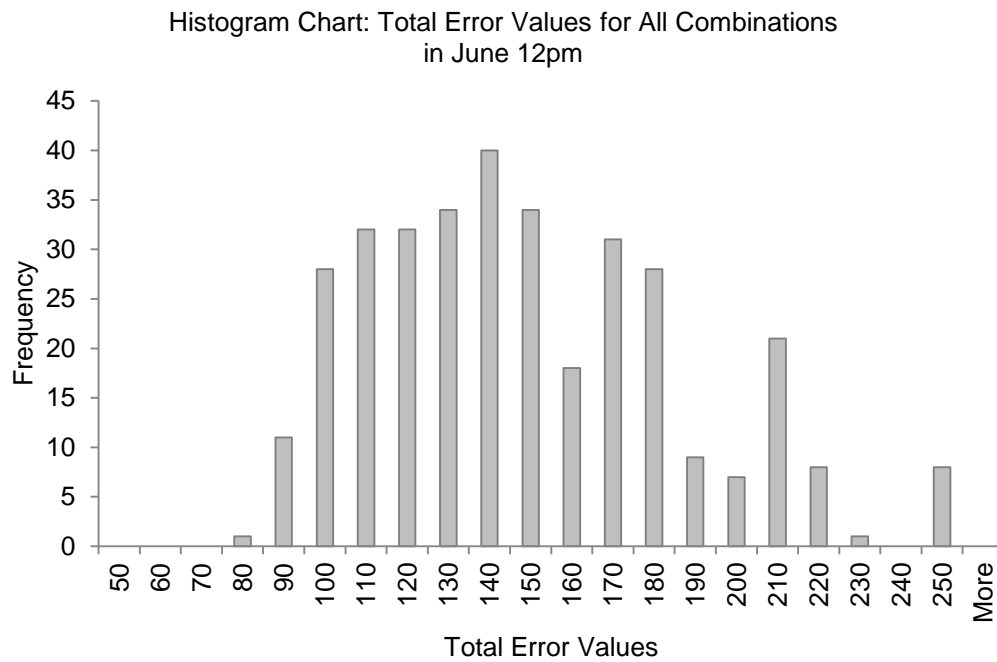


Figure 3. 6. Histogram Charts of total error values for all combinations in June 12pm.

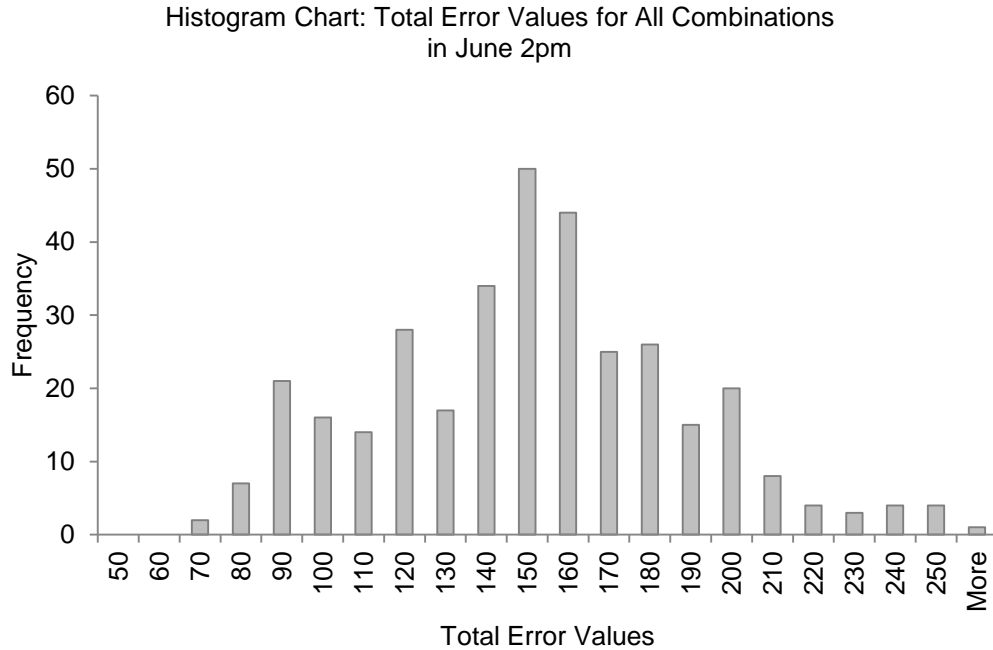


Figure 3. 7. Histogram Charts of total error values for all combinations in June 2pm.

Figure 3.5, 3.6 and 3.7 illustrates three histogram charts for June 21<sup>st</sup>, 10am, 12pm and 2pm. These histograms show the values of calculated total errors, (TE) for 343 different blind combinations on June 21<sup>st</sup> based on equations 3. Regarding the definition of TE, smaller values indicate to a more uniform illuminance situation on the work plane and larger values point to significant differences between 250 desired lux level and illuminance levels read by 9 sensors on the work plane. As seen in the charts about 80% of all blind setting combinations show a TE value in a range of 90 to 200 which indicates to a less uniformed illuminance situation in the test cell on June 21<sup>st</sup>. However, for each hour, there are a few combinations with the smallest total error value, (TE values 60 to 80) which represent the optimal blind setting combination for those specific hours on June 21<sup>st</sup>.



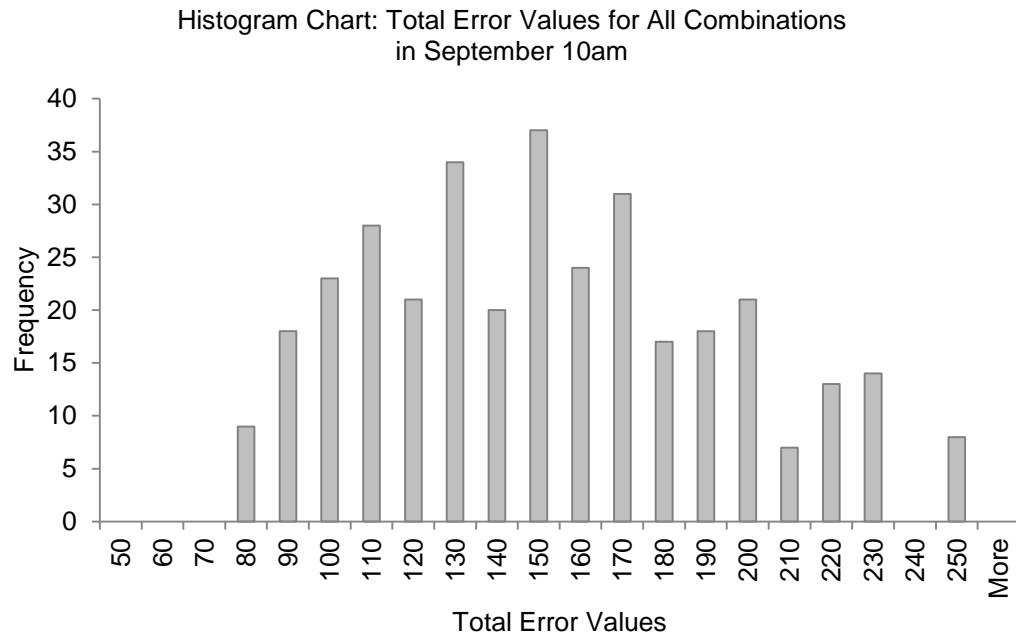


Figure 3. 8. Histogram Charts of total error values for all combinations in September 10am.

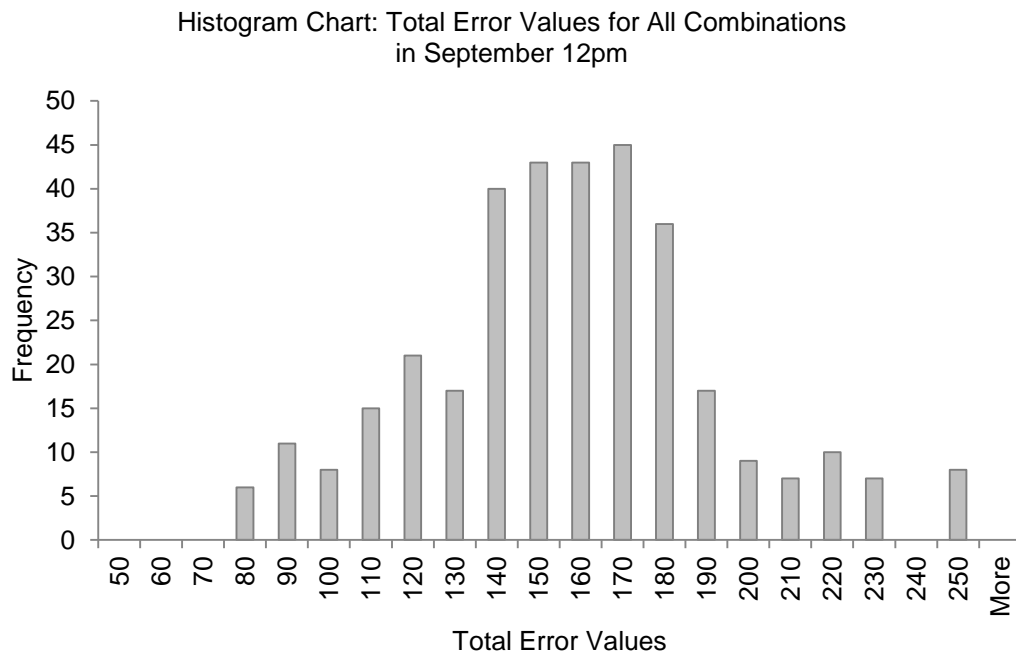


Figure 3. 9. Histogram Charts of total error values for all combinations in September 12pm.

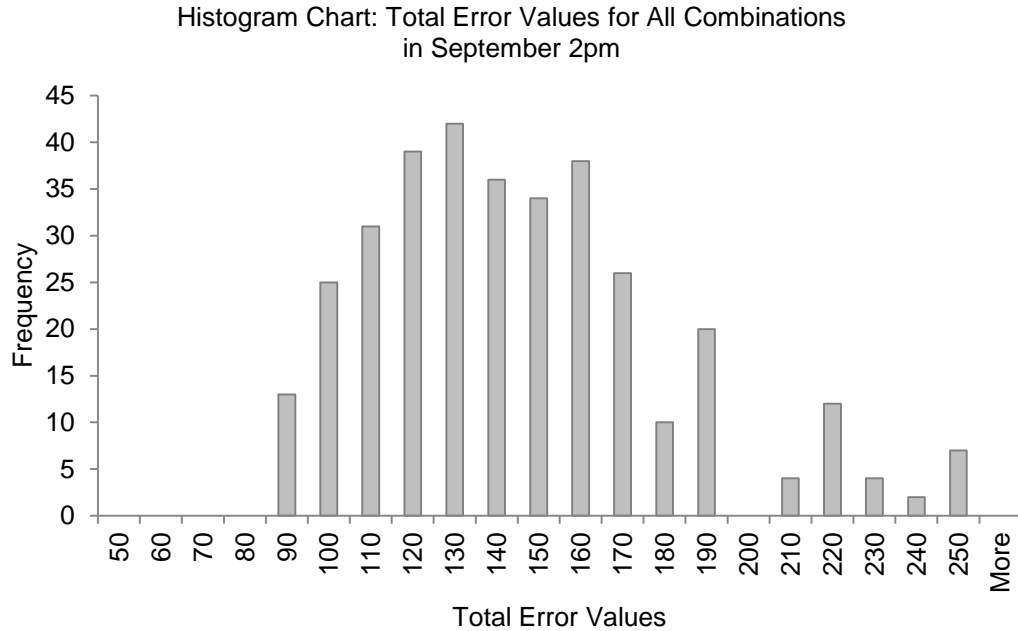


Figure 3. 10. Histogram Charts of total error values for all combinations in September 2pm.

Similar to the last Figures, the histograms in Figures 3.8, 3.9 and 3.10 show the TE values for all 343 different blind combinations on September 22<sup>st</sup>. As seen in the charts about 90% of all blind setting combinations show a TE value in a range of 90 to 200 which indicates to a less uniformed illuminance situation in the test cell. However, for each hour, there are a few combinations with the smallest total error value (TE values 80 to 90) which represent the optimal blind setting combination for those specific hours on September 22<sup>st</sup>. These blind slat angle combinations are then picked by the algorithm as best predicted optimal settings.

Furthermore, the same graphs are presented for December 21<sup>st</sup> in Figures 3.11, 3.12 and 3.13.

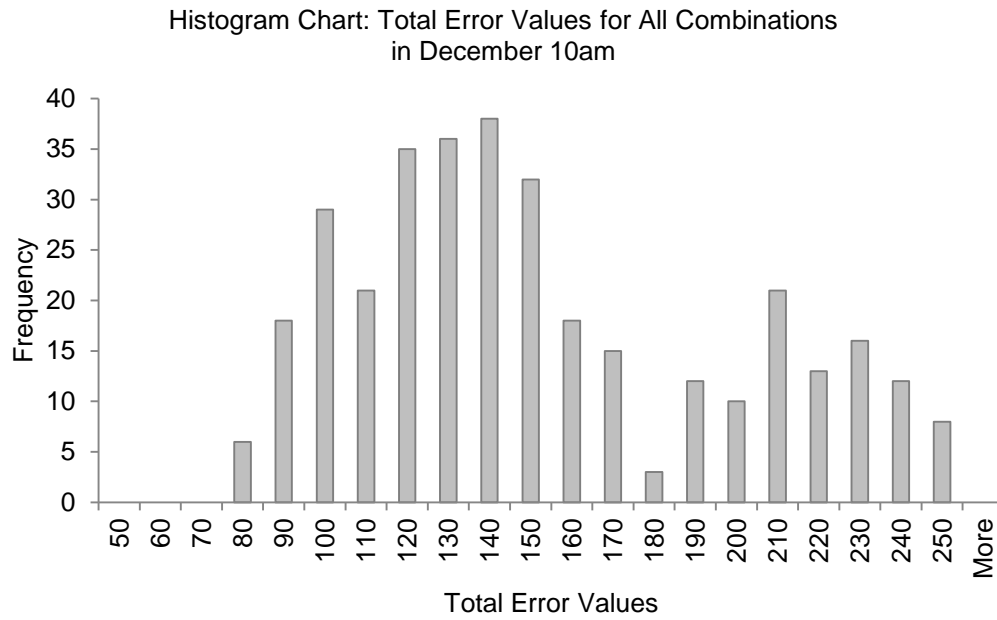


Figure 3. 11. Histogram Charts of total error values for all combinations in December 10am.

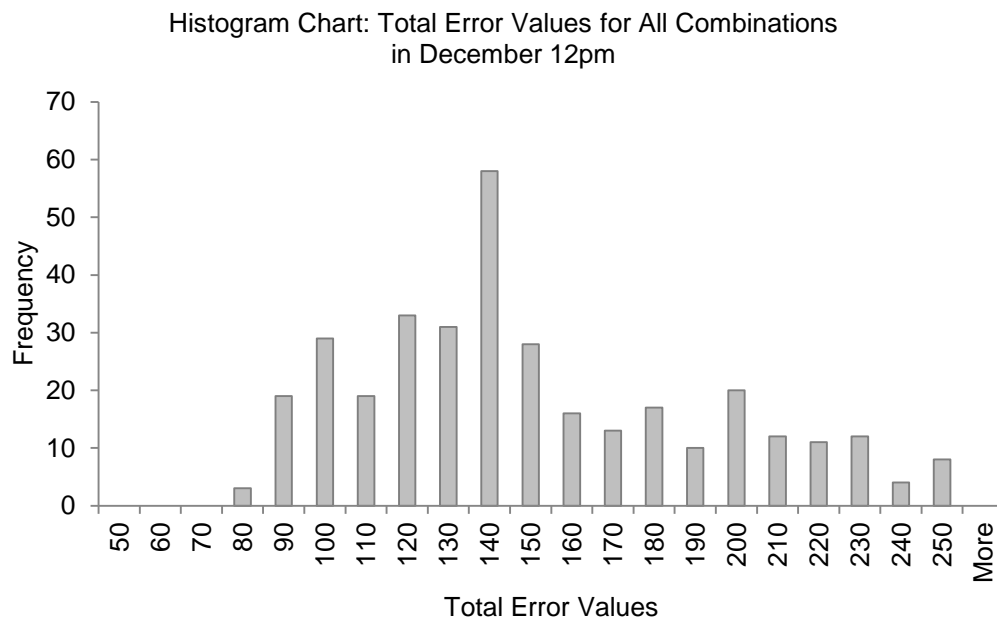


Figure 3. 12. Histogram Charts of total error values for all combinations in December 12pm.

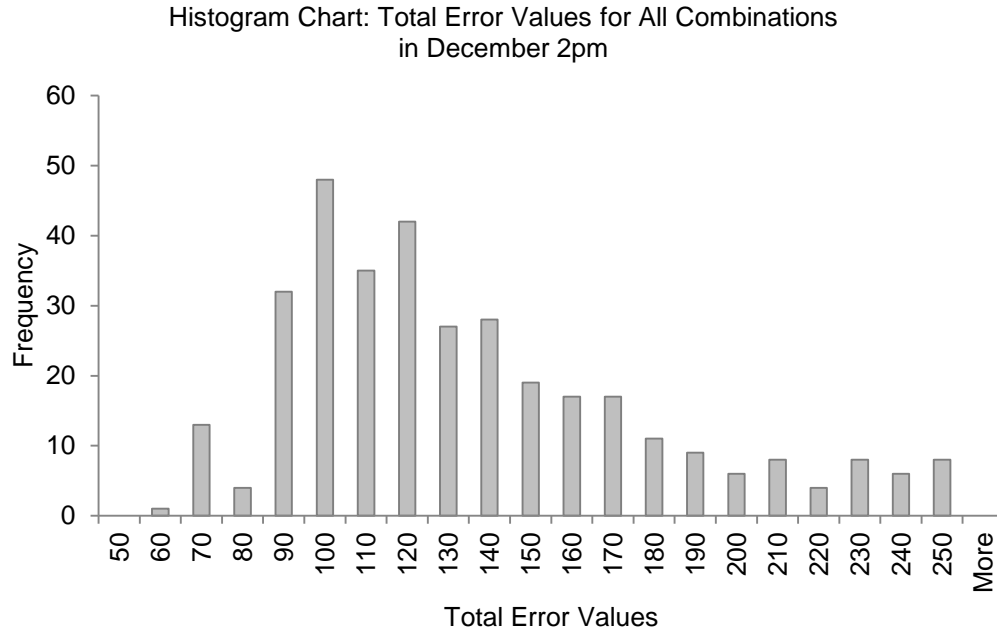


Figure 3. 13. Histogram Charts of total error values for all combinations in December 2pm.

The TE histograms for December 21<sup>st</sup> indicate to larger values of TE among the 343 blind combinations. The reason for this fact could be the decreased daylight availability in winter time, thus the lower illuminance levels in the test cell. The few combinations with the smallest total error value (TE values 60 to 80) represent the optimal blind setting combination on December 21<sup>st</sup>.

### 3.3.3 Cost Function Calculation for All Combinations

One of the important aspects in controlling the blinds in an optimized setting is visual comfort. The amount of change in the blind slat angle in each setting needs to be minimized to avoid the distraction caused by blinds motor noise and visual discomfort.

To achieve this goal, a cost function was defined that takes the total error values and the amount of changes in blinds slat angle into account. The cost function contains a weight

factor  $\alpha$  which defines the importance of the total error and amount of change in angles for the next setting. The cost function is defined as below:

$$\text{Cost function} = (1 - \alpha)TE + \alpha \sqrt{\frac{(A_i - A_x)^2 + (B_i - B_x)^2 + (C_i - C_x)^2}{3 \times 90^2}} \quad (3)$$

Where the variables are defined as follows:

$\alpha$ : Weight factor

$A_i$ : Current blinds slat angle for window A (north-side)

$B_i$ : Current Blinds slat angle for window B (west-side)

$C_i$ : Current blinds slat angle for window C (south-side)

$A_x$ : Optimal blinds slat angle for window A

$B_x$ : Optimal blinds slat angle for window B

$C_x$ : Optimal blinds slat angle for window C

The cost function has to be made as small as possible in order to maintain the most uniform lighting situation on the work plane and to have the smallest changes from one blind slat setting to the next one. As mentioned before, in this equation  $\alpha$  is defined as a weight factor between TE values and slat angle changes which has to be chosen properly. When weight factor  $\alpha = 0$  the cost function value equals to the smallest TE value without taking the slat angle changes into consideration. On the other, for  $\alpha = 1$ , the TE value weight factor is ignored and the objective would be to maintain the blind slat angle settings constant and to keep the cost function value close to zero. In other words, if  $\alpha$  is 1 the blinds will be set on their optimal predicted setting based on smallest TE values in the morning, but then they will stay on the same position for the rest of the day. Table 3.1 illustrates the

optimal blind slat setting angles based on smallest total error with  $\alpha = 0$  (changes in blind settings are ignored).

Table 3. 1 Optimal blind slat angle settings for three simulation days based on smallest cost function when  $\alpha=0$ .

| Time      | Total Error | Ave. Lux | Window A (North) | Window B (West) | Window C (South) | Cost Function |
|-----------|-------------|----------|------------------|-----------------|------------------|---------------|
| June 10am | 56.28       | 241.25   | 0                | 90              | 0                | 56.28         |
| June 12pm | 78.16       | 223.60   | 0                | 30              | 30               | 78.16         |
| June 2pm  | 68.57       | 239.54   | 60               | 75              | 0                | 68.57         |
| Sep. 10am | 74.68       | 258.05   | 45               | 15              | 0                | 74.68         |
| Sep. 12pm | 71.03       | 235.15   | 45               | 0               | 15               | 71.03         |
| Sep. 2pm  | 81.47       | 251.19   | 0                | 15              | 15               | 81.47         |
| Dec. 10am | 73.38       | 233.08   | 45               | 90              | 0                | 73.38         |
| Dec. 12pm | 74.34       | 233.65   | 45               | 0               | 15               | 74.34         |
| Dec. 2pm  | 59.70       | 248.50   | 45               | 0               | 15               | 59.70         |

As shown in the Table 3.1, when  $\alpha=0$  the algorithm operates only based on only smallest total error values without taking the blind slat angle changes into account. In this case, the cost function value is equal to the total error value.

One of the interesting points in Table 3.1 is the average illuminance values of 9 sensors on the work plane. The selected blind slat angle combinations for the three windows in all three days indicate to an average illuminance very close to the desired illuminance level which is 250 lux. This points out to the accuracy of the prediction algorithm.

### 3.3.4 Optimal Control Setting Prediction

As explained before, the number of simulations is limited to three days: June 21<sup>st</sup>, September 22<sup>nd</sup> and December 21<sup>st</sup> and three times of the day namely at 10am, 12pm and 2pm. A prediction method based on smallest (best) cost function values has been developed which includes two different approaches in order to predict best blind slat angle settings for three windows in the test cell model during a year and also during a chosen day. Thus, the prediction approach is divided into two different categories:

- Yearly prediction approach
- Daily prediction approach

Yearly prediction approach: For yearly predictions of the best blind settings, the weight factor  $\alpha$  in the cost function equation is equal to zero, ( $\alpha = 0$ ) since the amount of changes in blind slat angles are not significantly important for yearly prediction. Based on this fact, the cost function will be just based on the best TE values. In this case, the initial condition of all blinds have been set to zero, (Window A=0°, Window B=0°, Window C=0°).

In this approach, TE values for the three simulated months, (June, September and December) were used to predict the best blind settings for each randomly selected month. Graphs in Figures 3.8, 3.9 and 3.10 show that if the optimal blind situation for three windows in June would be applied on other 11 months of the year at the exact time, the applied setting is also one of the optimal settings for at least two month before and two months after June. This also applies for September and December values. Based on simulated values this approach is represented in the following graphs.

Total Errors Based on Predicted Blind Slat Angles in June 21st at 10 am,  
(Window A:0 Window B:90 Window C:0)

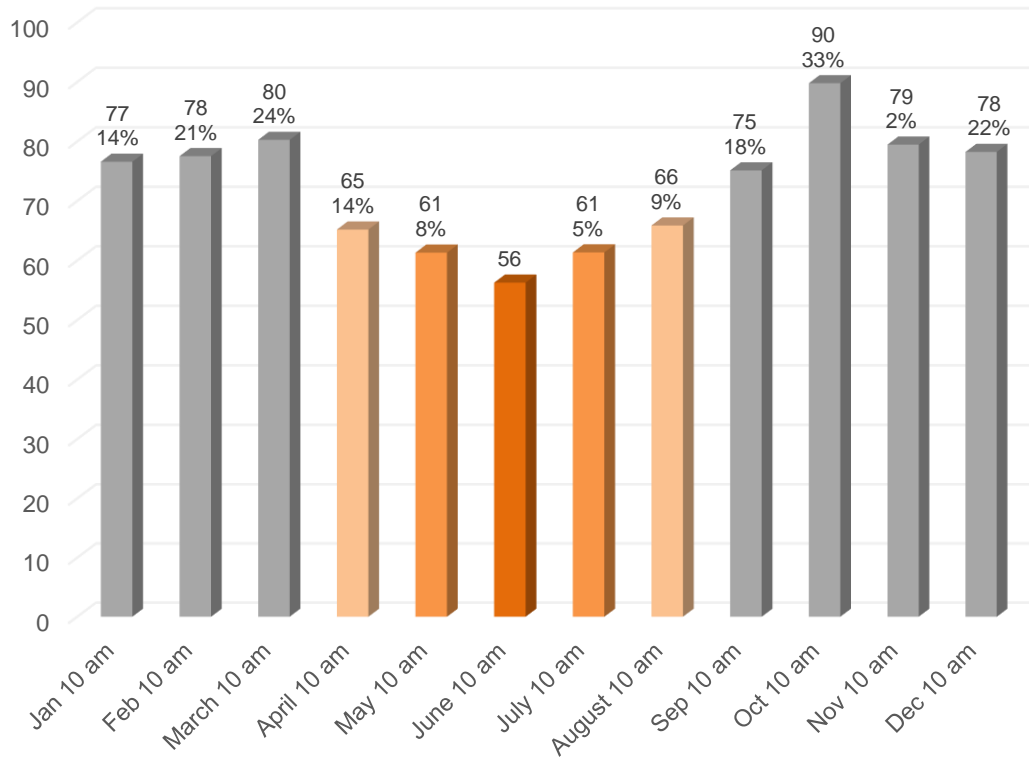


Figure 3. 14. Yearly prediction approach based on June 21st, 10am. The highlighted months in red show that by applying the optimal setting of June 21st on the same time of other 11 months the TE values for two months before and after June are very close to optimal setting's TE value.



Total Errors Based on Predicted Blind Slat Angles in June 21st at 12 pm,  
(Window A:0 Window B:30 Window C:30)

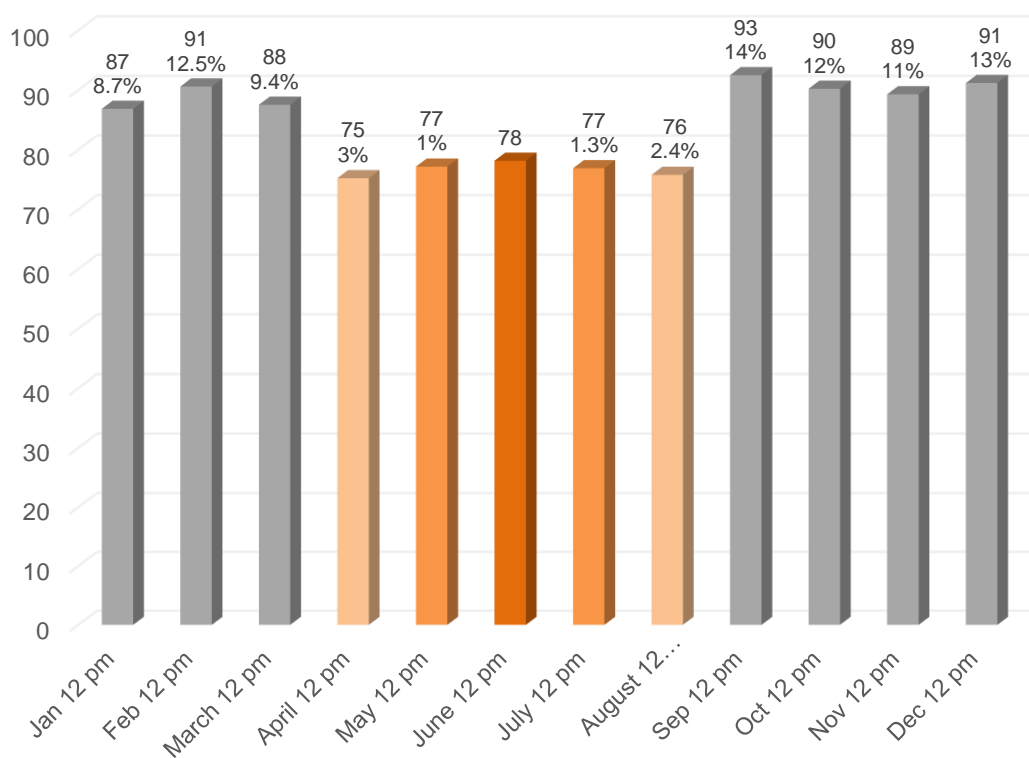


Figure 3. 15. Yearly prediction approach based on June 21st, 12pm. The highlighted months in red show that by applying the optimal setting of June 21st on the same time of other 11 months the TE values for two months before and after June are very close to optimal setting's TE value.

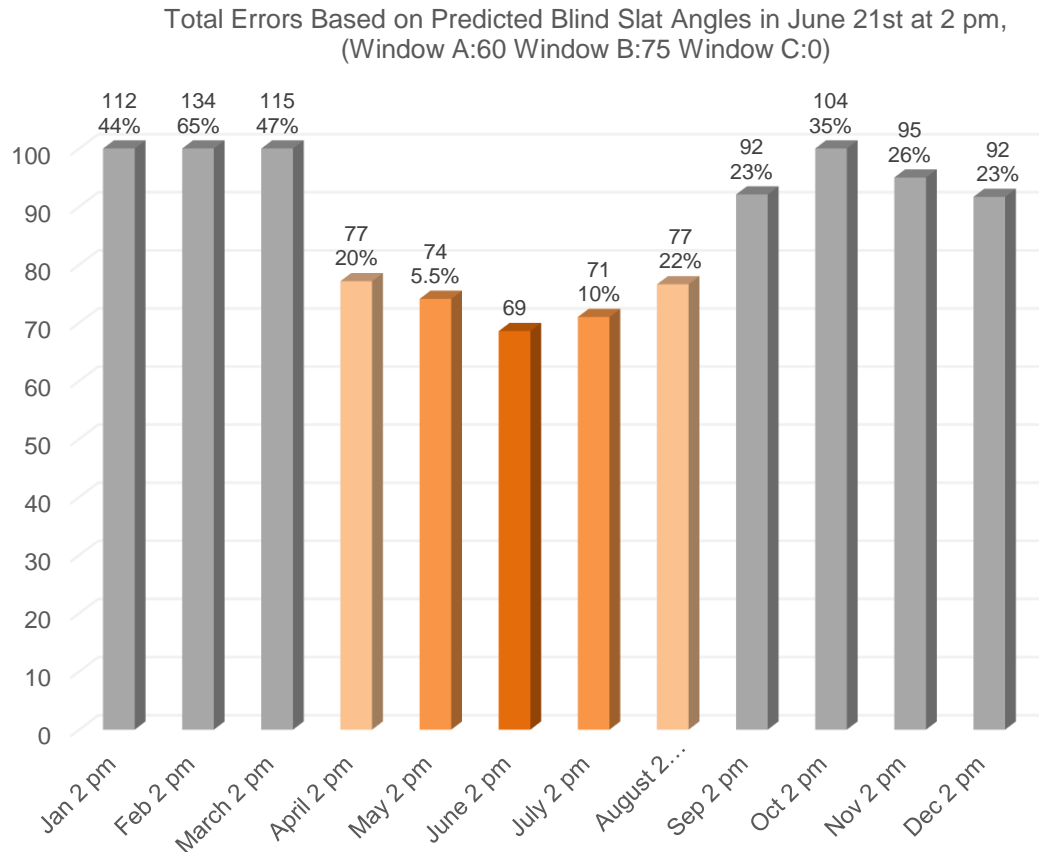


Figure 3. 16. Yearly prediction approach based on June 21st, 2pm. The highlighted months in red show that by applying the optimal setting of June 21st on the same time of other 11 months the TE values for two months before and after June are very close to optimal setting's TE value.

Figures 3.14 to 3.16 illustrate the TE values, when the best setting in June 21<sup>st</sup>, 10 am, 12 pm and 2 pm are applied to the same time of other 11 months. According to the smallest cost function values which are equal to total error values in June at 10 am, the best settings for the blinds are window A=0°, Window B=90° and window C=0°. This blind slat angle setting has been applied on all other 11 month at 10 am to determine how well the best setting in June fits as an optimal set up for the rest of the year.

The results from daylighting simulation confirms that optimal blind settings for June 21<sup>st</sup> are also optimal for April, May, July and August which indicate a total error difference

of 10% and less. This fact shows that the optimal blind settings for June 10 am, ( $0^\circ 90^\circ 0^\circ$ ) could be applied as one of the optimal setting's combinations to predict the setting for two month before and two month after June.

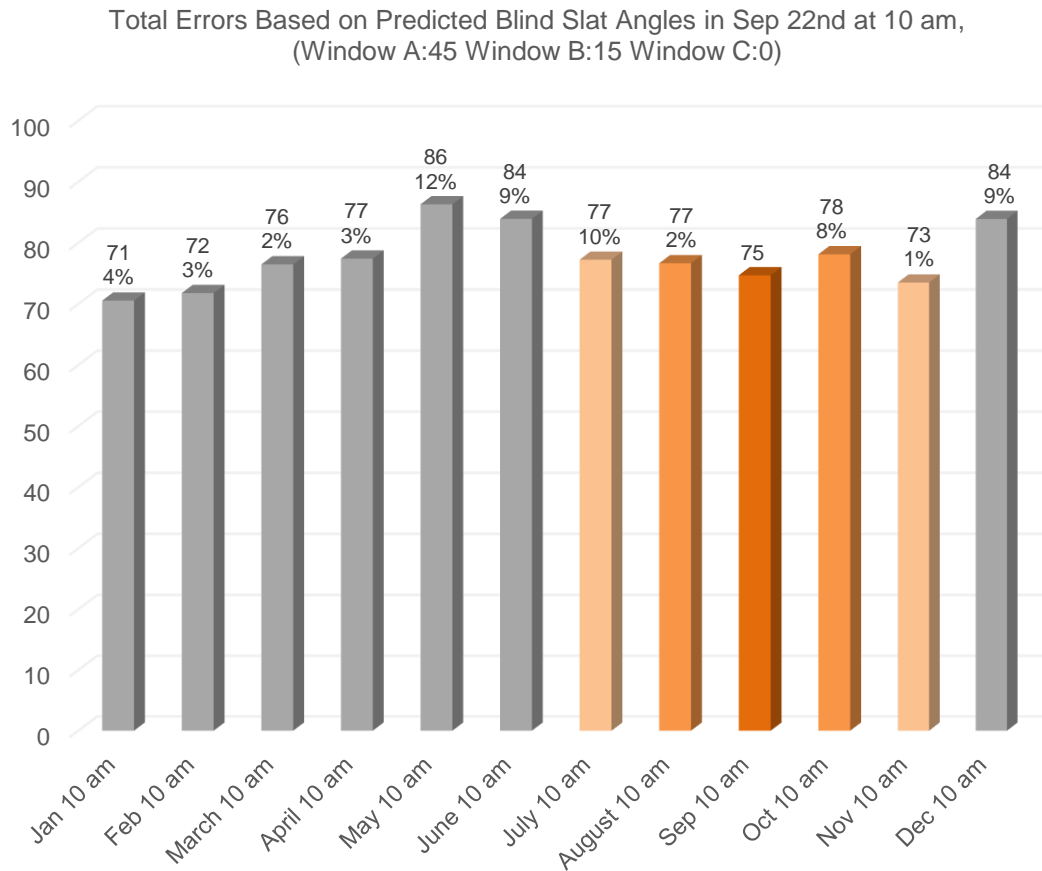


Figure 3. 17. Yearly prediction approach based on September 22nd, 10am. The highlighted months in red show that by applying the optimal setting of September 22nd on the same time of other 11 months the TE values for two months before and after September are very close to optimal setting's TE value.

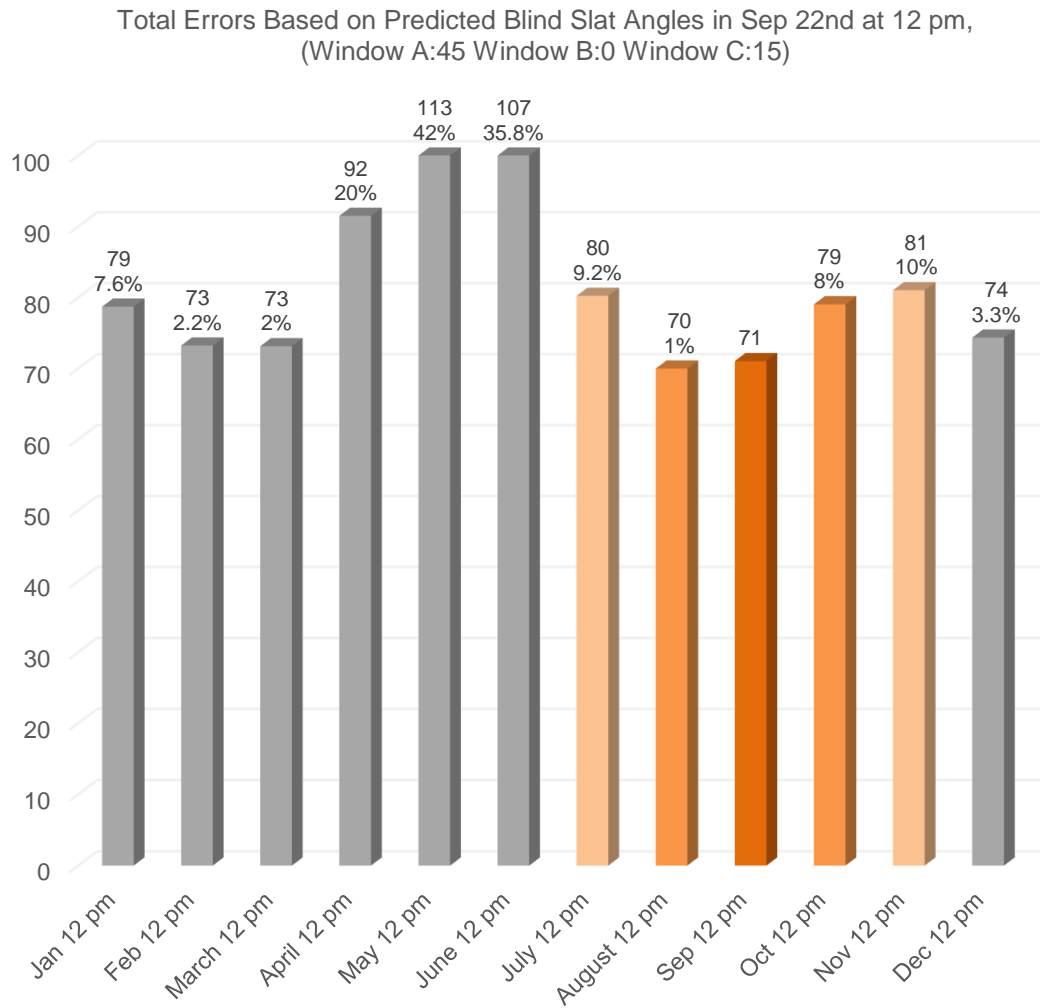


Figure 3. 18. Yearly prediction approach based on September 22nd, 10am, 12pm and 2pm. The highlighted months in red show that by applying the optimal setting of September 22nd on the same time of other 11 months the TE values for two months before and after September are very close to optimal setting's TE value.

Total Errors Based on Predicted Blind Slat Angles in Sep 22nd at 2 pm,  
(Window A:0 Window B:15 Window C:15)

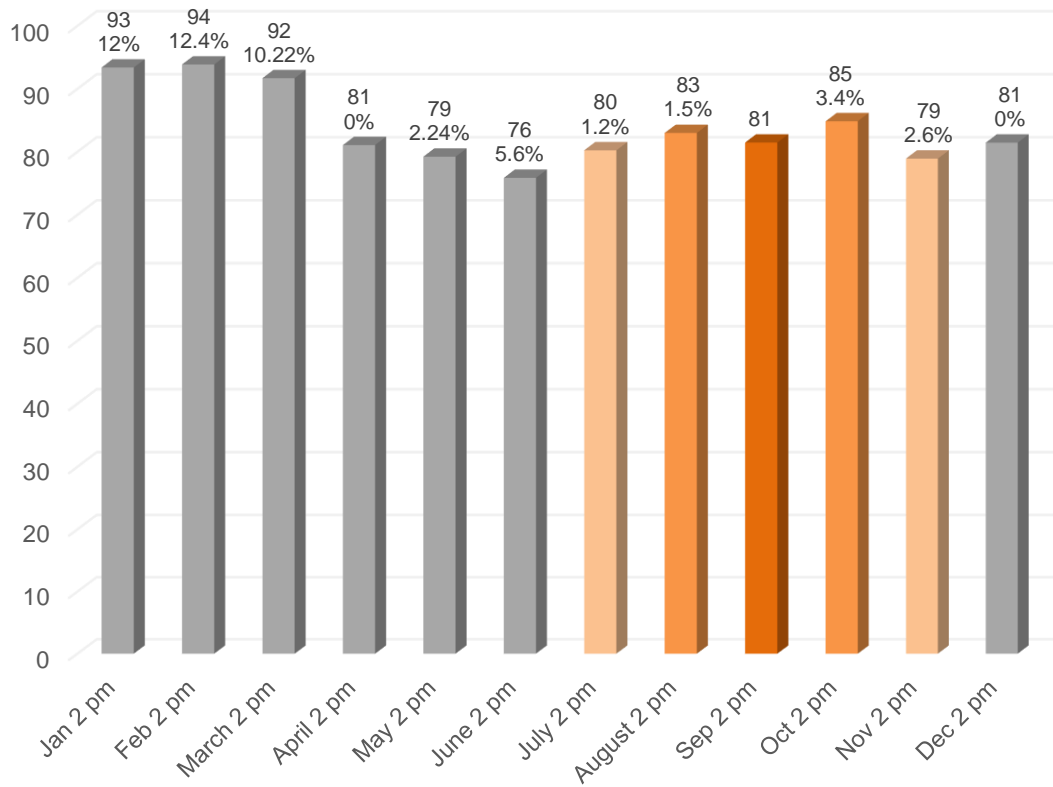


Figure 3. 19. Yearly prediction approach based on September 22<sup>nd</sup>, 2pm. The highlighted months in red show that by applying the optimal setting of September 22nd on the same time of other 11 months the TE values for two months before and after September are very close to optimal setting's TE value.

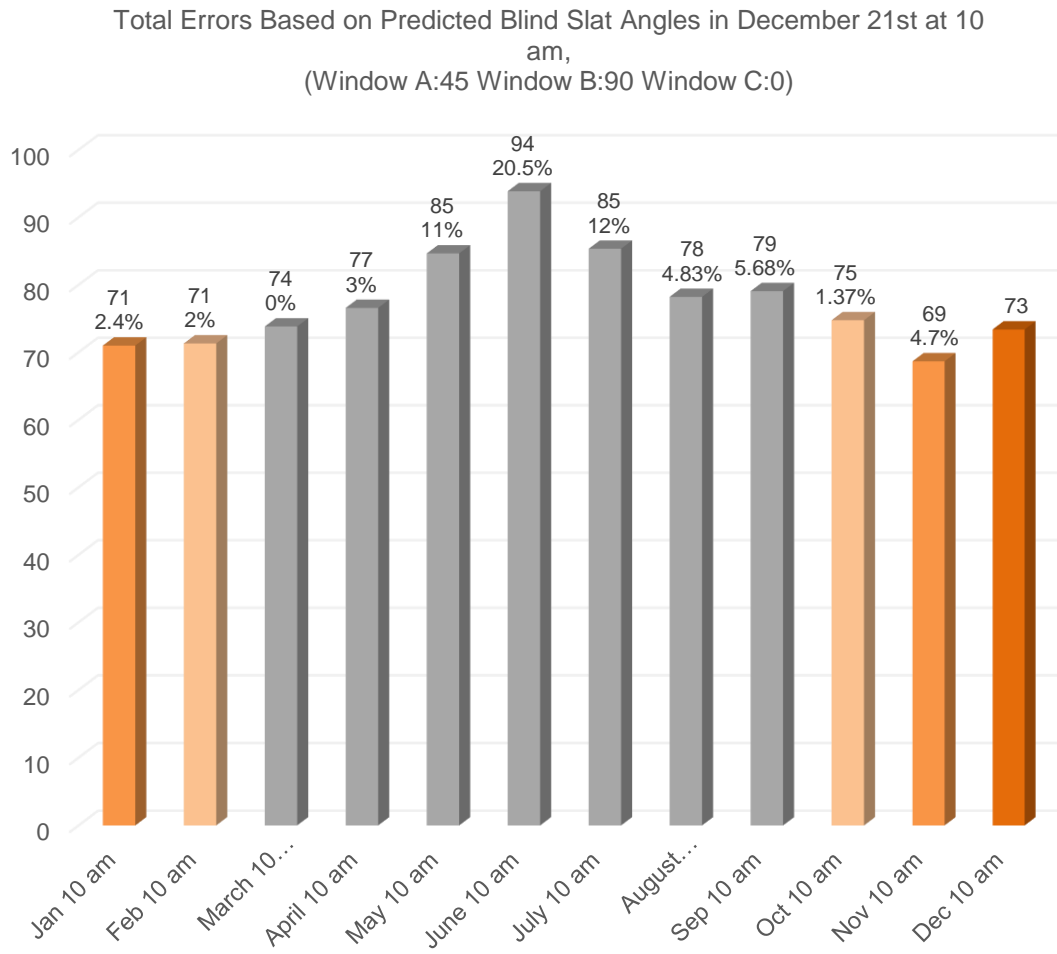


Figure 3. 20. Yearly prediction approach based on December 21st at 10am. The highlighted months in red show that by applying the optimal setting of December 21st on the same time of other 11 months the TE values for two months before and after September are very close to optimal setting's TE value.

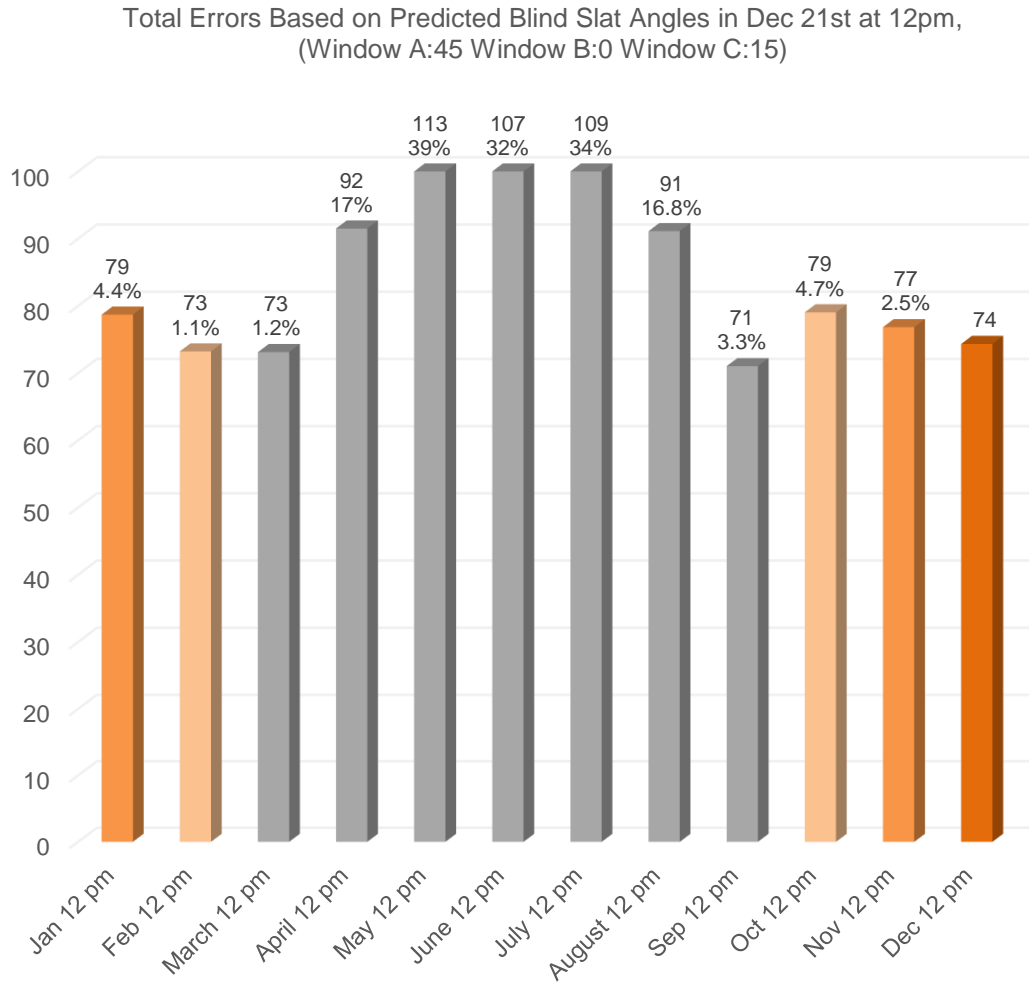


Figure 3. 21. Yearly prediction approach based on December 21<sup>st</sup> at 12pm. The highlighted months in red show that by applying the optimal setting of December 21<sup>st</sup> on the same time of other 11 months the TE values for two months before and after September are very close to optimal setting's TE value.

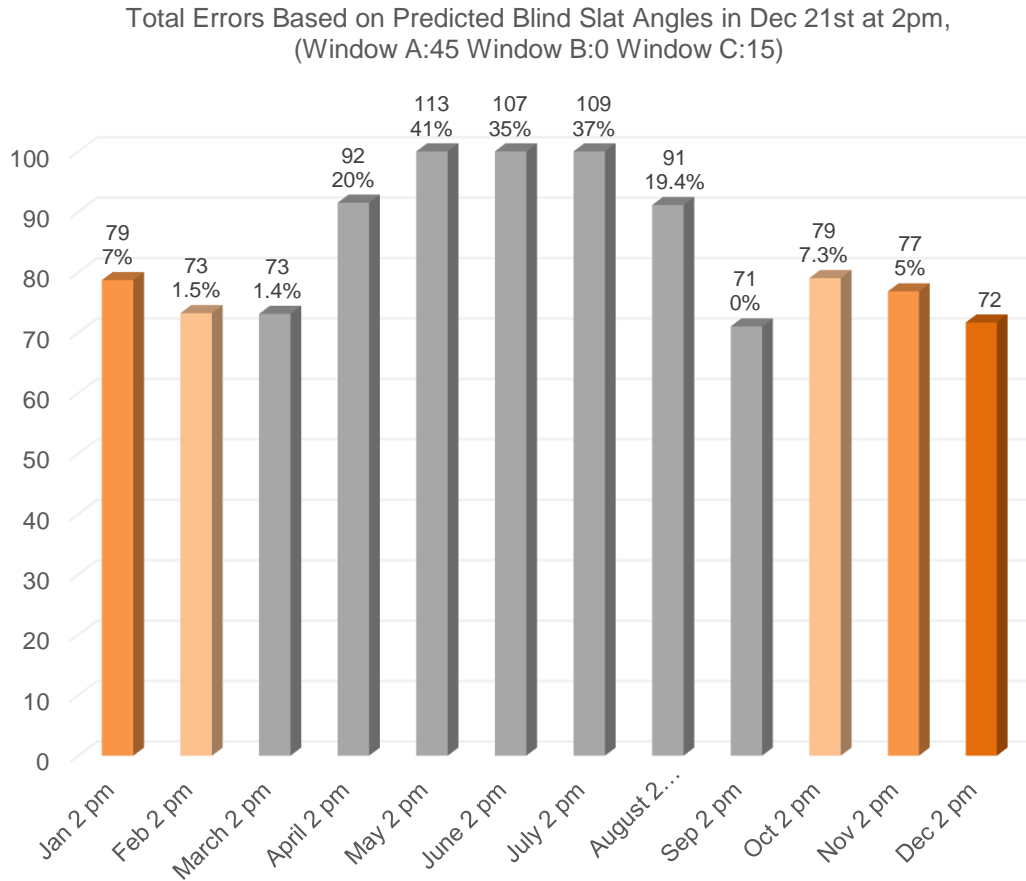


Figure 3. 22. Yearly prediction approach based on December 21<sup>st</sup> at 2pm. The highlighted months in red show that by applying the optimal setting of December 21<sup>st</sup> on the same time of other 11 months the TE values for two months before and after September are very close to optimal setting's TE value.

The graphs in Figures 3.17 to 3.22 show the same approach for September and December. The results suggest that similar to June, the best angle settings in September/December could be applied in order to predict the optimal blind slat settings for at least two month before and two month after September/December. For example, the best simulated settings for December 10 am are (45°, 90°, 0°). The same setting is applied to all other 11 months and the TE values have been compared with TE value of December 10 am optimal setting. The graphs in Figure 3.22 indicate that this setting is also one of the optimal



blind slat settings for January, February, October and November at 10 am, since the difference between TE values is not significant (smaller than 10%).

According to this yearly prediction approach, based on a limited simulation days, the annual optimal settings for blind slat angles inside the test cell could be determined. This approach will provide a base-line for conceptual design process and help building designers to plan for daylight systems more accordingly. In the next section, a daily prediction method will be introduced to predict the optimal blind slat angles during a whole day which is again based on few initial simulation runs.

Daily prediction approach: To predict the optimal blind setting during a day and based on initial limited simulation runs, the weight factor  $\alpha$  plays a very important role in cost function, since it is responsible for changes in the blind slat angles thereby affecting visual comfort. Based on these criteria, the impacts of different values of  $\alpha$  on cost function and optimal blind settings for three windows in June, September and December have been investigated and shown in Figures 3.23, 3.24 and 3.25.



Figure 3. 23. The blind slat angle and total error values comparison diagramms for different values of  $\alpha$  in the cost function, in June.

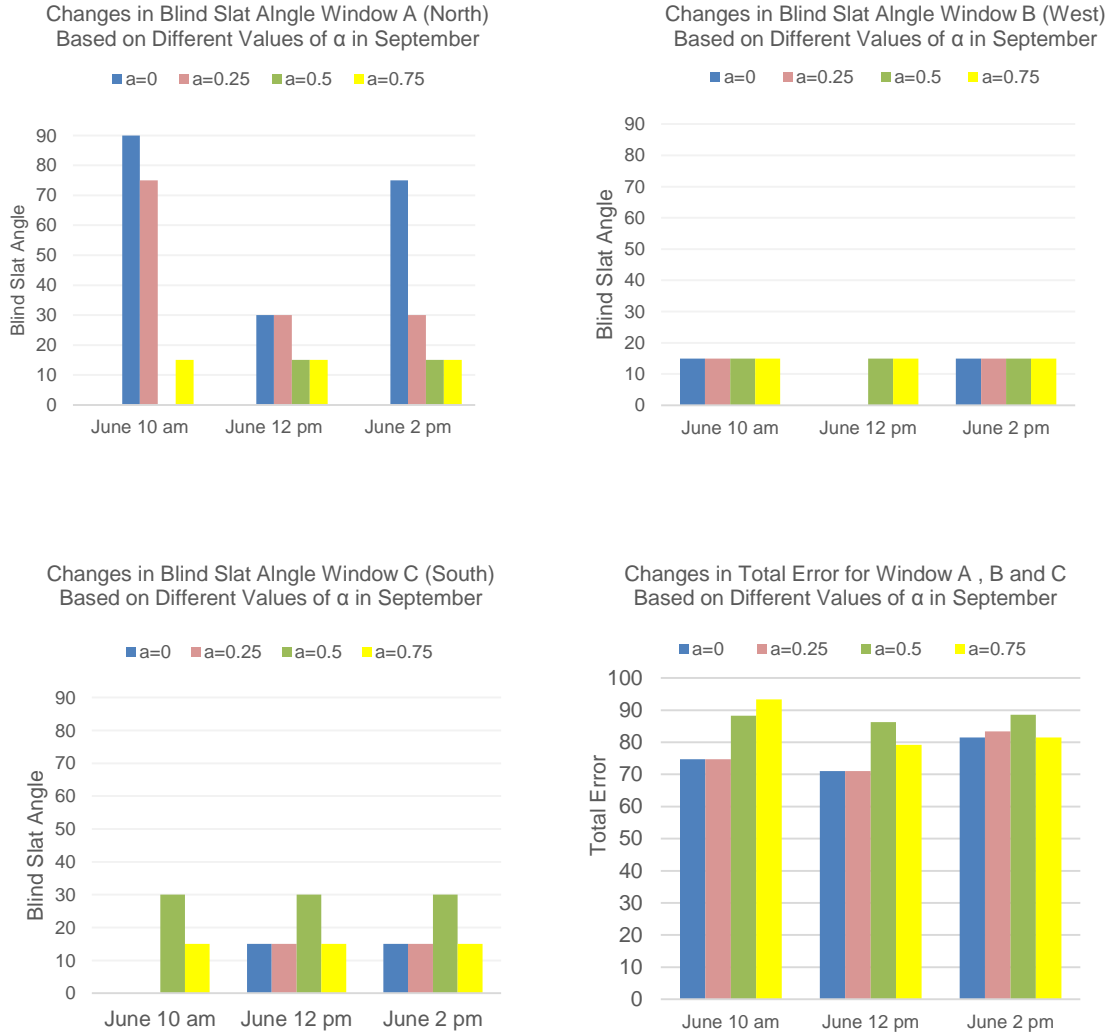


Figure 3. 24. The blind slat angle and total error values comparison diagramms for different values of  $\alpha$  in the cost function, in September.

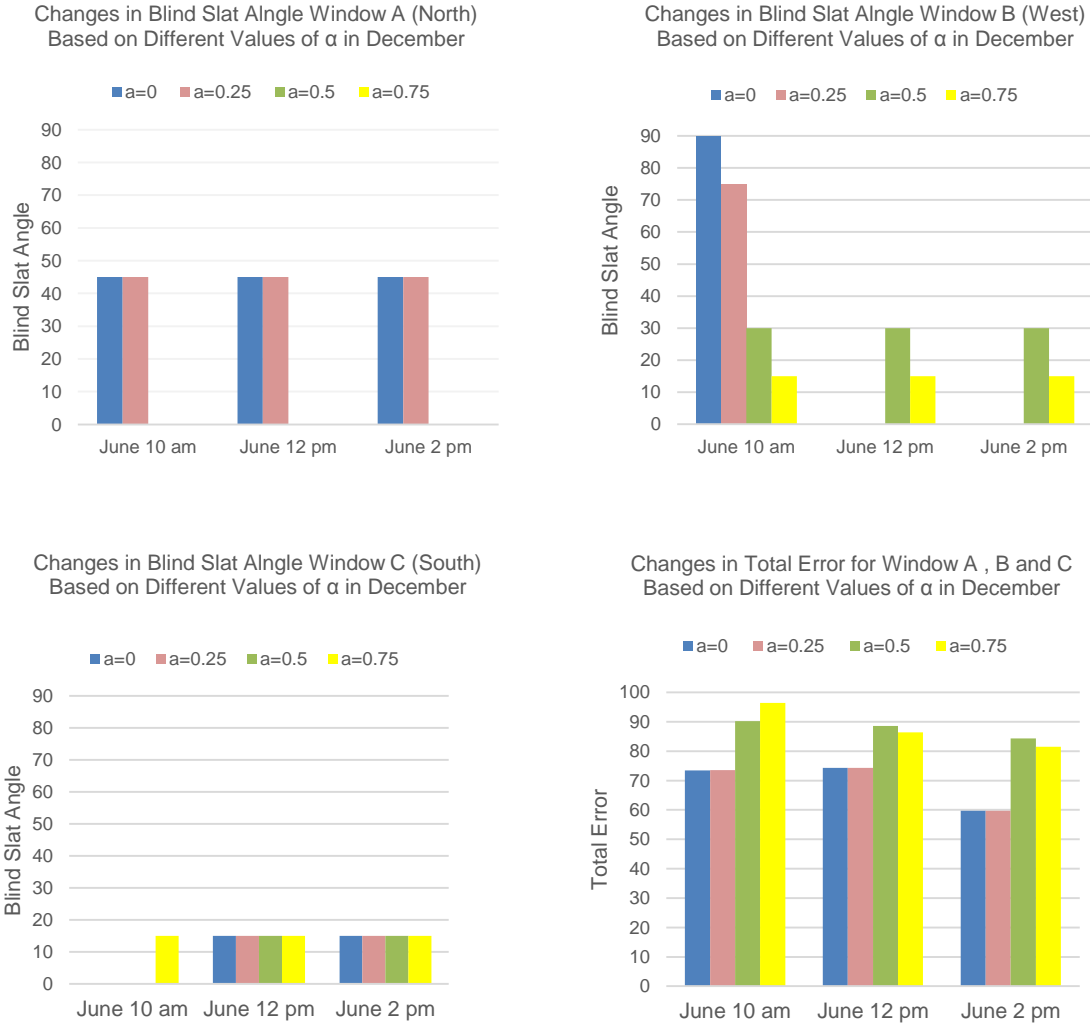


Figure 3. 25. The blind slat angle and total error values comparison diagrams for different values of  $\alpha$  in the cost function, in December.

As shown in Figures 3.23 to 3.25, different values of weight factor  $\alpha$  have been applied to the cost function in MATLAB to investigate their impact on optimal predicted blind slat angles and total error values for June, September and December. The graphs indicate that in all three simulated days when  $\alpha$  is equal to 0.25 the optimal blind slat settings for windows A, B and C and also the total error values are the closest to the ideal situation when  $\alpha$  is equal to zero which represents the best optimal setting based on only TE values.

Therefore, for daily prediction approach,  $\alpha$  was chosen equal to 0.25, to have the most optimal TE values at the same time take the blind slat angle changes into account. In this case cost function will be as follows:

*Cost function*

$$\begin{aligned}
 &= (1 - 0.25)TE \\
 &+ 0.25 \sqrt{\frac{(A_i - A_x)^2 + (B_i - B_x)^2 + (C_i - C_x)^2}{3 \times 90^2}}
 \end{aligned} \tag{4}$$

Based on the above cost function, the optimal blind slat angles for June, September and December months have been calculated and illustrated for each window as illustrated in Figures 3.26 to 3.28.

The daily prediction method assumes that the start and final setting of blinds are zero degree which demonstrates fully open blinds. Then, by interpolating the blind slat angle values at start point (9am), three simulated values (10am, 12pm and 2pm) and end point at 4pm, the blind angle values for rest of the hours are predicted. Such an interpolation is a line that connects the given points to each other as shown in the Figures 3.26 to 3.28.

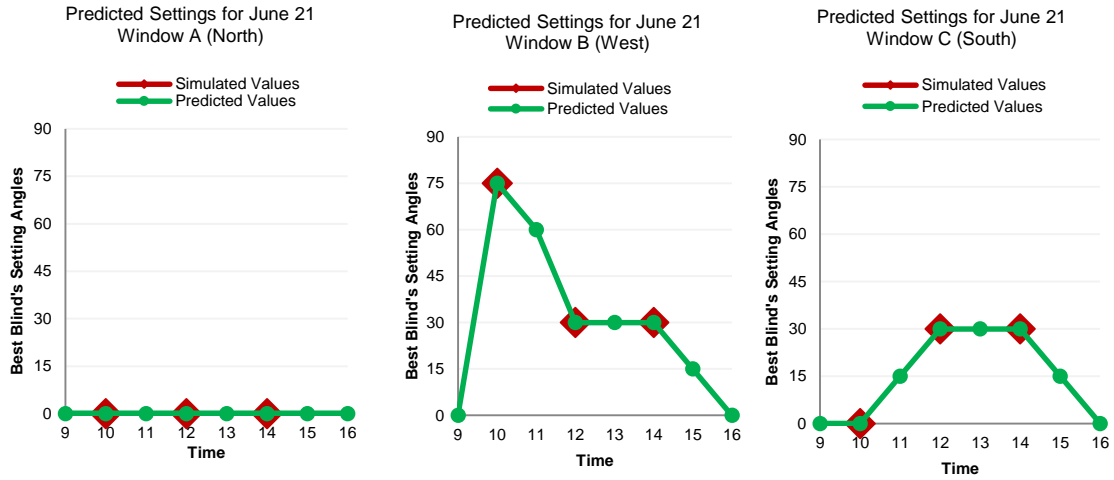


Figure 3. 26. Predicted blind slat settings for the whole day, based on optimal settings in June 21, (10 am, 12 pm and 2 pm) when  $\alpha=0.25$  in the cost function.

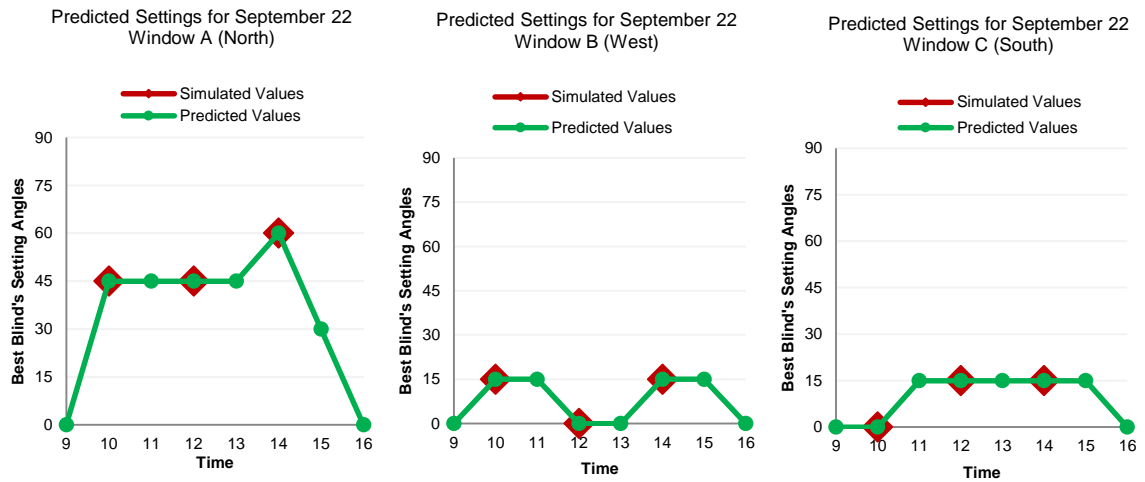


Figure 3. 27. Predicted blind slat settings for the whole day, based on optimal settings in September 22, (10 am, 12 pm and 2 pm) when  $\alpha=0.25$  in the cost function.

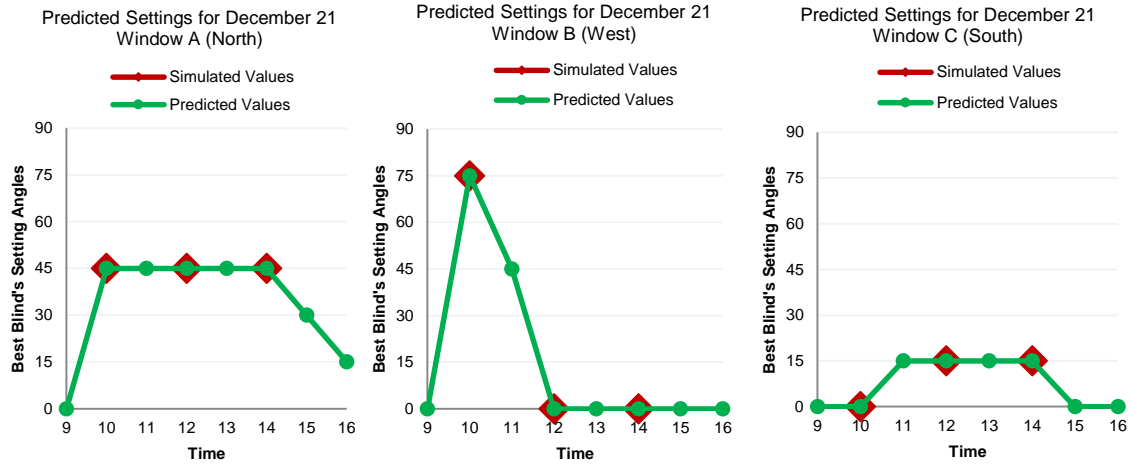


Figure 3. 28. Predicted blind slat settings for the whole day, based on optimal settings in December 21, (10 am, 12 pm and 2 pm) when  $\alpha=0.25$  in the cost function.

To validate the daily prediction approach, the blind slat angles for some randomly picked hours have been predicted from the three set of graphs. Then, in order to validate the accuracy level of predicted values, a daylight simulation has been run for those randomly chosen times. Total error values, average illuminance levels and blind slat settings of these chosen points have been compared to the best optimal situation conducted from the actual simulation data for those hours as shown in Tables 3.2 and 3.3.

Table 3. 2 Validation of predicted blind settings for June 21<sup>st</sup> , 9am, 11am and 1pm with comparing them to the best optimal settings resulted from actual simulation data for June 21<sup>st</sup> , 9am, 11am and 1pm when  $\alpha = 0.25$ .

| June 21 <sup>st</sup> | Hour  | Total Error | Ave. Lux | Window A<br>(North) | Window B<br>(West) | Window C<br>(South) |
|-----------------------|-------|-------------|----------|---------------------|--------------------|---------------------|
| Predicted Data        | 9 am  | 56.30       | 241.36   | 0                   | 0                  | 0                   |
| Simulated Data        | 9 am  | 64.35       | 264.30   | 0                   | 15                 | 0                   |
| Predicted Data        | 11 am | 91.30       | 180.10   | 0                   | 60                 | 15                  |
| Simulated Data        | 11 am | 98.19       | 257.60   | 0                   | 60                 | 30                  |
| Predicted Data        | 13 pm | 73.38       | 233.08   | 0                   | 30                 | 30                  |
| Simulated Data        | 13 pm | 76.48       | 242.53   | 0                   | 30                 | 30                  |

Table 3. 3 Validation of predicted blind settings for December 21<sup>st</sup> 9am, 11am and 1pm with comparing them to the best optimal settings resulted from actual simulation data for December 21<sup>st</sup>, 9am, 11am and 1pm when  $\alpha = 0.25$ .

| December 21 <sup>st</sup> | Hour  | Total Error | Ave. Lux | Window A<br>(North) | Window B<br>(West) | Window C<br>(South) |
|---------------------------|-------|-------------|----------|---------------------|--------------------|---------------------|
| Predicted Data            | 9 am  | 98.90       | 295.00   | 0                   | 0                  | 0                   |
| Simulated Data            | 9 am  | 87.54       | 245.58   | 30                  | 30                 | 0                   |
| Predicted Data            | 11 am | 94.46       | 187.18   | 45                  | 45                 | 15                  |
| Simulated Data            | 11 am | 90.47       | 189.14   | 45                  | 60                 | 15                  |
| Predicted Data            | 13 pm | 59.69       | 248.49   | 45                  | 0                  | 15                  |
| Simulated Data            | 13 pm | 59.69       | 248.49   | 45                  | 0                  | 15                  |

As shown in the Tables 3.2 and 3.3, the total error values and average illuminance levels of blind settings based on daily prediction method and actual simulations on June



21<sup>st</sup> and December 21<sup>st</sup> are compared. The compared values indicate to a very small difference in total errors, average illuminance levels and blind slat angles between simulated and predicted data. This difference in TE values is about 15%, in average illuminance levels is about 10% and is  $\leq 15^\circ$  in blind slat angles.

### **3.4 Conclusions**

The experimental result confirm that the daily and yearly prediction approach is accurate when applied on randomly chosen days/month. The values suggest that the predicted optimal blind settings are providing the optimal average light levels and the most uniform lighting situation on the work plane in a virtual test cell environment.

### **3.5 Future Work and Limitations**

The results of the analysis approach indicate that the predicted blind settings based on daily and yearly prediction methodologies are proper approaches with high accuracy to predict the optimal blind slat settings in similar building spaces. This methodology could be applied as an initial baseline setting for lighting control in buildings in conceptual design process. Since this approach is based on a limited set of simulations and requires a simple input for the control strategy, it is easily applicable to any building size and orientations in different geographical locations.

However, there are some limitations with the performance of the Relux lighting software when the building model has a more complicated shape and includes many windows and blinds. There are many issues with importing the CAD model into Relux when the building model is more detailed and/or contains curvy walls. In this situation, the

only solution will be to simplify the building model by dividing it into smaller spaces and change the curved walls into flat type in order to be able to import and analyze it in Relux which requires long processing times. Moreover, in this case, the process will not be automated and easy to adopt.

In addition to the building complexity limitation, there is also a limitation with the number of blinds in Relux. Since any type of shading devices can't be imported to Relux, the venetian blinds have been chosen from the lighting software library and separately installed in the test cell model. Relux does have a limitation in the number of blinds in the model and if this limit is exceeded software crashes during the daylight simulation.

Based on software limitations in simulating complex situations, it is important for the future work to investigate the availability and ability of other lighting software in the market when applied for the proposed prediction methodology.

## **4 PHASE II: VALIDATION OF PREDICTING CONTROL ALGORITHM**

### **4.1 Introduction**

In chapter 3 a prediction approach was developed based on simulated data inside a virtual small-scale test cell. The goal of this control strategy was to regulate the slat angle of three venetian blinds inside the model during a day and during a whole year based on a very limited simulation set. The main focus of this chapter which describes phase II of research is to apply and validate the control approach based on real-time experiments inside an actual test room.

Outdoor test cells are the best tools to evaluate the control systems before applying it on a full-scale building. In test cells, there is a high degree of control of the indoor environment, well-specified constructions and high levels of instrumentation and this can fill the gap between laboratory testing and full-scale building testing. In most research cases, the objective of test cells is to extract component performance characteristics that give some confidence as to how those components perform in realistic climatic conditions.

Furthermore, the other main application of testing in outdoor test cells is the link with simulation modelling. The main goal here is predicting energy and environmental performance of buildings. However, where a new component is under development, for example an advanced glazing, a hybrid photovoltaic module or shading component, then high quality data sets from outdoor experiments can be used to ensure that the simulation tool is capable of modelling that component. If so, it is considered that the simulation program can then be applied to model the component when integrated into a full-scale building.

Based on this fact, the developed control algorithm was implemented on a bigger scaled test room which was built on the roof of Design Building South in Arizona State University Tempe campus. The virtual daylight model was then calibrated and fine-tuned based on actual measured data in test room.

Furthermore, in this phase of study, based on some limitations of Relux lighting tool in simulation length and simulation output data, Radiance lighting simulation was implemented instead. As mentioned in literature review chapter, Radiance<sup>1</sup> is the most efficient lighting tool especially for researchers and computer graphics communities (USDOE, 2014a; Ward 1994; Ward & Shakespeare, 1998; LBL, 2010a). Radiance was the first software to generate calculation results for a fixed viewpoint, using as input data three-dimensional geometrical description of a scene and physical properties of its materials. It has also advanced some of the current calculation techniques available in most lighting simulation models (Ward et al., 1988).

This chapter includes the approach to evaluate and validate the optimal blind slat setting prediction methodology from the last chapter, based on actual measured data in the test room. The simulations are done with Radiance plugin in IES virtual environment, (IES, 2010). We start with an overview about the test room structure, size, openings materials and location.

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<sup>1</sup> According to the online list of lighting software provided by USDOE and based on Ward's and Shakespeare's book that has recorded 294 citations in the Scopus database.

## 4.2 Test Room

To evaluate the applicability of developed control approach, a test room was built on the roof of design building north at Arizona State University Tempe campus. The geographic location for Tempe, Arizona is  $33^{\circ} 27' 0''$  N,  $112^{\circ} 4' 0''$  W.

As shown in Figure 4.1, the test room pertains to an 8 by 8 by 8 feet office area with seven 21 by 32 inches windows on the North, East, West and South walls. Since the test room was built to be used for different research studies by other students at Herberger Institute, it has more features than needed for this research study.



Figure 4. 1. The view of test room on the roof of design building north in Tempe campus.

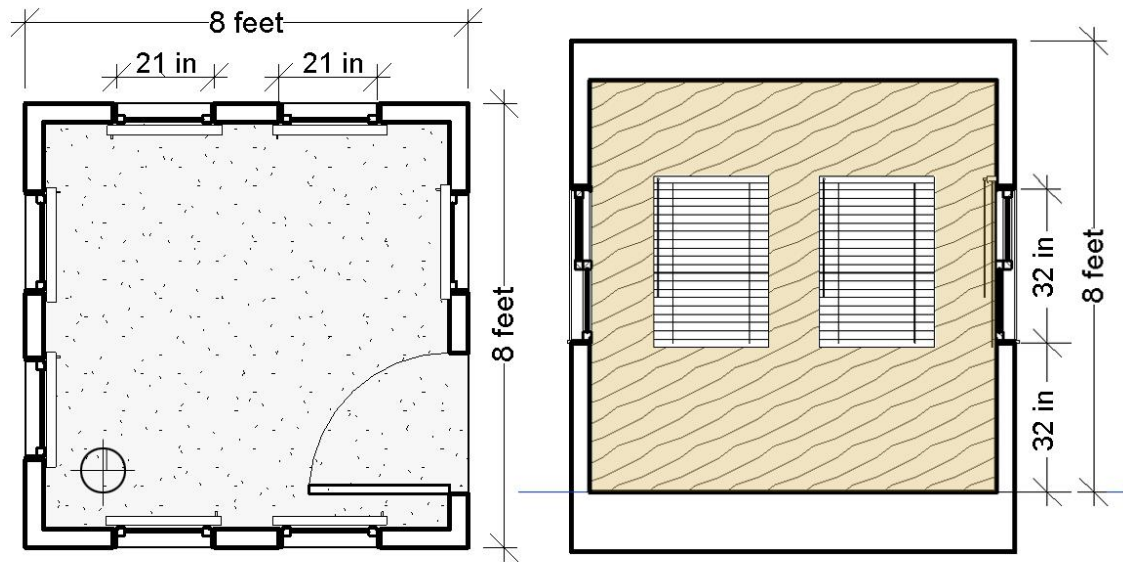


Figure 4. 2. Plan and section of the test room.

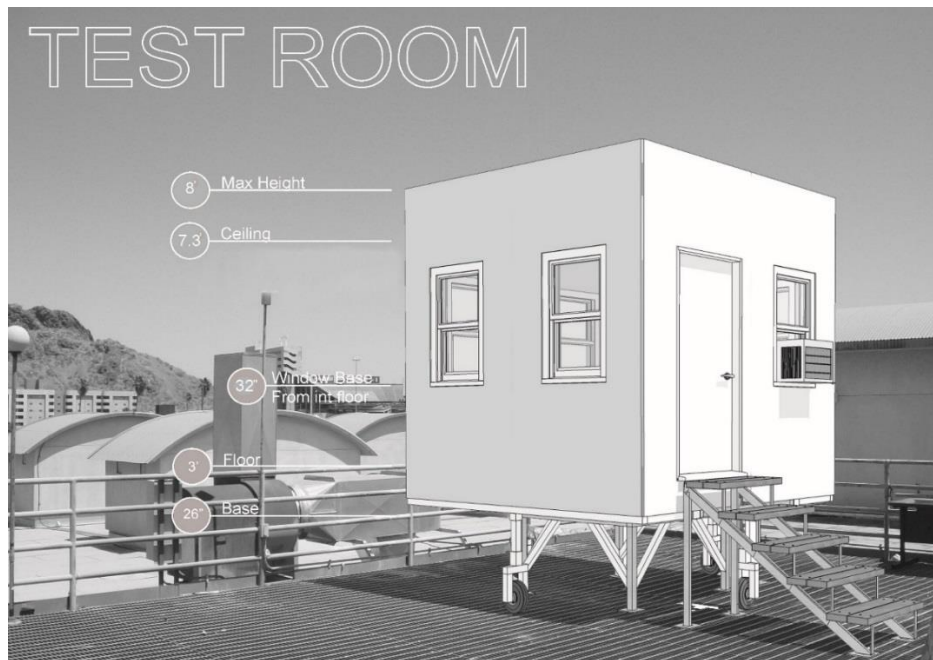


Figure 4. 3. Perspective of the test cell on the roof of Design Building North, at ASU Tempe campus.

As mentioned before, not all the features and equipment of the test room were for the purposes of this research. For example, as shown in Figure 4.3, the number of windows was limited to only two windows on north and west walls for validation phase in order to create a more realistic test environment and also simplify the situation. The rest of the windows were covered with matte grey colored sheets. In Figure 4.4 these windows are referred to inactive windows.

#### **4.2.1 Materials**

The test room has a wooden structure with plytanium Pine sheathing plywood as the interior layer. The window frames are made of wood and painted with white paint. A single glazed with clear glass is applied on all windows. The whole room was built on a metal structure as a base which was on four wheels to turn the whole structure to different directions on the roof.

#### **4.2.2 Blinds**

The active (in use) windows on north and west side were equipped with SmartBlind from Intelligent Building Envelopes Company based in Canada as shown in Figure 4.5.

The SmartBlind system consists of the following components:

- One 24VDC, 1 Amp, wall mount power supply
- One Power and Interface Unit
- One Command Unit
- One RJ12 Adapter
- One Sunlight Sensor
- One or more blinds up to 6 maximum

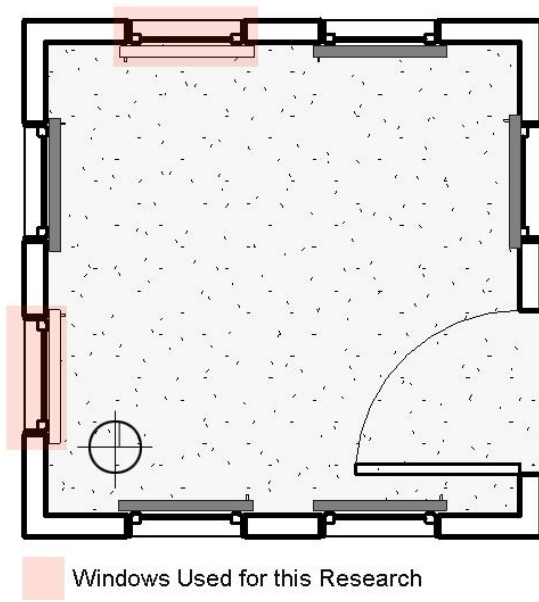


Figure 4. 4. Active and inactive windows in test room.



Figure 4. 5. View of windows inside test room.



Figure 4. 6. View of SmartBlinds installed in the test room.

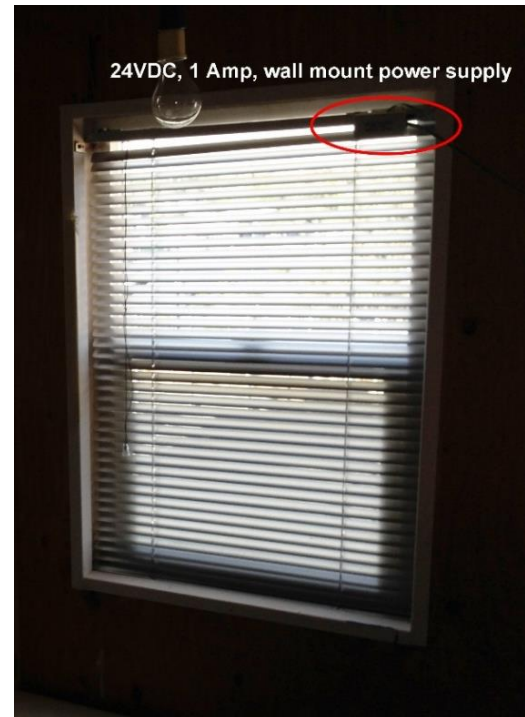


Figure 4. 7. View of the SmartBlinds in test room.



Generally, it is important to decide how to best group the blinds within a system. In automatic mode, all of the blinds within the system will respond to the signal from a single sunlight sensor. Therefore, it may not make sense to group a north facing blind with west facing blinds, since they will experience very different daylight conditions throughout the day. Figure 4.8 demonstrates the blinds' configuration system in automatic mode in case of 6 blinds in one orientation.

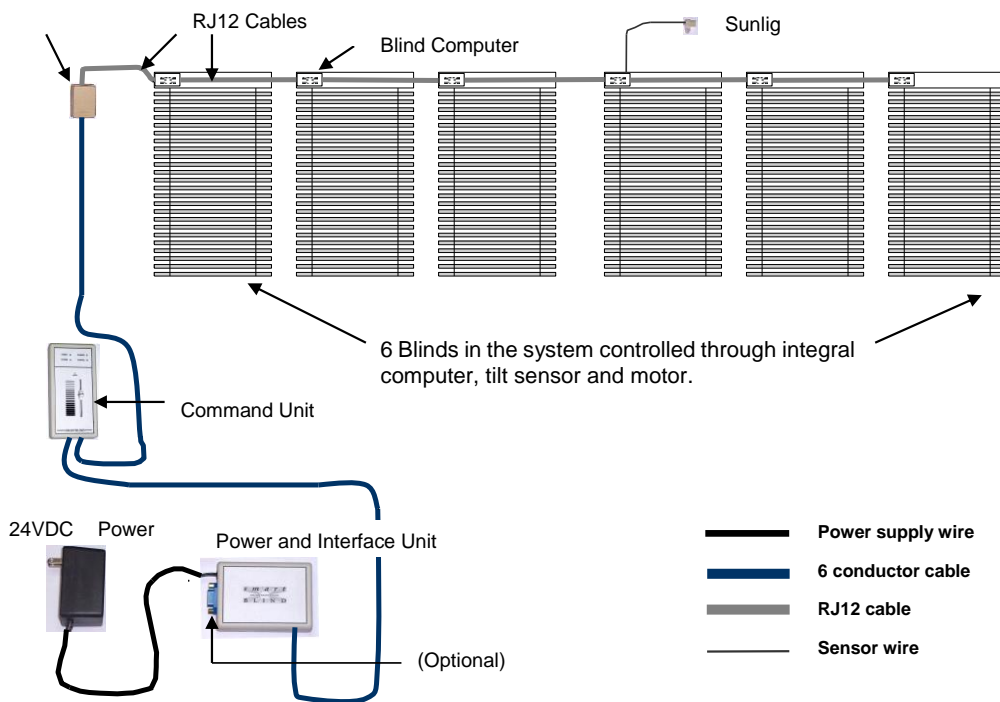


Figure 4. 8. SmartBlinds configuration diagram with 6 blinds in the system as an example.

The configuration shown in Figure 4.8 is the interface for controlling all blinds in the same manner with one single control unit. However, in order to operate the single blinds separately a local command unit is needed. This device operates in the same manner as the system command unit but is specific to a single blind. It connects to the individual blind

computer via a sub-miniature, four-pin connector and is wall mounted near the blind it will control. When this device is operated along with the centralized system, it will override any system commands and will move the individual blind to the requested position. A small LED (shown in Figure 4.8) indicates if the blind is currently under system control (LED is lit) or is in manual mode (LED is not lit). This device allows remote computer control of the entire SmartBlind system.

Each blind in the system is individually addressable by the remote computer and the remote computer can direct individual blinds to move to a requested position at either high speed (immediate change) or low speed (imperceptible motion). The remote computer can also request all blinds to move simultaneously to a requested position (global command) at either high or low speed, also it can request data from the SmartBlind system including solar radiation intensity and system health. Each blind in the SmartBlind system has the potential to include the Local Command Unit option.



Figure 4. 9. Local command unit for SmartBlinds.

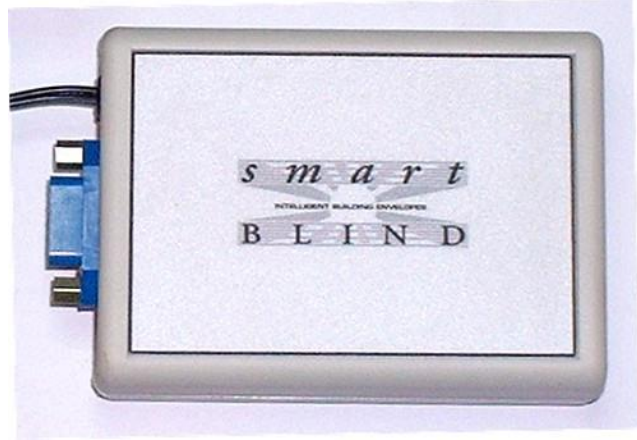


Figure 4. 10. Female DB-9 RS-232 connector for remote computer interface.

In the test room environment, there are two SmartBlinds installed as shown in Figure 4.5 which are controlled through a computer remote system. A code in C++ was written to regulate and set the blind slat angles based on control algorithm commands.

### 4.3 Objective and Scope

As mentioned before, the main goal of conducting this research study is to develop an adaptive control method to optimally regulate and maximize daylighting in buildings of any size, shape and vintage. By introducing this adaptive automated algorithm, it is intended to enhance the capabilities of control systems by almost completely automating their deployment, operation and by empowering them to adapt to environmental changes.

The objective of this phase was to firstly, calibrate the lighting software and secondly, validate and evaluate the reliability and accuracy of the developed control approach through an experimental set of tests on test room.

#### **4.4 Methodology**

In order to compare the measured data with simulated data, the first step was to build the virtual model of test room which has a bigger scale than the first model. Since Relux has some limitations regarding model import and simulation lengths, for this stage Radiance as a plugin in IES was applied. The Test room CAD model was built in Revit and imported to RadianceIES. The test room models in Revit and imported model in RadianceIES are displayed in Figures 4.11 and 4.12.

After the virtual model was set up, the developed blind slat control algorithm was implemented on the test room based on three limited day simulation method and calculation of total error for each blind combination. The optimal predicted blind angles have been implemented on the blinds on test room for a chosen day and the lighting situation inside the test room was investigated.

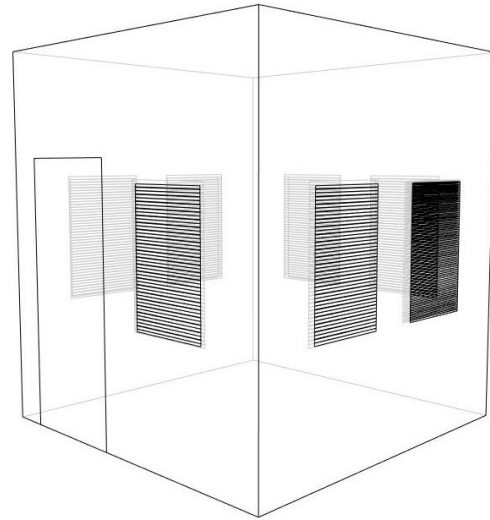
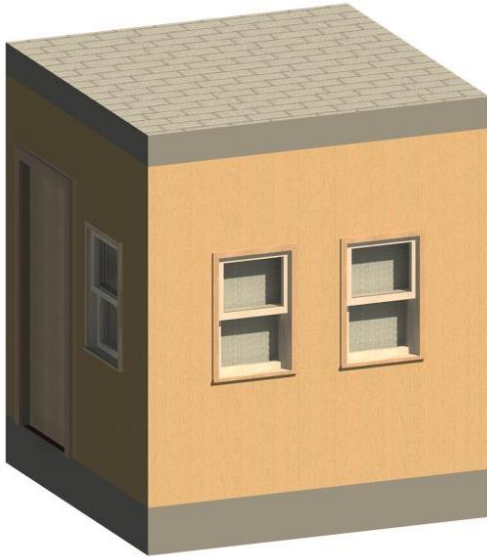


Figure 4. 11. Virtual test room model built in Revit.

Figure 4. 12. Imported test room model in IES.

#### 4.5 Calibration of RadianceIES Lighting Model

To verify the reliability of the RadianceIES lighting program, the actual daylight levels in test cell have been measured on April 29<sup>th</sup> from 9am to 5pm. The actual illuminance levels in test room have been measured and recorded by 9 MEMSIC wireless sensor motes distributed in the room similar to the 9 sensor locations in phase I (Figure 4.12). These measured data have then been compared to simulated illuminance data.

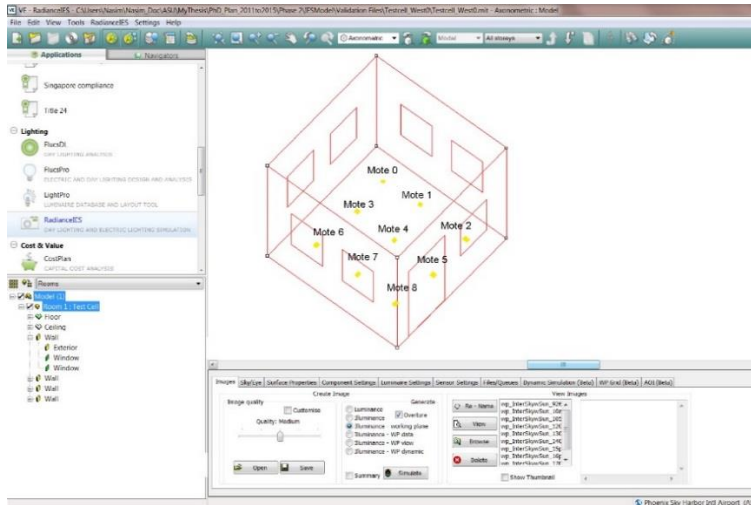


Figure 4. 13. The location of 9 light sensors in test room in RadianceIES software environment.



Figure 4. 14. MEMSIC wireless sensor motes inside the test room.

A MATLAB code was written to compare the results of actual experiment and lighting software output. Some small changes were made to the virtual model materials in order to fine tune the data to match the experimental measurements. The graphs in Figures 4.15 and 4.32 show the comparison between these two data sets for two combination of blind setting, for all 9 sensor motes on April 29<sup>th</sup>.

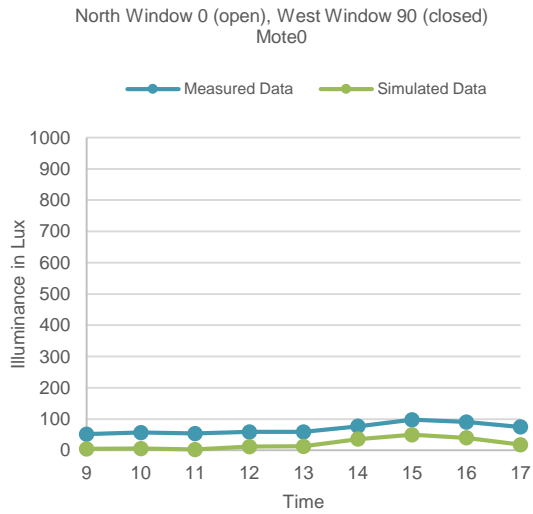


Figure 4. 15. Comparison graphs between measured and simulated illuminance levels in test room when window North's blind is set open and window West's is closed on April 29th from 9am to 5pm.

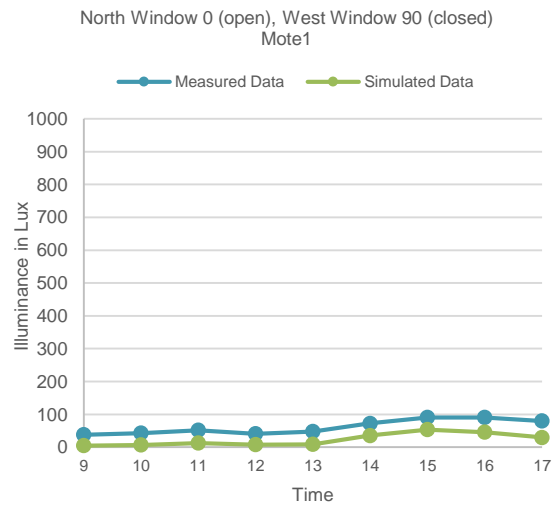


Figure 4. 16. Comparison graphs between measured and simulated illuminance levels in test room when window North's blind is set open and window West's is closed on April 29th from 9am to 5pm.

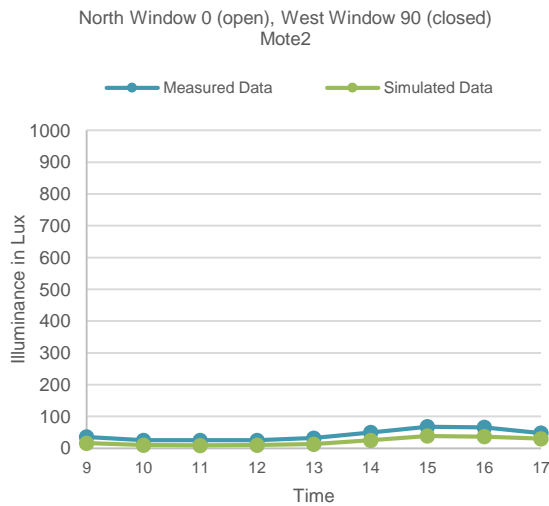


Figure 4. 17. Comparison graphs between measured and simulated illuminance levels in test room when window North's blind is set open and window West's is closed on April 29th from 9am to 5pm.

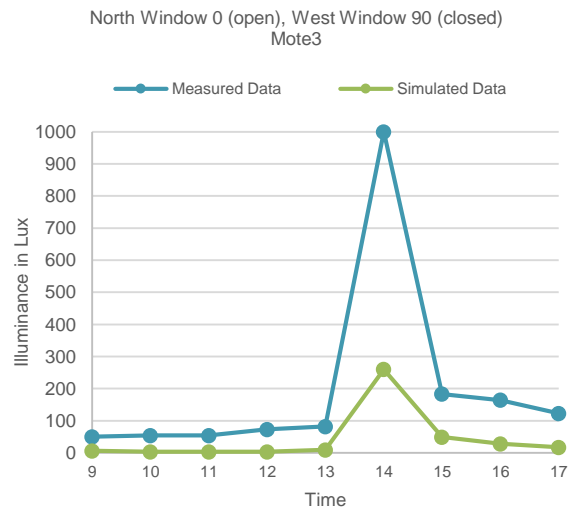


Figure 4. 18. Comparison graphs between measured and simulated illuminance levels in test room when window North's blind is set open and window West's is closed on April 29th from 9am to 5pm.

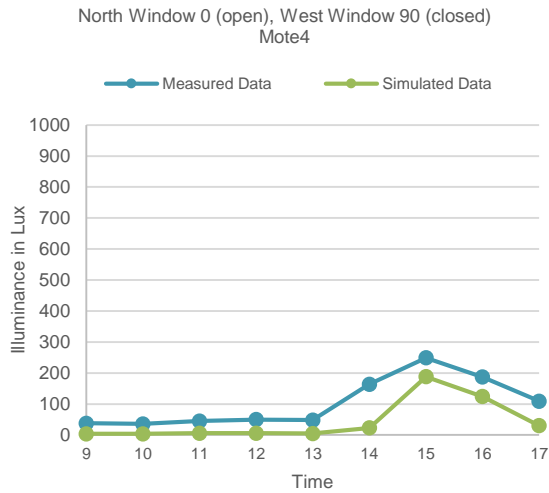


Figure 4. 19. Comparison graphs between measured and simulated illuminance levels in test room when window North's blind is set open and window West's is closed on April 29th from 9am to 5pm.

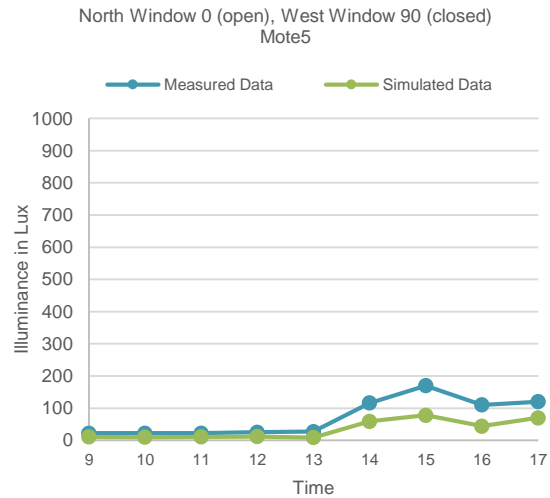


Figure 4. 20. Comparison graphs between measured and simulated illuminance levels in test room when window North's blind is set open and window West's is closed on April 29th from 9am to 5pm.

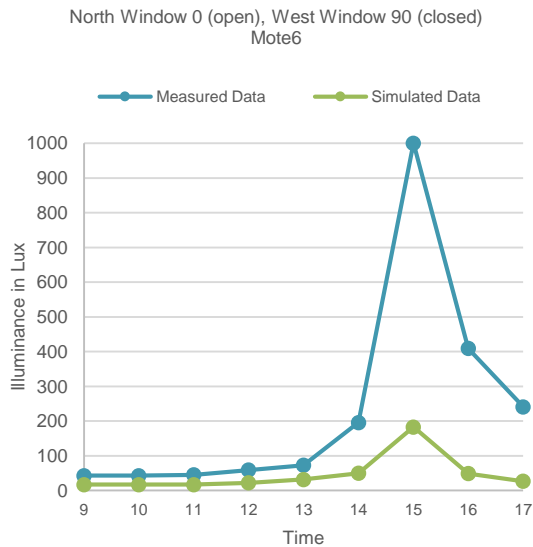


Figure 4. 21. Comparison graphs between measured and simulated illuminance levels in test room when window North's blind is set open and window West's is closed on April 29th from 9am to 5pm.

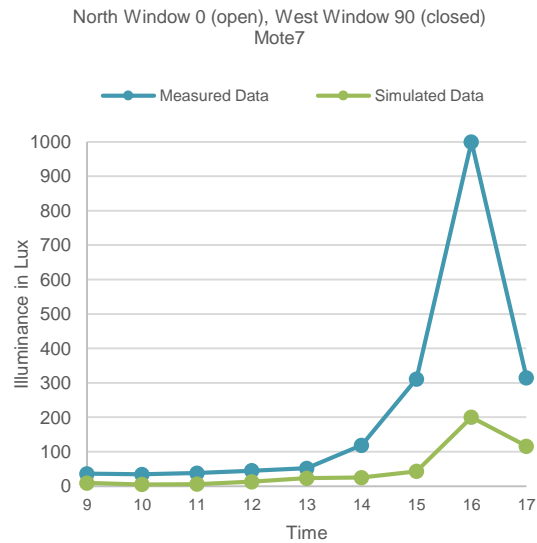


Figure 4. 22. Comparison graphs between measured and simulated illuminance levels in test room when window North's blind is set open and window West's is closed on April 29th from 9am to 5pm.



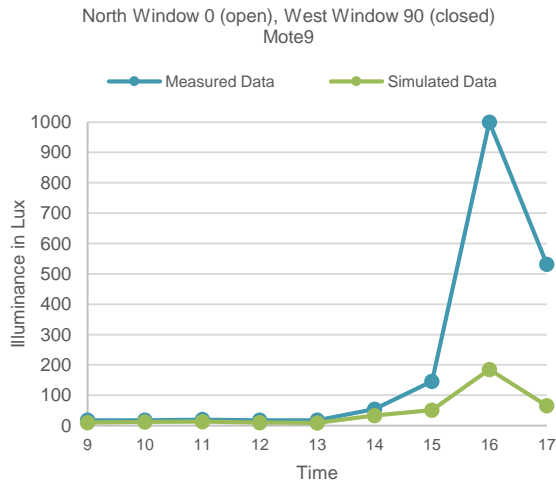


Figure 4. 23. Comparison graphs between measured and simulated illuminance levels in test room when window North's blind is set open and window West's is closed on April 29th from 9am to 5pm.

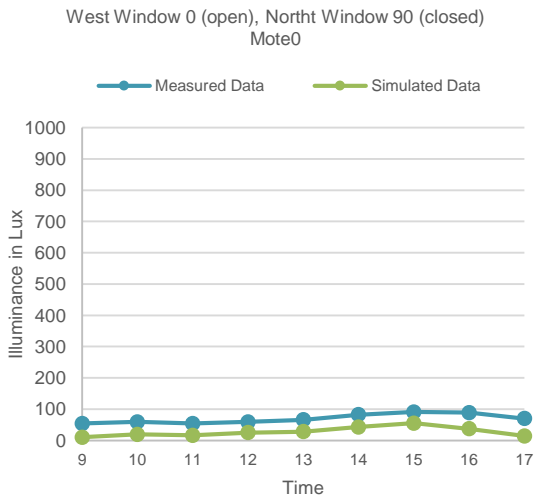


Figure 4. 24. Comparison graphs between measured and simulated illuminance levels in test room when window West's blind is set open and window North's is closed on April 29th from 9am to 5pm.

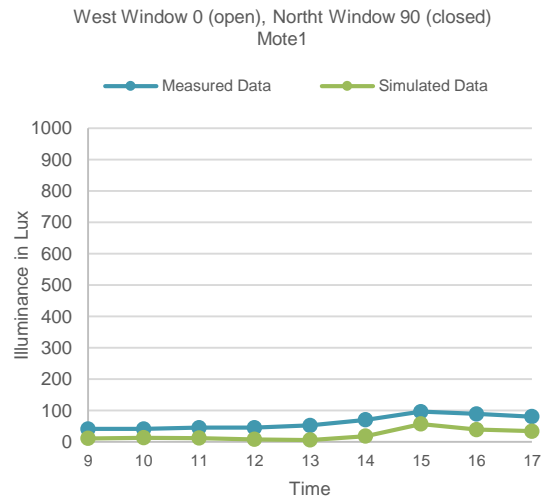


Figure 4. 25. Comparison graphs between measured and simulated illuminance levels in test room when window West's blind is set open and window North's is closed on April 29th from 9am to 5pm.

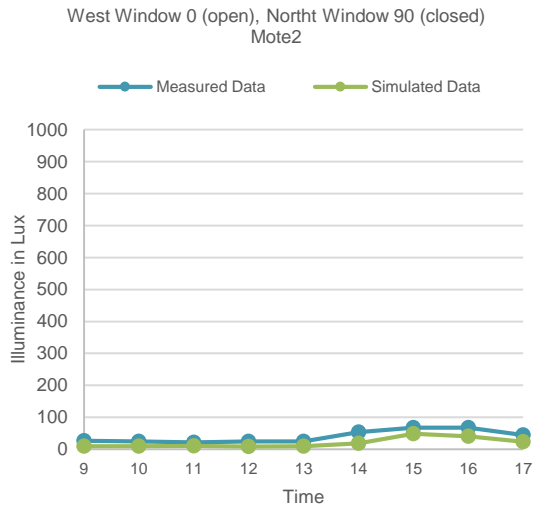


Figure 4. 26. Comparison graphs between measured and simulated illuminance levels in test room when window West's blind is set open and window North's is closed on April 29th from 9am to 5pm.

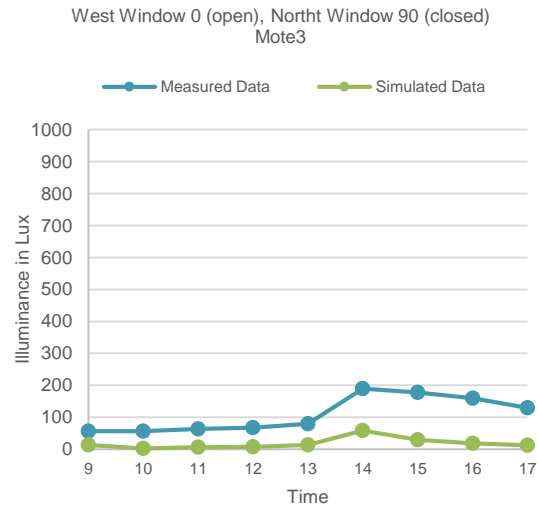


Figure 4. 27. Comparison graphs between measured and simulated illuminance levels in test room when window West's blind is set open and window North's is closed on April 29th from 9am to 5pm.

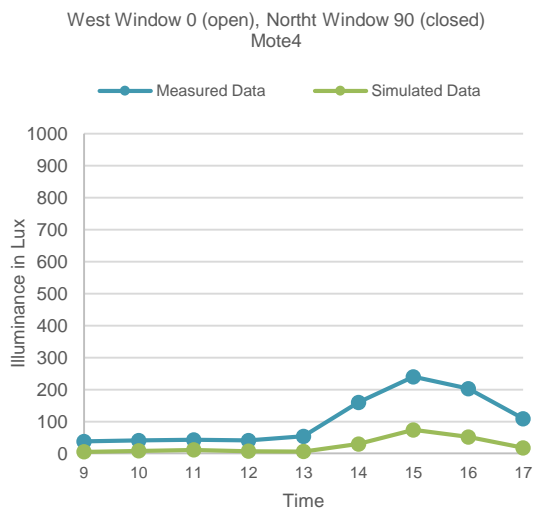


Figure 4. 28. Comparison graphs between measured and simulated illuminance levels in test room when window West's blind is set open and window North's is closed on April 29th from 9am to 5pm.

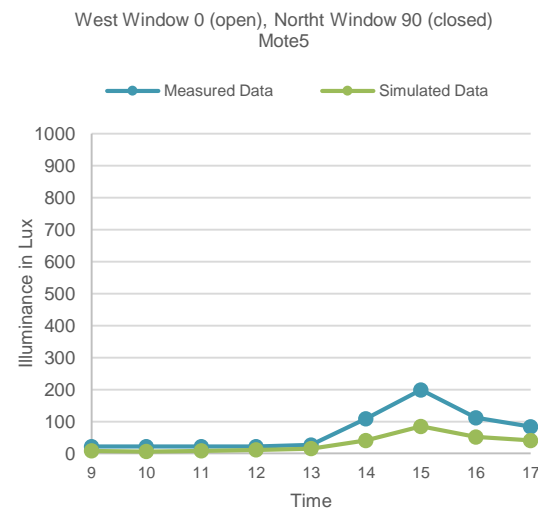


Figure 4. 29. Comparison graphs between measured and simulated illuminance levels in test room when window West's blind is set open and window North's is closed on April 29th from 9am to 5pm.

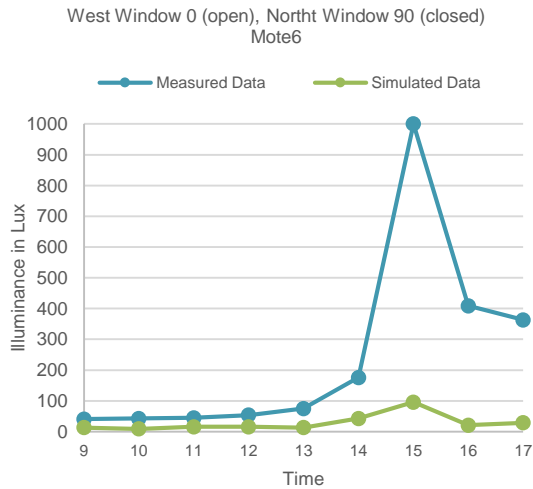


Figure 4. 30. Comparison graphs between measured and simulated illuminance levels in test room when window West's blind is set open and window North's is closed on April 29th from 9am to 5pm.

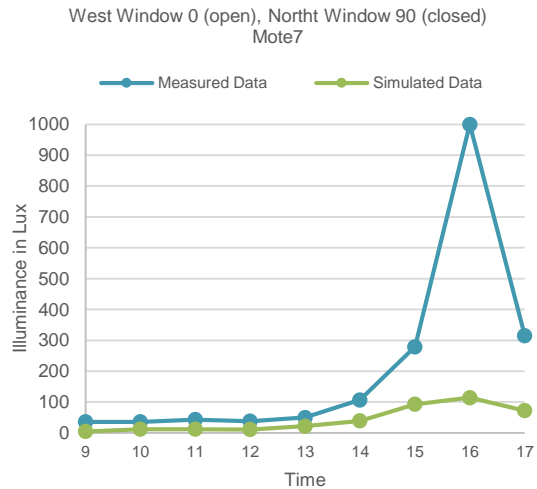


Figure 4. 31. Comparison graphs between measured and simulated illuminance levels in test room when window West's blind is set open and window North's is closed on April 29th from 9am to 5pm.

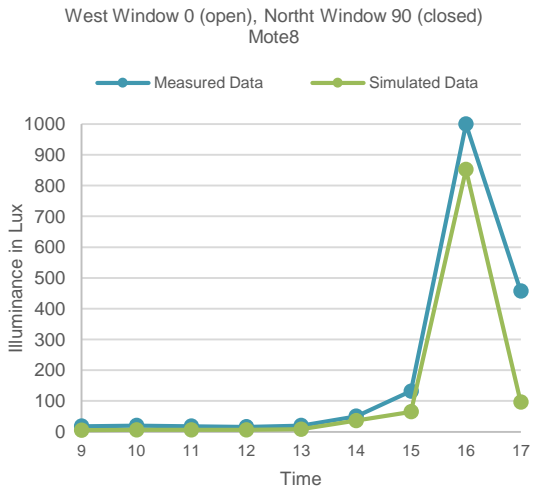


Figure 4. 32. Comparison graphs between measured and simulated illuminance levels in test room when window West's blind is set open and window North's is closed on April 29th from 9am to 5pm.

As illustrated in Figures 4.15 and 4.32 graphs, measured and simulated illuminance data resulted from motes inside the test room and simulations in RadianceIES indicate that

both data sets follow the same trend. However, measured data have greater values compared to simulated data. This offset value changes for different blind setting combinations for window North and West and for different time of the day. Thus, simulated and measured lighting data from fourteen tested combinations (7 blinds slat setting times two windows) including two active windows on north and west sides have been compared together. For linear approximation of the data, least squares method have been applied. In other words the square root of the error was minimized:

$$Error = y_i - f(x_i) \quad \text{where} \quad f(x_i) = ax_i + b \quad (5)$$

Based on this comparison, an offset value and a gain factor have been determined as follows:

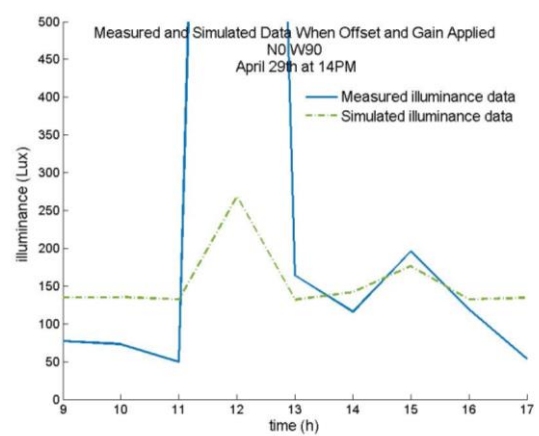
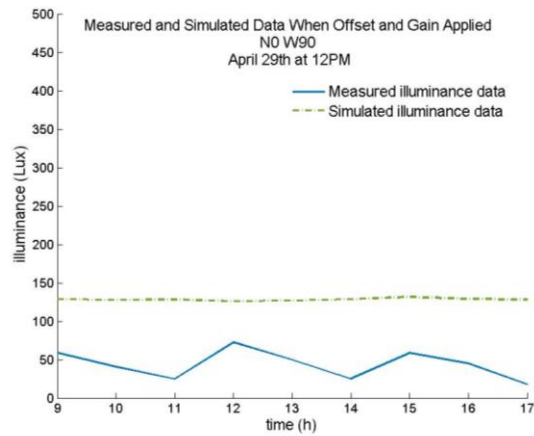
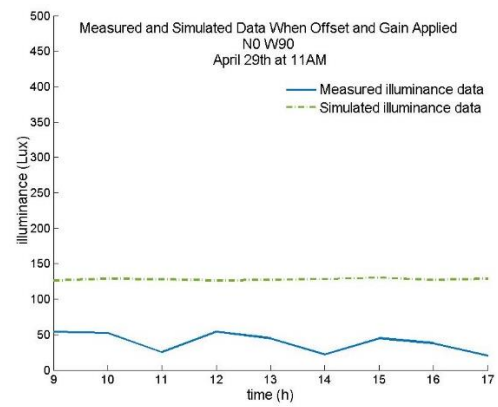
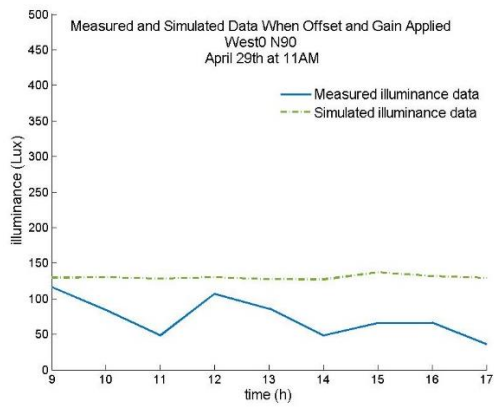
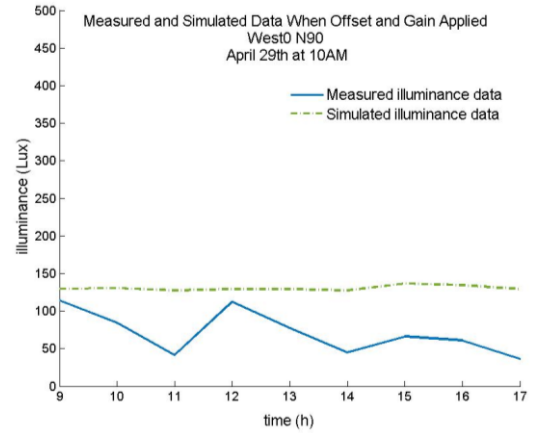
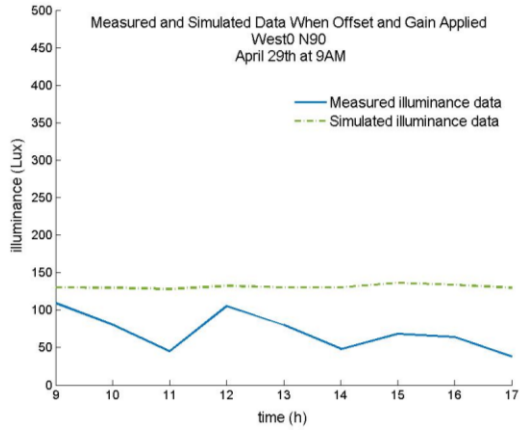
$$\begin{aligned} \text{Measured lighting data} & \quad (6) \\ &= \text{Offset value} + \text{Gain factor} \times \text{Simulated lighting data} \end{aligned}$$

Where:

Offset value= 125 Lux

Gain factor= 0.28

The regression analysis found the offset value for the all fourteen combinations to be 125 lux and the gain factor to be 0.28. The following graphs show the measured data and simulated data after applying the gain factor and offset values on them for certain combinations.



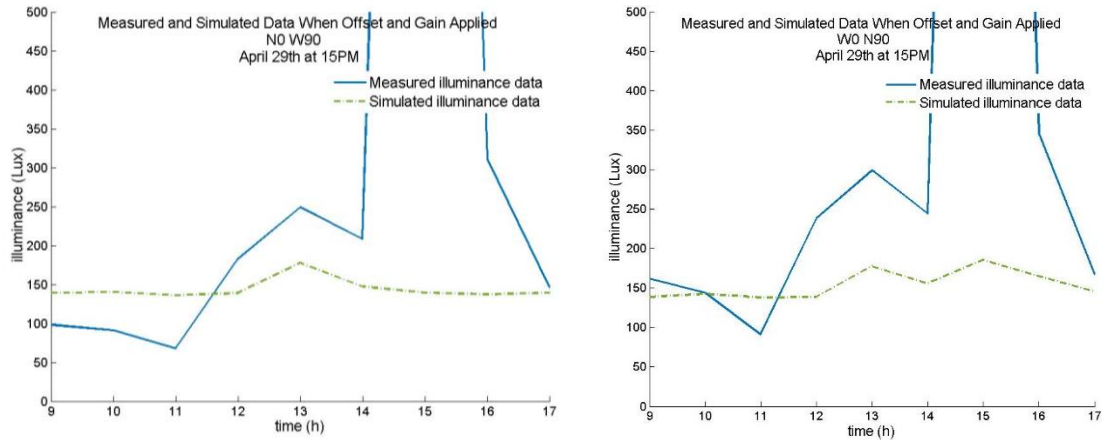


Figure 4. 33. Comparison graphs between measured data and simulated data when offset value and gain factor are applied on simulated illuminance values.

As displayed in Figure 4.33, the offset value and gain factor bring the two measured and simulated illuminance level curves closer together. However, in some cases, such as 14 pm N0° W90°, where the measured data points to a very high illuminance values caused by direct solar radiation on a specific sensor mote at a specific time of the day, these two curves differ significantly. This is because the lighting software is not able to simulate the exact value of illuminance at these points which could be referred to the difference between actual weather data on April 29<sup>th</sup> which was partly cloudy and weather file data uploaded and used in the software for sky harbor international airport weather file.

The goal of this step was to evaluate the RadianceIES lighting software in order to investigate the accuracy of the software. The result from the MATLAB comparison analysis suggests an acceptable accuracy of the simulation data. However, in order to match them with measured illuminance data in test room, an offset value and a gain factor had to be applied in order to compare these two sets of data in all possible combination for two windows.

In the next design step, the reliability and accuracy of developed control approach was investigated by applying it on the test room environment. This design process is demonstrated and discussed in the next section.

#### 4.6 Validation of Developed Prediction Algorithm

In phase I, a prediction approach was developed and evaluated based on limited simulations. In this phase and after investigation of RadianceIES lighting software's reliability, the prediction methodology has been applied on a test room virtual model in order to achieve optimal blind slat settings. Furthermore, the results of simulations were applied on the test room to investigate whether the optimal blind slat settings are also optimal in an actual test environment.

The experiment was done on December 3<sup>rd</sup> from 9am to 2pm with an overcast sky condition. Based on the fitness function with total errors and a weight factor of 0.25, the optimal blind angles settings for three windows on December 3 from 9am to 2pm were conducted. The cost function is as follows:

$$\begin{aligned}
 & \text{Cost function} \\
 &= (1 - 0.25)TE \\
 &+ 0.25 \sqrt{\frac{(A_i - A_x)^2 + (B_i - B_x)^2 + (C_i - C_x)^2}{3 \times 90^2}}
 \end{aligned} \tag{7}$$

As mentioned in the last section, to calibrate the lighting values read by virtual light sensors in RadianceIES, a gain factor and an offset value need to be applied on simulated values to have more accurate lighting levels and prediction. The optimal blind slat angles for two windows in the test room are as assembled in Table 4.1.

Table 4. 1 Optimal predicted blind slat angles for December 3<sup>rd</sup> based on developed prediction algorithm.

| <b>December 3rd</b> | <b>Total Error</b> | <b>Average Lux*</b> | <b>Window A (North)</b> | <b>Window B (West)</b> |
|---------------------|--------------------|---------------------|-------------------------|------------------------|
| 9 am                | 211.91             | 135.82              | 60                      | 60                     |
| 10 am               | 200.39             | 139.05              | 60                      | 45                     |
| 11 am               | 186.74             | 143.04              | 60                      | 45                     |
| 12 pm               | 182.08             | 144.42              | 60                      | 45                     |
| 1 pm                | 181.58             | 145.19              | 60                      | 60                     |
| 2 pm                | 194.79             | 140.71              | 60                      | 45                     |

*Average lux\* is the value before applying the 0.28 gain factor and 125 lux offset value.*

The predicted blind slat angles for December 3<sup>rd</sup> have been applied on SmartBlinds inside the test room and the light levels on 9 sensor nodes have been recorded. In order to investigate the reliability of the prediction approach, the predicted optimal blind combinations resulted from prediction algorithm (shown in Table 4.1) were applied on the actual blinds in test room. In order to find out if these settings are optimal in actual test environment, blind slats have been changed in steps of  $\pm 15^\circ$  in upward and downward directions for both windows to compare the average lighting levels with more open and less open blinds in each case. These results are shown in Table 4.2.



Table 4.2 the lighting situation inside the test room after applying the optimal blind slat setting and  $\pm 15$  degree on two windows on December 3<sup>rd</sup>.

| Degree  | December 3 <sup>rd</sup> | Average Lux** | Total Error | Window A (North) | Window B (West) |
|---------|--------------------------|---------------|-------------|------------------|-----------------|
| -15°    | 9 am                     | 44.78         | 206.13      | 75               | 75              |
| Optimal | 9 am                     | 142.33        | 114.00      | 60               | 60              |
| +15°    | 9 am                     | 106           | 146.74      | 45               | 45              |
| -15°    | 10 am                    | 60.22         | 192.10      | 75               | 60              |
| Optimal | 10 am                    | 116.11        | 155.13      | 60               | 45              |
| +15°    | 10 am                    | 86.11         | 177.35      | 45               | 30              |
| -15°    | 11 am                    | 95.23         | 152.61      | 75               | 60              |
| Optimal | 11 am                    | 131.89        | 126.23      | 60               | 45              |
| +15°    | 11 am                    | 120.56        | 148.39      | 45               | 30              |
| -15°    | 12 pm                    | 107.67        | 127.56      | 75               | 60              |
| Optimal | 12 pm                    | 150           | 119.15      | 60               | 45              |
| +15°    | 12 pm                    | 140.11        | 148.96      | 45               | 30              |
| -15°    | 1 pm                     | 104.33        | 158.48      | 75               | 75              |
| Optimal | 1 pm                     | 201           | 97.352      | 60               | 60              |
| +15°    | 1 pm                     | 139.89        | 125.50      | 45               | 45              |
| -15°    | 2 pm                     | 126.56        | 143.12      | 75               | 60              |
| Optimal | 2 pm                     | 220.11        | 103.94      | 60               | 45              |
| +15°    | 2 pm                     | 189.11        | 133.70      | 45               | 30              |

Average lux\*\* is the value after applying the 0.28 gain factor and 125 lux offset value.

As shown in Table 4.2, the average illuminance of 9 sensors in the test room and the total error values which was calculated based on 250 desired lux level have been calculated and displayed for December 3<sup>rd</sup>. The middle values in highlighted cells illustrate the optimal predicted angle setting for the blind slats. The other two values display the lighting situation when the slat angle changes 15° upwards and downwards which show the more open and less open blind situations.

According to the average lux levels and total error values listed in the Table 4.2, the optimal blind slat angle in all cases indicate a closer average lighting value to the desired lighting level (250 lux) and smaller TE values which indicates to an ideal uniformed lighting situations inside the room.

#### **4.7 Conclusions**

The experimental results confirm that the prediction algorithm performance is accurate when applied on a randomly chosen day. The values suggest that the predicted optimal blind settings do provide the optimal average light levels and the most uniform lighting situation on the work plane (on the floor) in the test room. This experiment validates the accuracy of the developed prediction algorithm when applied on actual test room environment.

#### **4.8 Limitations and Future work**

One of the most crucial limitation points in this phase is the simulation of dynamic blinds in the test cell. Venetian blinds have a more complicated behavior in daylight analysis in comparison to roller shades. The blind slat angles in some settings can cause direct solar penetrations into the room. This becomes a problem in the lighting simulation process. Most current software in the market are not able to simulate the exact behavior and intensity of light when there is direct solar radiations in the room. This problem causes some uncertainties in lighting levels read by virtual sensors when it is under direct solar radiation. The lighting values in these situations are much smaller than the actual measured lighting data read by sensors in the room.

Additionally, regarding the dynamic shading devices the other problem was that it was impossible to import them from CAD model to Radiance lighting tool. They needed to be created separately in Radiance based on IES library elements. These built venetian blinds were static and were not able to change dynamically in the program environment. Thus, it was necessary to create different models with different blind settings manually. This fact prevented the whole process to be automated and required long model preparation time. With the progressive development in software design, hopefully in the future these lighting problems will have a proper solution.

Furthermore, the other crucial problem in the lighting software was the weather data used in the lighting software and how it differed from actual weather data in experiment days. For this research study, the weather data for Tempe, AZ was uploaded directly from U.S. Department of Energy website. These information can slightly differ from the actual weather situation which can cause different lighting values in simulated and measured data. For example, in some specific blind slat angles some of the sensors in the actual model indicate to direct solar radiation with very high lux levels, but the same sensors at the same time do not display same lighting behavior in the virtual model in Radiance environment. There are significant differences between simulated data and measured data when actual sensors are under direct solar radiation.

Another limitation of this phase accrued in the performance of SmartBlinds in the test room. It was not easy to adjust the blinds in smaller degrees, (15 degree change) when needed. Even though theoretically, SmartBlinds have the ability to be adjusted in 1 degree

steps. This limitation led to less accuracy in result when the optimal predicted blind slat angles were applied on the actual blinds in test room.

Finally, to validate the control approach, the predicted optimal blind slat angles were applied on test cell on December 3<sup>rd</sup>. It would have been very interesting to prove the accuracy of the system for different days in different seasons when the solar altitude changes. Since the research time schedule didn't allow us to repeat the experiment for more days, this could be a part of future work to investigate the control algorithm precision in different seasonal conditions and maybe other locations.

## **5 PHASE III: DEVELOPMENT OF A SENSOR-BASED ADAPTIVE DAYLIGHT CONTROLLER**

### **5.1 Introduction**

Phase III and IV (next Chapter) of the study include the development of a sensor-based integrated lighting control system for office buildings. The control process includes the optimal blind slat angle prediction approach from phase I as a start-up baseline setting, yet improves these initial settings based on data read by sensors distributed in the room in order to effectively regulate the lighting situation. Phase III concludes the development of an adaptive sensor-based daylight responsive controller, which then in the next chapter integrates the daylighting and artificial lighting systems in order to increase the quality of lighting and energy efficiency in buildings.

As discussed in chapter 2 under control algorithms in buildings, there are two different types of control algorithms when it comes to regulating the lighting systems in buildings; the classic controllers and Optimal, predictive, and adaptive controllers. The first category controllers with a very simple structure control algorithms were used in the early phases of controller development and included Integrate–Derivative (PID) controllers (Alm et al., 1999; Astolfi and Pellerey, 2008). These controllers are able to make significant improvements in the lighting situation, however it is not easy to choose the proper variables such as gain factor in the PID controller. This fact causes some instability and complexities in the controller design.

The second category of controllers is the adaptive controllers where artificial intelligence is applied in order to achieve the ability to self-regulate and adapt to the

different climatic conditions and to various building configurations. Some of these controllers are described in chapter 2.

Based on complex mathematical algorithms implemented in these types of controllers, the Optimal, predictive, and adaptive controllers are not often applicable in real buildings, since they have various constraints such as their need for a detailed building model which includes several parameters in the system that need to be defined and estimated in actual buildings. Furthermore, the use of elements of bioclimatic architecture in them which complicates the process of minimization of their cost functions, and even if such a minimization is obtained, the results are not applicable in practice. That is why, under real conditions, such techniques may give inaccurate results.

In this phase of the study, the design of a simple Integral controller is described which was applied to control the lighting situation in a small office space. The controller, which was further developed in the next chapter, is integrated, adaptive and has a simple manageable structure which makes it easy to implement and operate in buildings unlike other current controllers.

Due to the investigation and evaluation of the controller performance, the system was designed for a virtual office model that conforms to the experimental Office model in Oakland California assumed by Lee et al. (1998). This way the performance of the controller can be compared to the published results in Lee's research study.

## 5.2 Objective and Scopes

In this phase of research, an adaptive controller is designed, which has a very straightforward and manageable structure and performs based on illuminance data read by sensors distributed in the room. The simple structure of the controller leads to an easy implementation and operation of the control system that regulates the blind slat angles for sufficient daylight. Subsequently in chapter 6, integration of the controller to the electrical lighting system is demonstrated and evaluated in order to improve the lighting situation in the room.

A part of the controller is based on the prediction control approach described in chapter 3 of the dissertation. This approach is applied to provide initial optimal blind settings for the controller; however for further developments, some refinements and advanced adjustments have been applied based on the illuminance data received from virtual sensors distributed in the office model.

Additionally, to optimize the control process, an innovative approach has been proposed to minimize the number of sensors in the room. In real time buildings, one of the challenges of control systems is to choose an efficient number of sensors for the project and place them properly. This innovative approach suggests a methodology based on the genetic algorithm to find the best minimum number of sensors and their proper location of them which is understandable and manageable by building designers.

Finally, as the last objective of this phase, the controller structure, performance and results are demonstrated and discussed. In the further development steps which are

explained in chapter 5, artificial lighting systems are linked into the controller and the energy saving potentials are discussed.

### **5.3 Methodology**

#### **5.3.1 Virtual Office Model**

As mentioned in the literature review chapter 2, one of the first studies in this field was conducted by Lee et al. (1998). She studied the potential energy saving of automated venetian blinds operating in synchronization with daylighting controls in Oakland, California. To measure the electric lighting power consumption and the cooling energy called for the window and lighting systems, the full-scale Oakland Federal Building demonstration facility was constructed. The facility consists of two adjacent identical rooms (4.57m width, 3.71m depth and 2.68m height). For comparison, each room was equipped with a ‘base case’ and a ‘dynamic’ control system. For the base case system, the venetian blind was set to one of three static positions throughout the day to simulate manual control: Blind slat angles in horizontal position,  $-30^{\circ}$  (partly closed, downward position) and  $68^{\circ}$  (pushed to the limits and closed).

For the dynamic system, a prototype system was developed to activate the blind every 30 seconds for blocking direct solar radiation and maintaining a daylight illuminance of 540 lux–700 lux. The range of blind motion was restricted to  $0^{\circ}$  to  $68^{\circ}$  (Horizontal blind slat positions to  $68^{\circ}$  downward movement to limit sky view). Data were collected for 14 months from June 1, 1996 to August 31, 1997. Lee concluded that an integrated lighting



system (or prototype system) could achieve energy savings of 7%–15% for cooling and 1%–22% lighting energy, respectively, compared to the static blind slat angle of 0°.

However, because the automated blind system only blocked the solar radiation, it can be disadvantageous in places where the heating load is an important factor for the heating concept. Figures 5.1 to 5.3 illustrate the plans of Lee's office which was located in Oakland California.

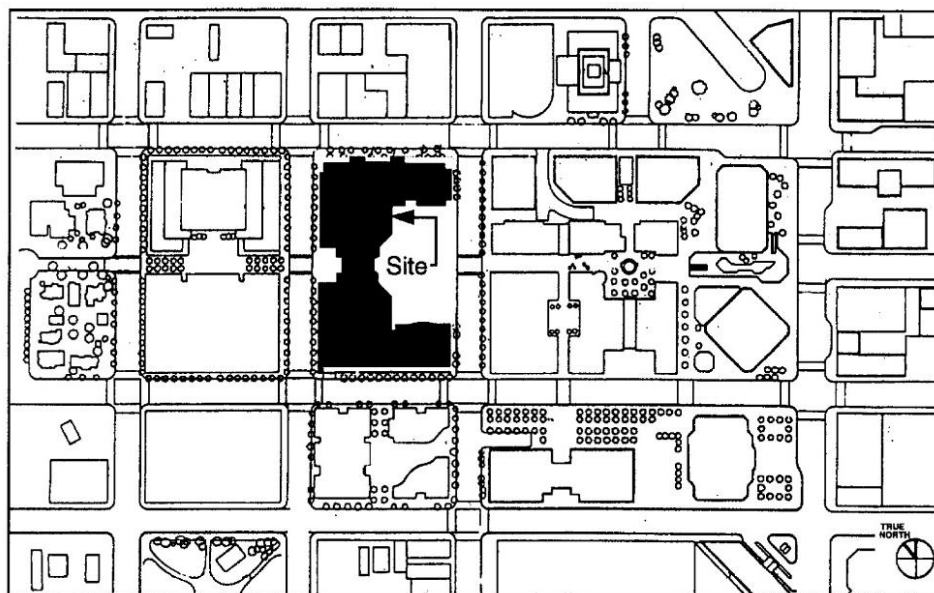


Figure 5. 1. Site plan of the Lee's experimental office, (Lee at al., 1998).

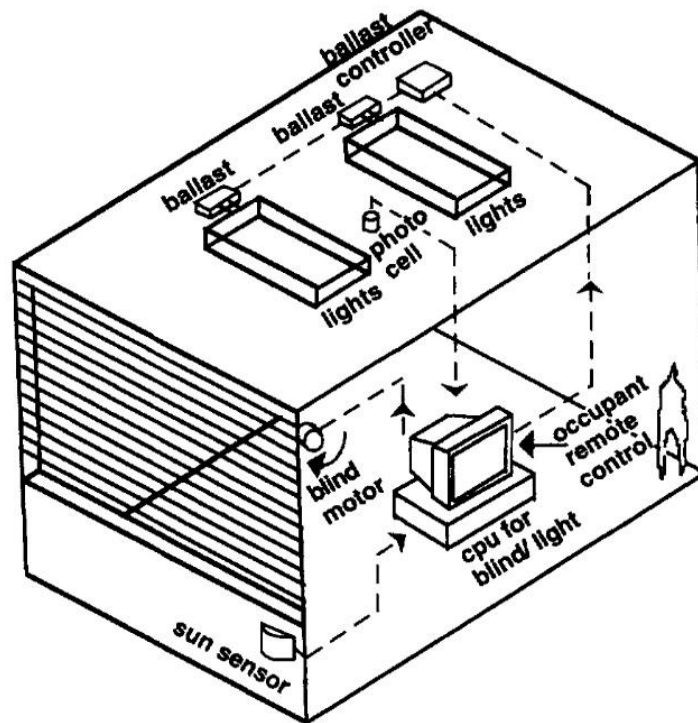


Figure 5. 2. Schematic perspective of the automated venetian blind and lighting system, (Lee et al., 1998).

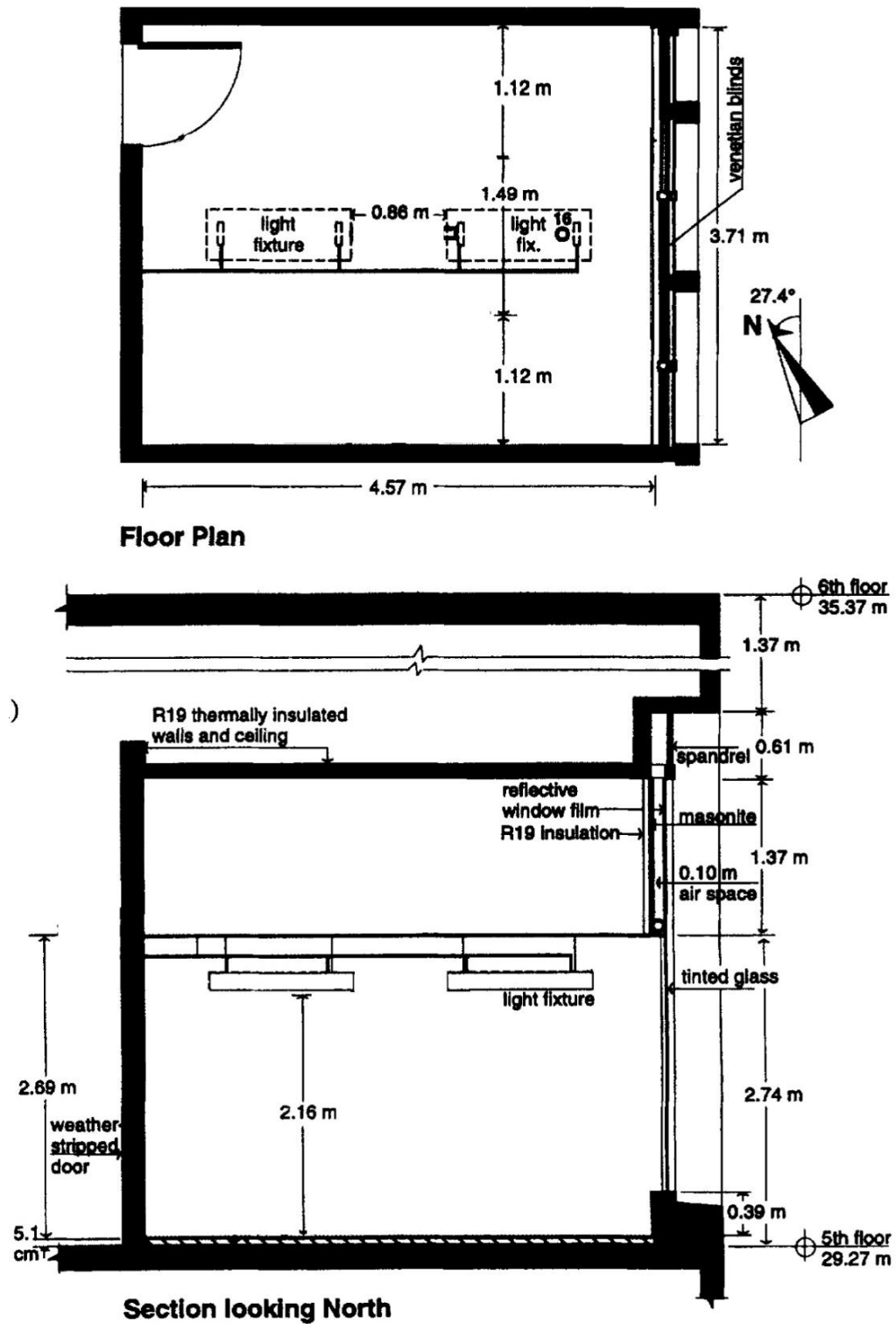


Figure 5. 3. Floor plan and section of Lee's experimental office, (Lee et al., 1998).

Based on the information in the plans provided in the Lee et al. paper, the virtual model of the Lee's experimental office was built in Revit and then imported to IES Virtual Environment. Figure 5.4 shows the imported CAD model in IES.

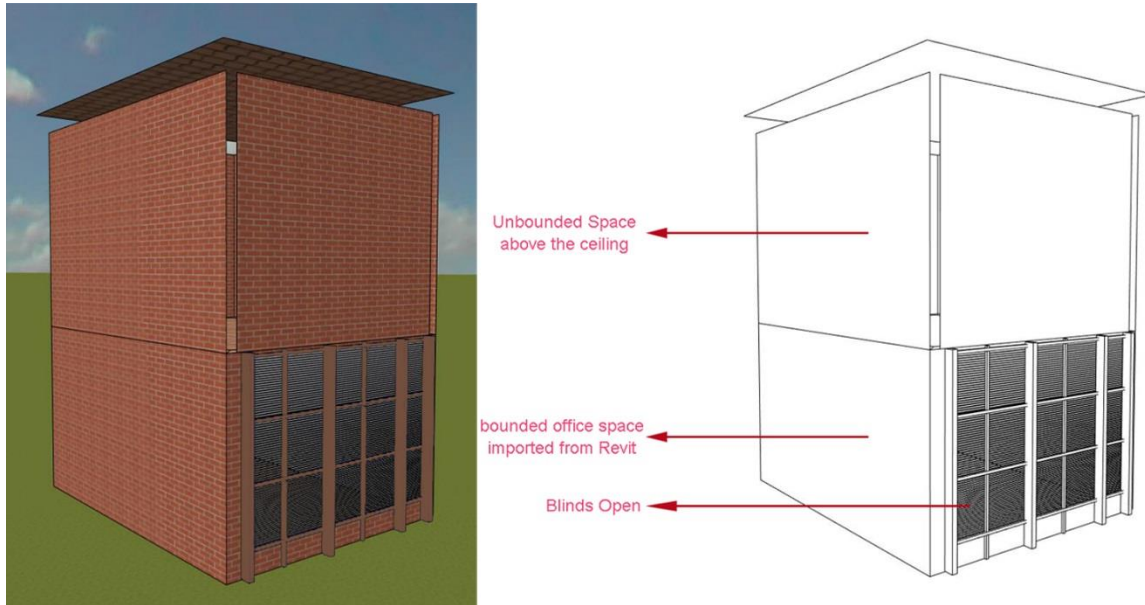


Figure 5. 4. The experimental office model in IES Virtual Environment based on Lee et al. study.

### 5.3.2 Simulations

After importing the CAD model to IES virtual environment, a set of simulations was performed through the Radiance plugin in IES which is called RadianceIES. The Radiance plugin uses weather data file based on different standards. In this case, the weather data was uploaded from Department of Energy website. A dynamic daylighting simulation was run for 12 months, on the 15th of each month for all blind slat angle settings from open ( $0^\circ$ ) to closed ( $90^\circ$ ) in steps of  $15^\circ$ . A work plane at the height of 85 cm was defined in the office which included virtual sensors that were distributed with a default setting of 50 cm spacing (Figure 5.5).

The RadianceIES produces different output formats for the illuminance data. However, for the MATLAB analysis the text format (.txt format) output data available after each simulation run were chosen for further analysis.

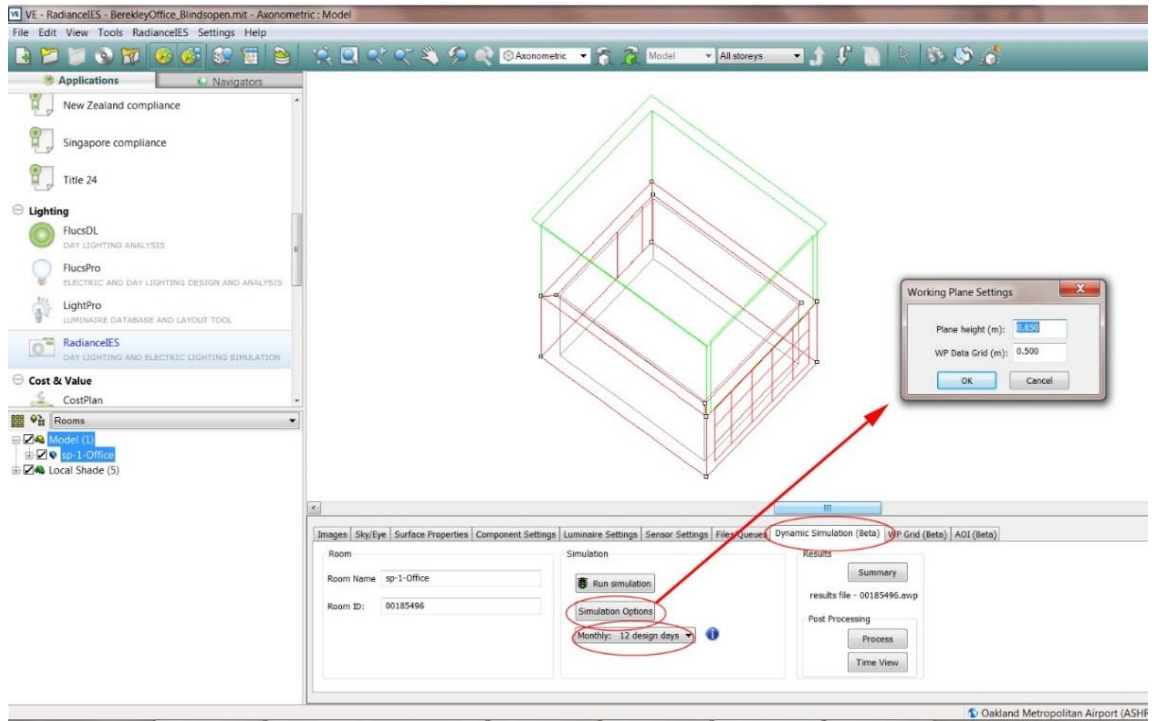


Figure 5. 5. The RadianceIES environment and model settings for the daylighting simulation.

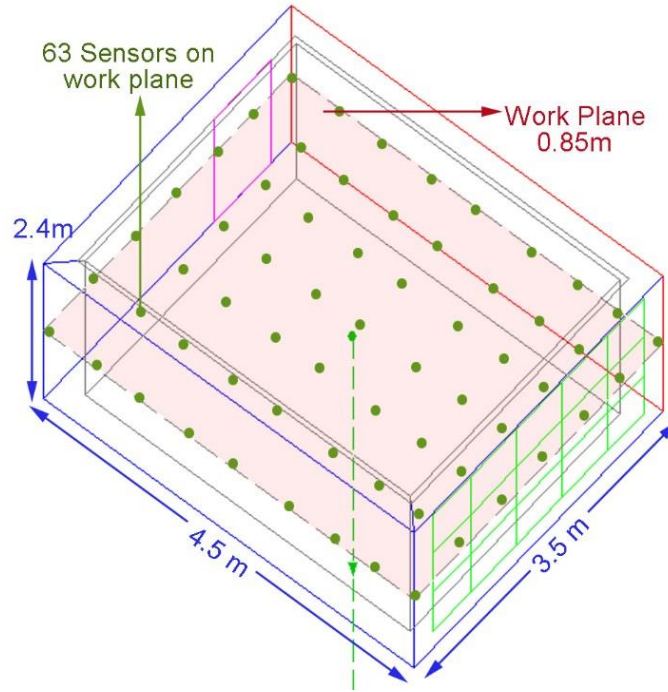


Figure 5. 6. Sensor distribution in RadianceIES for the daylighting simulations.

## 5.4 Sensor Optimization

As mentioned earlier, virtual sensors are placed on the work plane every 50 cm apart. This means 63 (7x9) sensors are distributed in the office model, which is a large number of sensors. In real projects, finding an optimized number of wireless sensors and their locations inside a building is a challenging design problem. Implementation of too many sensors in the building could cause extra installation and maintenance effort and is expensive, so it is necessary to choose the right number of sensors for the project.

In the following section, an innovative automated approach is introduced and demonstrated to find the best optimized number and location of sensors among the 63 default sensors in the virtual office space which could be also applied for different buildings.

In this approach, by applying genetic algorithm, many different combination of sensors were produced and the most effective sensor settings based on their effectiveness to read and record the dynamic path of solar radiation inside the office were evaluated using a specially purposed MATLAB program. In order to explain the steps of sensor optimization process, a short description of genetic algorithm structure and its basic operation is included in the following paragraph.

#### **5.4.1 Genetic Algorithm**

Genetic Algorithms are part of computational models based on natural evolution. These algorithms search for a potential solution to a specific problem defined by simple chromosome-like data structure (also called individuals) and applying recombination operators to these structures to preserve critical information in the data set. Genetic algorithms are often viewed as function optimizers and have been applied to a rather extensive range of different problems. The function to be optimizes is usually called fitness or cost function.

An implementation of genetic algorithms begins with a population of random chromosomes called initial population. Then the chromosomes within the population are evaluated and allocated reproductive opportunities in such a way that those chromosomes representing a better solution to the target problem (better fitness value) are given more chance to reproduce than those chromosomes indicating poorer solutions (worse fitness value), (Whitley, 1993; Cao and Wu, 1999).

Generally, the term genetic algorithm has two meanings: In a strict interpretation, the genetic algorithm refers to a model introduced and investigated by John Holland (1975) and by his students (De Jong, 1975). It is still the case that most of the existing theory for genetic algorithms are applied either exclusively or primarily to the model introduced by Holland, as well as variations on what is referred as “canonical genetic algorithm” in literature. Recent theoretical advances in modeling genetic algorithms also apply primarily to the canonical genetic algorithm (Vose, 1993).

Holland’s early designs for CGA were simple, but were reported to be effective in solving a number of problems considered to be difficult at the time. The field of genetic algorithms has since evolved, mainly as a result of innovations in the 1980s, to incorporate more elaborate designs aimed at solving problems in a wide range of practical settings (Cao and Wu, 1999).

Characteristically, GAs are distinguished in the following features: firstly, they work with a coding of the parameter sets instead of the parameters themselves; secondly, they search with a population of points, not a single point; thirdly, they use the objective function information directly, rather than the derivatives or other auxiliary knowledge to find maxima; fourthly, they process information using probabilistic transition rules, rather than deterministic rules. These features make GAs robust to computation, readily implemented with parallel processing and powerful for global optimization (Whitley, 1993; Cao and Wu, 1999).

In a broader usage of the term, a genetic algorithm is any population-based model that uses selection and recombination operators to generate new sample points (generation of



chromosomes) in a search space. Many genetic algorithm models have been introduced by researchers largely working from an experimental perspective. Many of these research studies are application oriented and typically use genetic algorithms as an optimization tool.

Based on the broader definition, genetic algorithms are adaptive algorithms for finding the global optimum solution for an optimization problem. The canonical genetic algorithm (CGA) developed by Holland is characterized by binary representation of individual solutions, simple problem-independent crossover and mutation operators, and a proportional selection rule.

The population members are chromosomes, which as originally conceived are binary representations of solution vectors. CGA undertakes to select subsets (usually pairs) of solutions from a population, called parents, to combine them to produce new solutions called children. Rules of combination to yield children are based on the genetic notion of crossover, which consists of interchanging solution values of particular variables, together with occasional operations such as random value changes (called mutations). Children produced by the mating of parents, and passing a survivability test, are then available to be chosen as parents of the next generation. The choice of parents to be matched in each generation is based on a biased random sampling scheme, which in some (nonstandard) cases is carried out in parallel over separate subpopulations whose best members are periodically exchanged or shared. The individuals with better fitness values have a better chance to be selected as parents and survive through the next generation. The key parts of a CGAs are shown in Figure 5.7 and described in detail as follows:

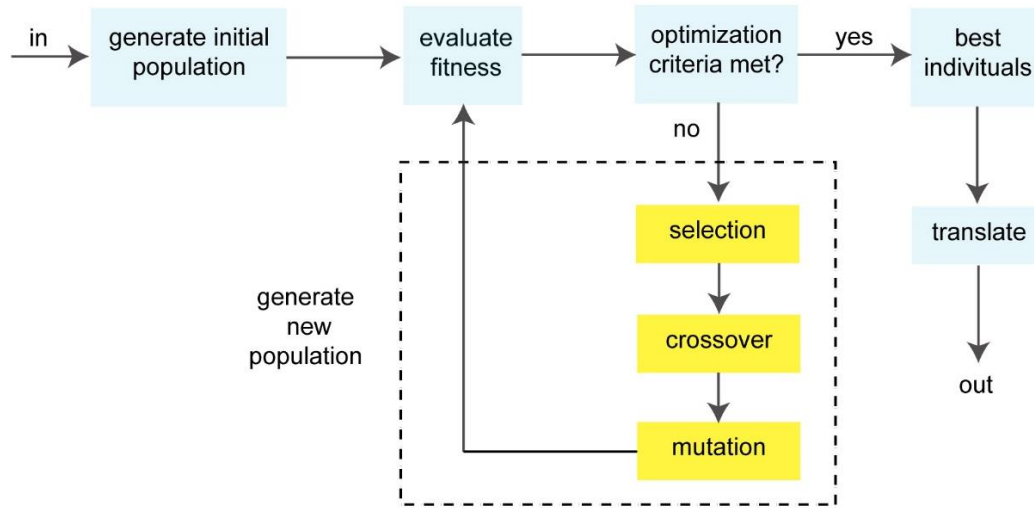


Figure 5. 7. Standard procedure of a canonical genetic algorithm (Cao and Wu, 1999).

Problem statement and fitness function: GA solves an optimization problem with a genetic representation. This requires a fitness function to be defined for a possible solution represented as an array of bits  $\{0, 1\}$ . These components of the chromosome are then labeled as genes. In other words, a chromosome or individual is a multibit array and represents a possible solution to the original optimization problem. It should be possible to calculate the fitness function for every individual. The number of bits that must be used to describe the parameters is problem dependent.

Initialization: GA searches for the best solution within a given population and generates better children. Therefore, an initial population is required to start the process. The length of the chromosomes and the size of the population is problem dependent. Let  $m$  be the size of the population and  $L$  the length of each individual. Each solution in the population can be represented as  $x_i$  where  $i = 1, 2, 3, \dots, m$ , be a string of symbols  $\{0, 1\}$  of length  $L$ .

Typically, the initial population of  $m$  solutions is selected completely at random, with each bit of each solution having a 50% chance of taking the value 0.

Selection: CGA uses proportional selection, the population of the next generation is determined by  $n$  independent random experiments; the probability that individual  $x_i$  is selected from the tuple  $(x_1, x_2, x_3, \dots, x_m)$  to be a member of the next generation at each experiment is:

$$P\{x_i \text{ is selected}\} = \frac{f(x_i)}{\sum_{j=1}^m f(x_j)} > 0 \quad (8)$$

Where  $f(x)$  is the fitness function.

This process is also called “roulette wheel parent selection” and may be viewed as a roulette wheel where each member of the population is represented by a slice that is directly proportional to the member’s fitness values. A selection step is then a spin of the wheel, which in the long run tends to eliminate the least fit population members.

Crossover: Crossover is an important random operator in CGA and the function of the crossover operator is to generate new or ‘child’ chromosomes from two ‘parent’ chromosomes by combining the information extracted from the parents. By this method, for a chromosome of a length  $L$ , a random number  $c$  between 1 and  $L$  is first generated which is called crossover point.

The first child chromosome is formed by appending the last  $L-c$  elements of the first parent chromosome to the first  $c$  elements of the second parent chromosome. The second

child chromosome is formed by appending the last  $L-c$  elements of the second parent chromosome to the first  $c$  elements of the first parent chromosome. Typically, the probability for crossover ranges from 0.6 to 0.95.

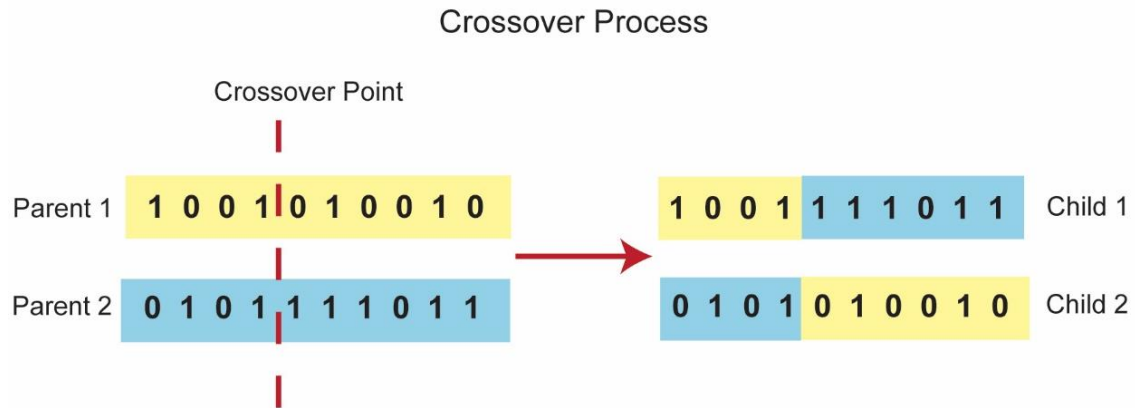


Figure 5. 8. One-point crossover operators in genetic algorithm concept.

**Mutation:** Mutation is another key component in CGA, though it is usually conceived as a background operator. It operates independently on each individual by probabilistically perturbing each bit string. A usual way to mutate used in CGA is to generate a random number  $v$  between 1 and  $L$  which is called mutation point and then make a random change in the  $v^{th}$  element of the string with probability  $p_m \in (1, 0)$ , which is shown in Figure 5.8. Typically, the probability for bit mutation ranges from 0.001 to 0.01.

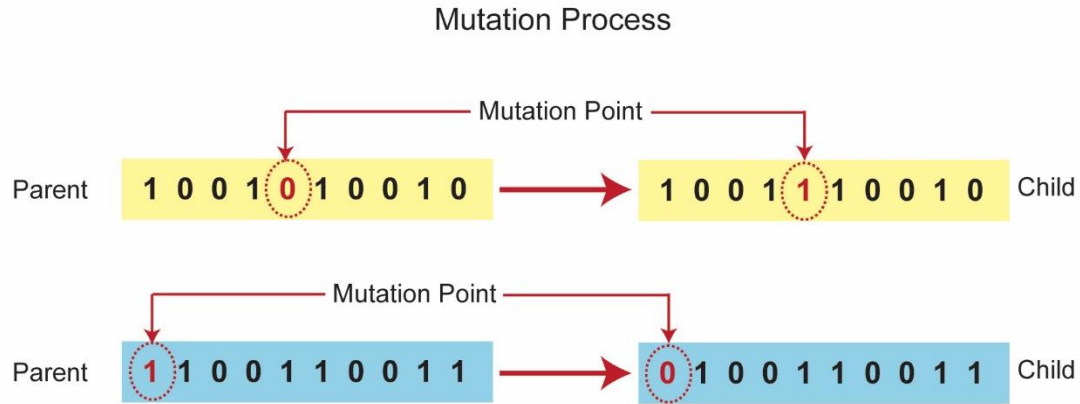


Figure 5. 9. One-point crossover and mutation operators.

Based on this introduction about genetic algorithms and its application on optimization problem, the same CGA structure is used to optimize the problem in this case which is the number and location of the sensors in the controller design.

#### 5.4.2 Problem Statement

As mentioned in the previous section, one of the challenging problems of controllers' design in real time buildings is to reduce the number of wireless sensors in order to decrease the system cost, system maintenance and operation issues in the controller. Additionally, from the occupants' point of view, having few wireless sensors in the working space which are efficiently cooperating with the controller to regulate the lighting situation in the room is much more convenient. So the first objective of this phase is to reduce this number, but at the same time try to keep the system output close to the ideal situation.

### 5.4.3 Methodology

Figure 5.10 displays the ideal situation of the office model with 63 sensors (every 50 cm spacing in every direction) on the work plane. Work plane is 85 cm high similar to the Lee office arrangement in Oakland.

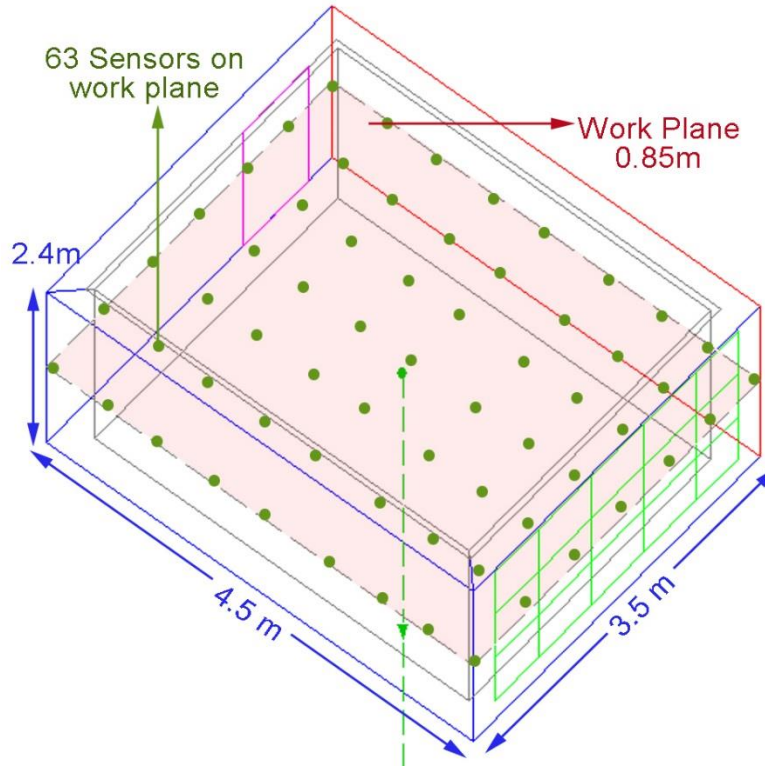


Figure 5. 10. The default setting of the software for number of sensor and their locations in the office model.

As discussed before, to reduce the number of sensors in the room a genetic algorithm code in MATLAB is used to investigate the impacts of each sensor based on Total Error values for 12 months and different blind settings, ( $0^\circ$ ,  $15^\circ$ ,  $30^\circ$ ,  $45^\circ$ ,  $60^\circ$ ,  $75^\circ$  and  $90^\circ$ ).

The main objective of the approach is to explore the quality of the lighting in the office space based on fitness values. In an iteration loop process, the MATLAB code compares

the fitness values of two scenarios; one ideal situation with fully populated room where all 63 sensors readings are used for Total Error calculation and the other scenario when some of sensors are missing. To eliminate the sensors, the illuminance data read by virtual sensors are removed from the TE calculation. This way the sensors with less contribution to the TE values are recognized. The fitness function is defined as following:

$$fitness\ function = \frac{(1 - \beta)}{TE_{error}} + \beta \cdot n \quad (9)$$

Where

$$TE_{error} = \sum |TE_{with\ 63\ sensors} - TE_{with\ (63-n)sensors}| \quad (10)$$

And n is the number of missing sensors.

Fitness function is a weighted combination of the inverse of  $TE_{error}$  and the number of missing sensors. By maximizing this function, the error is minimized and the number of missing sensors is increased. The value of weight factor  $\beta$  could be chosen between 0 and 1. By changing the weight factor  $\beta$  the output of fitness function is changed. Decreasing  $\beta$  leads to the situation where the algorithm tends to fully populate the room with sensors. In the opposite situation when  $\beta$  is increased the algorithm starts to reduce sensors. The value of  $\beta$  depends on 2 facts:

- How big is the value of  $TE_{error}$  compared to the number of sensors?  $TE_{error}$  is up to several hundred while the number of sensors is between 0 and 63.
- Which part of the fitness function is more important to be minimized:  $TE_{error}$  or the number of sensors?

The goal is to set the value of  $\beta$  such that  $TE_{error}$  does not increase but the number of sensors decreases. For this optimization problem, the weight factor  $\beta$  has been chosen 0.99 based on several trials to find out the best weight for the two parts of the equation. Only with this value of  $\beta$ , the algorithm starts to reduce the number of sensors. The fitness function is displayed as follows:

$$fitness\ function = \frac{0.01}{TE_{error}} + 0.99n \quad (11)$$

Where  $n$  is the number of missing sensors.

In the process of genetic algorithm, the selection of best chromosomes is based on higher fitness function values. In order to investigate and display the sensors with less impact on the control process for the course of a day or a year, the error value of over 2000 individuals' population with different number of sensors has been calculated and investigated.

Recall that these individuals are defined as a vector of zeros and ones where one means existence of a sensor and zero means missing sensor (no sensor). The plane of sensors has been mapped into a string of solution as follows:

$$\begin{bmatrix} s_{11} & \cdots & s_{17} \\ s_{21} & \cdots & s_{27} \\ \vdots & \ddots & \vdots \\ s_{91} & \cdots & s_{97} \end{bmatrix}_{9 \times 7} \rightarrow [s_{11} \quad \cdots \quad s_{17} \quad s_{21} \quad \cdots \quad s_{27} \quad \cdots \quad s_{91} \quad \cdots \quad s_{97}]_{1 \times 63}$$



Where  $s_{ij}$  can only 0 or 1 and represents the existence of the sensor in location  $i$  and  $j$  on the work plane.

With mutation, one bit of the individual is flipped from 0 to 1 or 1 to 0. Through this part of GA as a limitation point, the number of sensors could be reduced to less than 10 if the probability of mutation is decreased.

As a stopping criterion, a maximum number of iterations of 500 and a desired number of sensors of 9 have been applied. If any of these conditions has been met, the program exits the iterations and generates the results.

Table 5.1 includes the parameters in MATLAB GA optimization algorithm process.

Table 5. 1 The important parameters for the sensor optimization algorithm.

| Parameters Name                        | Value   |
|--|---------|
| $\alpha$ Weight factor from equation 3 | 0.25    |
| $\beta$ Weight factor from equation 9  | 0.99    |
| Initial Starting Blind slat angle      | [0 0 0] |
| Crossover probability                  | 0.6     |
| Desired illuminance level              | 550     |
| Mutation probability                   | 0.15    |
| Desired Number of Sensors              | 10      |
| Number of iterations in program        | 500     |
| Number of initial population           | 40      |
| Number of original sensors             | 63      |

#### 5.4.4 Results

As mentioned before, the objective of the GA approach is to maximize the given fitness function values. Figures 5.11 demonstrates the changes in fitness function values in terms of 268 iterations. The GA process reached the stopping criterion of finding a solution of less than 9 sensors after 268 iterations. Please note that in each iteration, there are 40 individuals as possible solutions in the GA population. In Figures 5.11, 5.12 and 5.13, only the best solution within the current populations has been plotted.

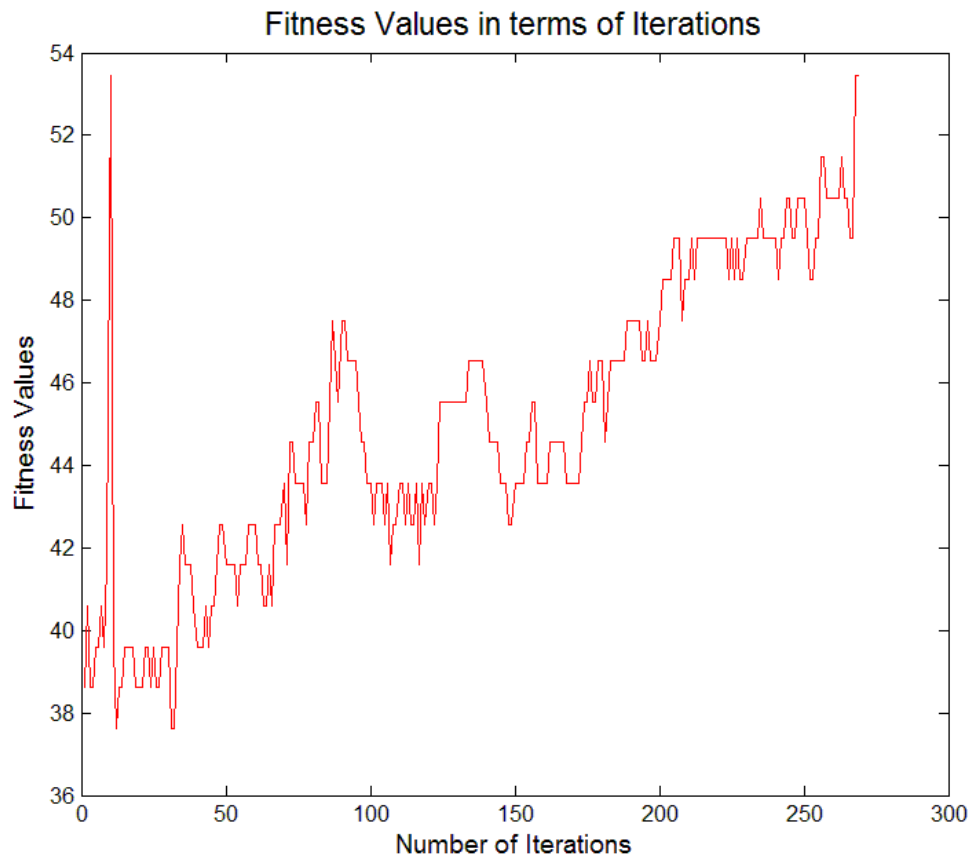


Figure 5. 11. The fitness values of the best solution in every iteration in terms of iteration numbers.

As one of the characteristics of GA, the fitness value of the solutions fluctuates and increases non-monotonically. In some iterations, GA might find an exceptionally good solution which is extinct in following iterations. This behavior can be seen in iteration number 10. GA actually promotes the whole population towards an optimized solution and an exception has no chance to survive.

The other characteristic of GA is that of oscillating by continuing the process beyond a semi-optimal solution. This means that if the iterations continue beyond 268 in this application, the number of sensors do not necessarily decreases, but only will start to oscillate or even increase. Such an oscillating behavior can be seen around the 100<sup>th</sup> iteration. It should be noted that one of the methods to generate children is mutation which means adding or removing one sensor. Therefore, GA is not able to optimize the number of sensors to a very low number. As soon as it finds a good solution, mutation adds another sensor and the oscillation behavior takes effect.

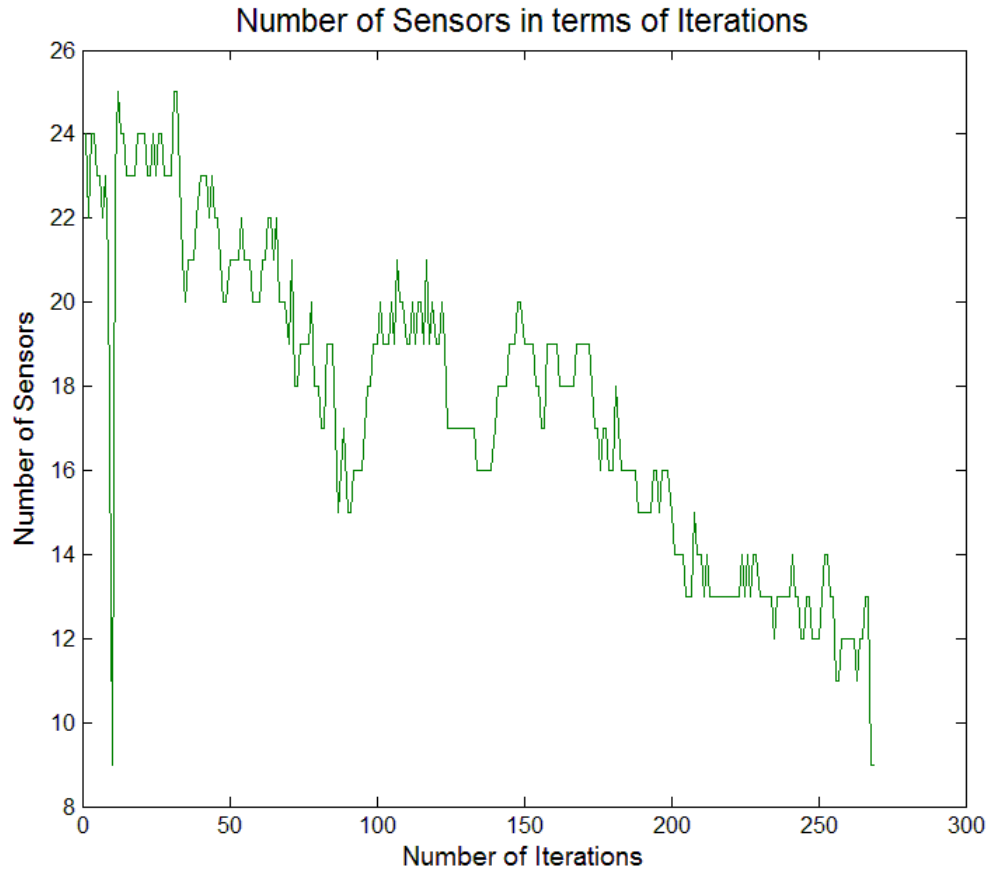


Figure 5. 12. Reduction of sensors of the best solution in every iteration in terms of iteration numbers.

Figure 5.12 represents the number of sensors of the best solutions within the current population in terms of iterations where the same behavior as in fitness function diagram can be identified. Since, the initial population has been randomly selected, most of the individuals have around 31 sensors on average which is half of total number of sensors, (63). This is the reason why the best solution of initial population includes 24 sensors.

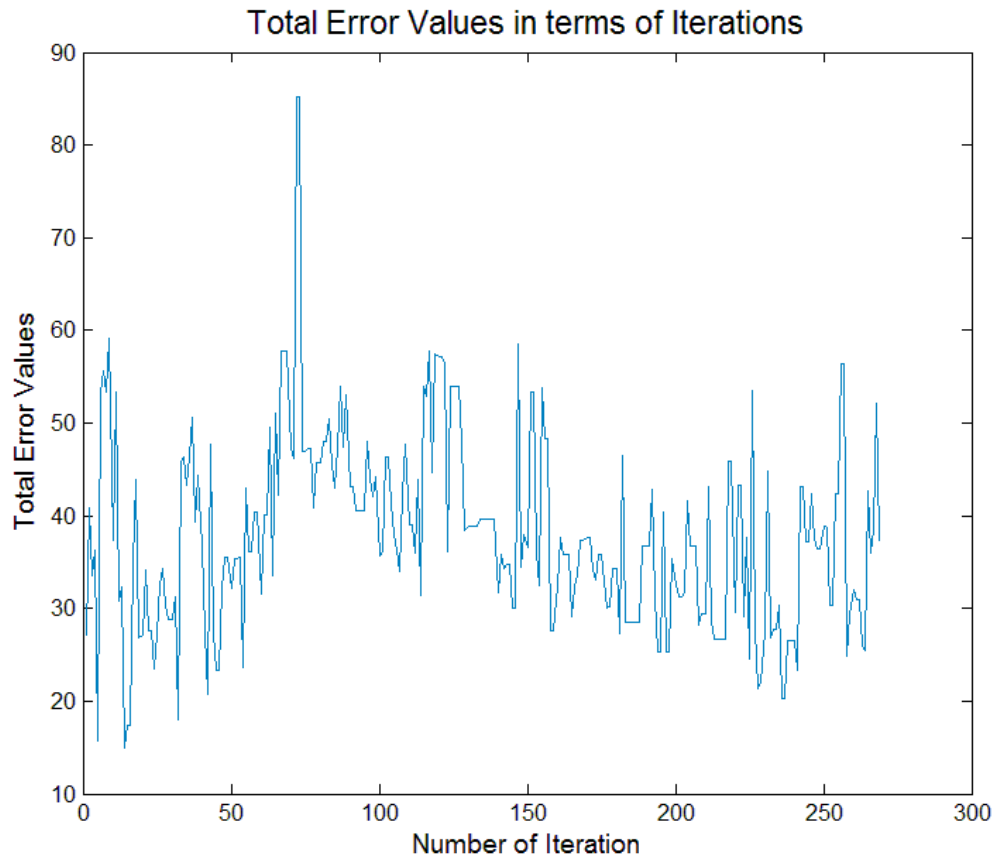


Figure 5. 13.  $TE_{error}$  values diagram of the best solution in every iteration in terms of iteration numbers.

Figure 5.13 illustrates the  $TE_{error}$  (the difference of the  $TE_{63}$  and  $TE_{solutions}$ ) values of the best solutions in every iteration. As expected, the total error value does not dramatically increase in all iterations. By comparing Figures 5.12 and 5.13 we can detect the point at which the number of sensors decreases while the  $TE_{error}$  values do not significantly change.

The following graphs demonstrate the results of the GA optimization approach. The MATLAB code is designed to plot the three best solutions with the minimum number of sensors in the room. These three sensor settings are shown in Figures 5.14 to 5.16.

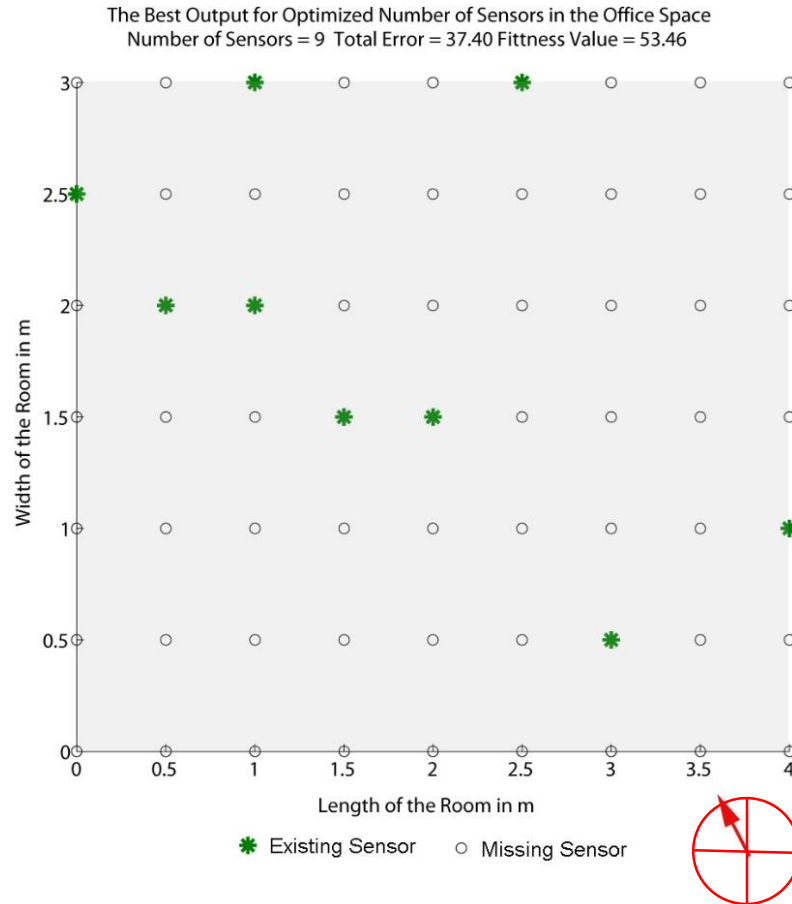


Figure 5. 14. Best optimized sensor setting with 9 sensors based on genetic algorithm optimization approach.

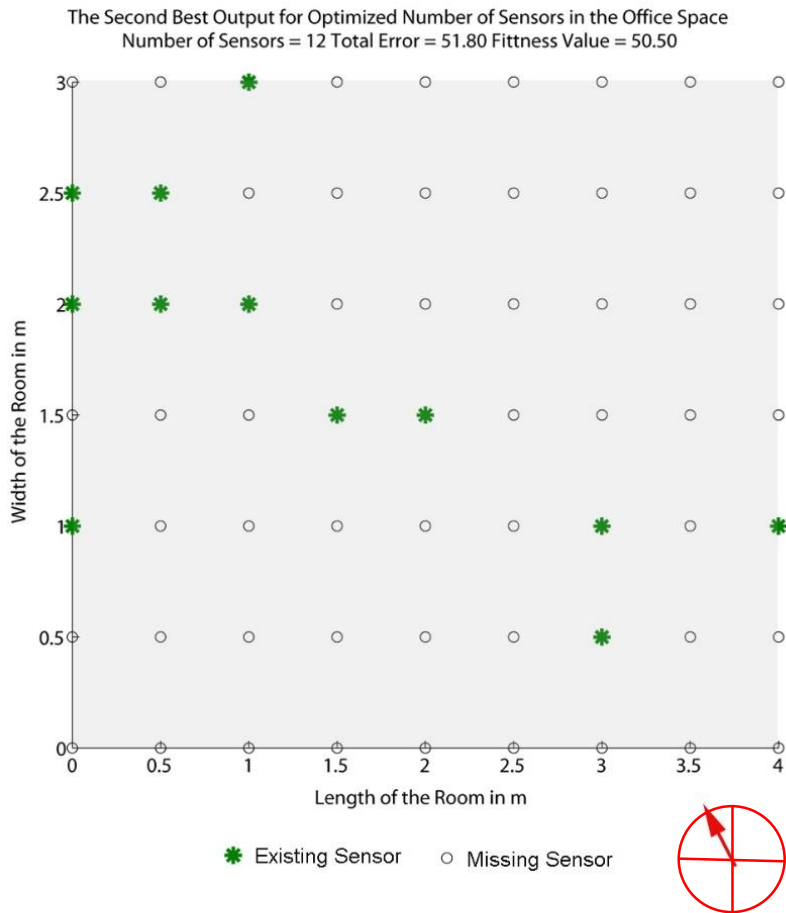


Figure 5. 15. Second best optimized sensor setting with 12 sensors based on genetic algorithm optimization approach.

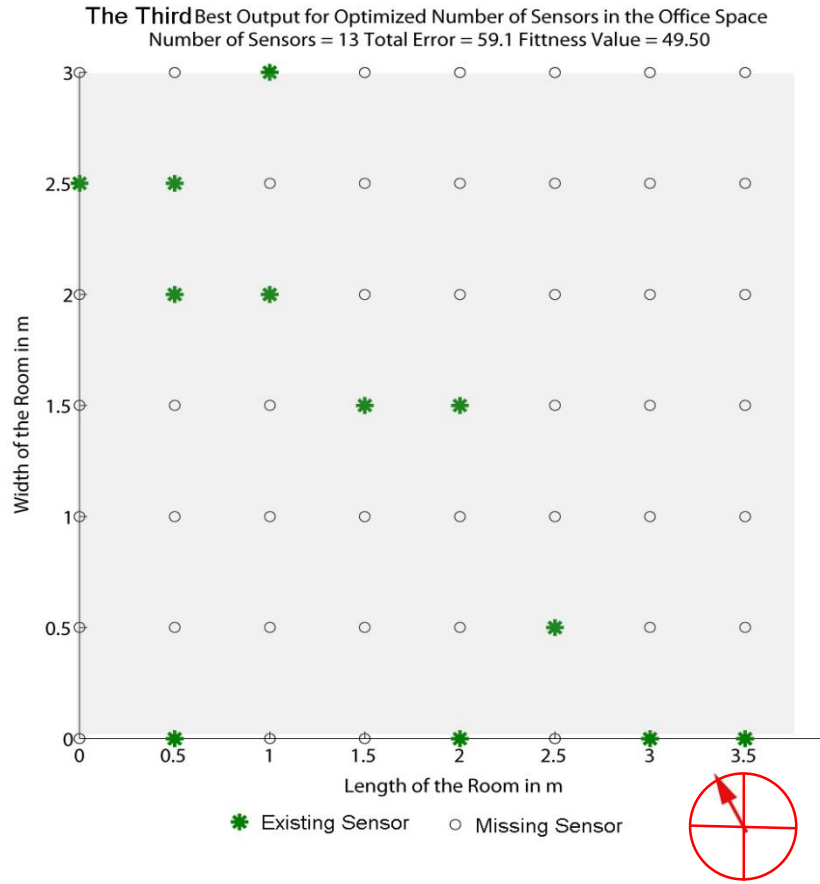


Figure 5. 16. Third best optimized sensor setting with 13 sensors based on genetic algorithm optimization approach.

The sensor locations in all three solutions in Figures 5.14 to 5.16 overlap for many of the sensors which confirms the similarity of all solutions.

In order to have a comparison between three results of GA, reduced number of sensors, and their difference in total error values and fitness values with 63 sensor setting are listed in Table 5.2.



Table 5. 2 The comparison table between three optimized sensor setting as results of the optimization algorithm.

| Optimized number of sensors | TE(63 Sensor)-TE(reduced sensors) | Fitness(63 Sensor)-Fitness(reduced sensors) |
|-----------------------------|-----------------------------------|---|
| 9                           | 37.4                              | 53.46                                       |
| 12                          | 51.8                              | 50.50                                       |
| 13                          | 59.1                              | 49.50                                       |

As mentioned before, the objective of GA process is to maximize the fitness value. With decreased number of sensors the fitness value increases while preventing the TE values from dramatic changes. This is confirmed by values in Table 5.2; i.e. by continuous iteration, the number of sensors has been reduced from 13 to 9 while the TE values have been decreased and fitness values have been increased.

#### 5.4.5 Validation

To validate the results of the optimization process, firstly, the total error values for the 9 sensor scenario are compared to the ideal situation with 63 sensors. Figure 5.17 illustrates this comparison. As shown in the diagram, the total error curves for 63 sensors and 9 sensors are very close. However, as seen in the zoomed diagram, when the TE values are too high or too low, the values do not exactly match and indicate a very small difference, (between 10 to 15) which is according to the scale of the total error values of several thousand very insignificant.

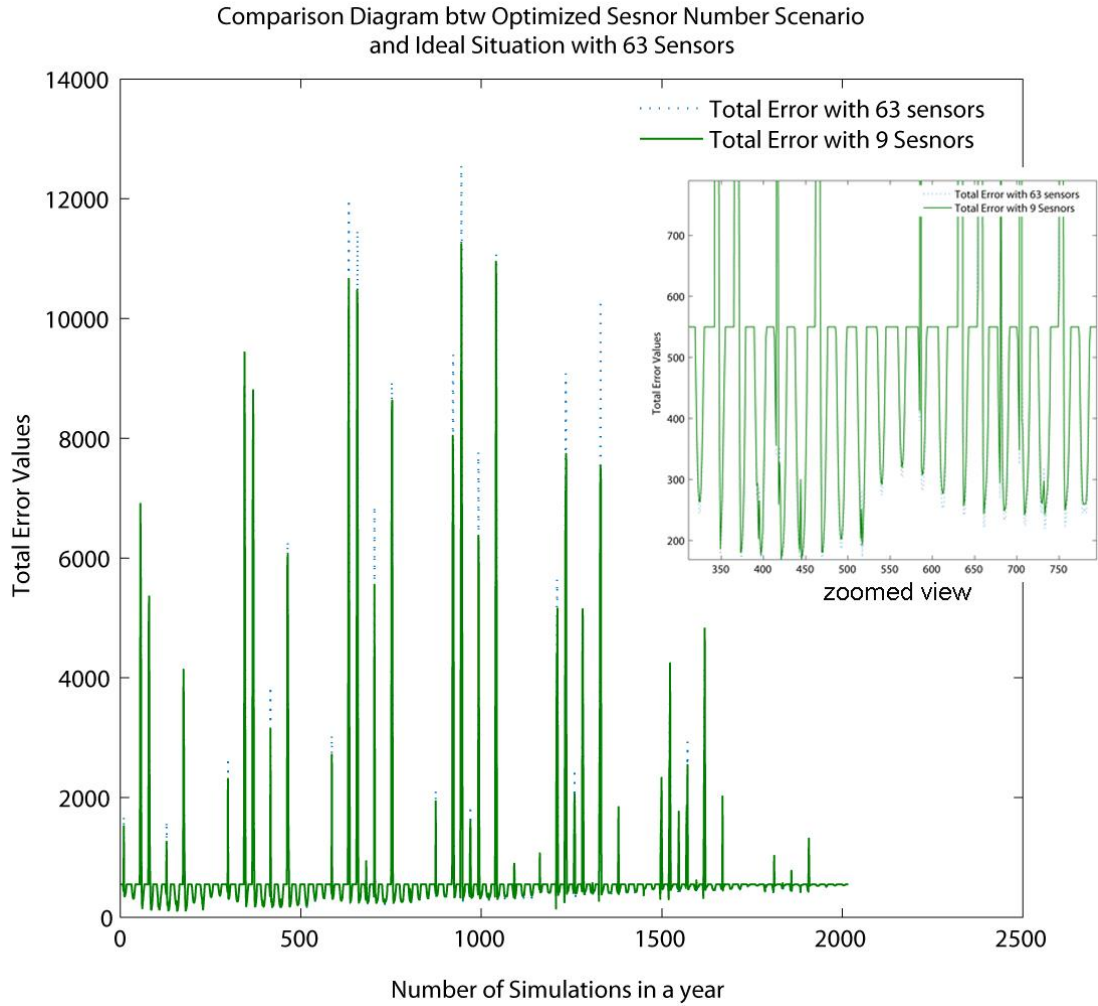


Figure 5. 17. The comparison diagram between the Total Error values of ideal situation with 63sensors and the optimized scenario with 9 sensors based on optimization process.

In the second step of validation, the locations of the sensors in the optimized sensor setting are analyzed based on the actual renderings of work plane in the office model. A daylight simulation has been run for three different simulation days: 15<sup>th</sup> of January, April and October at 10am, 12pm and 2pm (with an intermediate sky condition with sun) to validate the sensor locations selected by GA optimization process based on actual lighting situation in the office. These images are displayed in Figure 5.18.

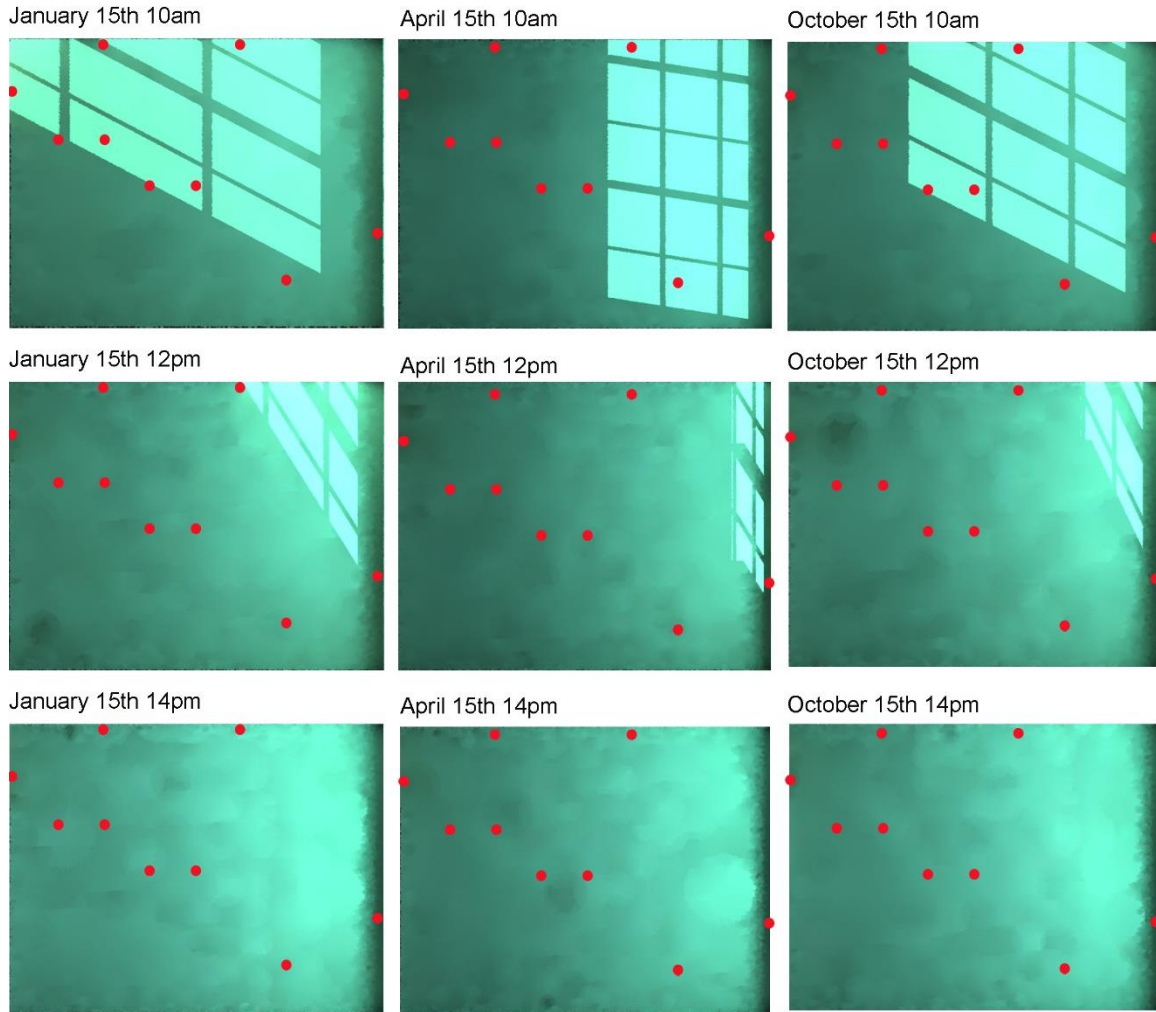


Figure 5. 18. Optimized number and location of 9 sensors on daylight simulation images of the work plane for three different days in January, April and October.

The images in Figure 5.18 illustrate the seasonal and daily direct solar radiation path inside the office model and the optimal number of sensors and their locations based on genetic algorithm approach in red points. As seen in the pictures and based on an illuminance data for a whole year, the North-West corner of the office has the 100% direct solar penetration, (daily and yearly) and has a significant impact on the lighting situation in the room. In Figure 5.19 the most daylit situations of these three days are layered and

shown in one image. As seen in the Figure the location of the 9 sensors shown in red validate the fact that sensors are effectively situated in the room in order to read and record the direct solar radiation path in the office.

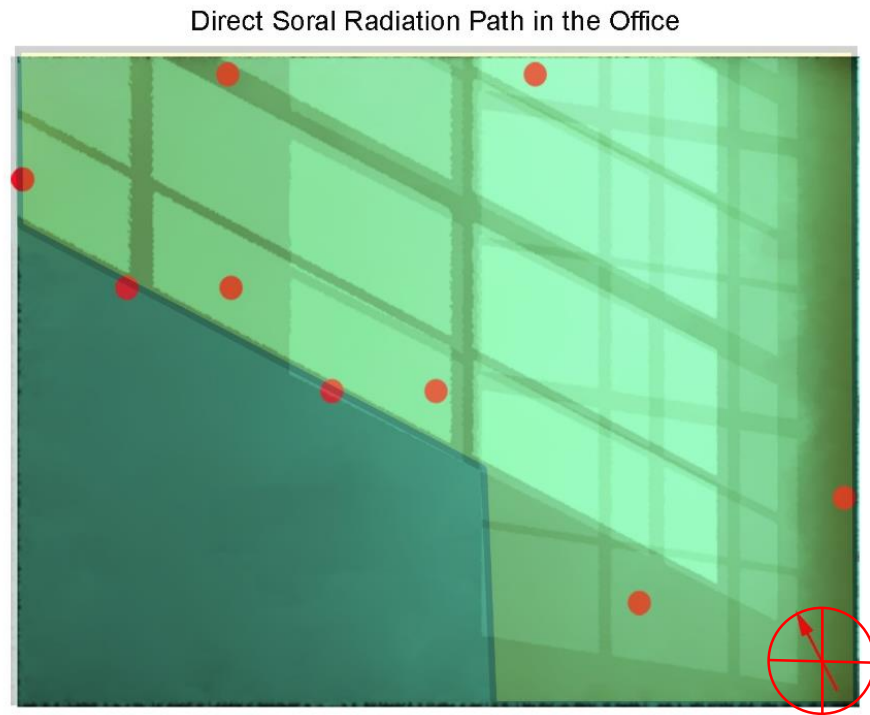


Figure 5. 19. Path of the direct daily and yearly solar radiation in the office.

#### **5.4.6 Conclusion**

The direct solar radiation analysis and the total error comparison diagram between ideal situation with 63 sensors and the sensor reduced situation with 9 remaining sensors indicate that the sensor optimization approach is a valid method to reduce the number of sensors and place them effectively on the work plane.

In the next step of this phase, the design and performance of a sensor-based integrated controller for the office model is demonstrated which functions based on the 9 optimized sensor data to regulate the daylighting situation.

### **5.5 Controller Design**

As mentioned in the introduction part, a simple controller is designed to regulate the daylight in the office. Currently, many high performance buildings' control systems include complicated control algorithms based on fuzzy logic and neural network theories. Some of them are a combination of both and proportional integral derivative controllers which makes the whole system very complex. Due to this fact, one of the main design objectives here was to keep the system structure very modest and manageable, so the implementation, operation and maintenance of the system would be at ease and doable without the need for highly expert professionals.

Thus a simple integral controller is applied to control the daylight situation in the office model. One of the advantages of integral controllers in general is that they have the unique ability to return the controlled variable back to the exact set-point following a disturbance.

However, a disadvantage of integral controllers is that the long respond times of the system are needed. In other words, they respond to error signals slowly and can initially allow a large deviation at the instant the error is produced. This can lead to system instability and cyclic operation and this is the reason, the integral control mode is not normally used alone, but is combined with another control mode. To overcome this problem in this study, based on the prediction method in phase II, the initial conditions of the blind slat angles are pre-defined and pre-set in the algorithm. This has two advantages for the designed system; firstly, it reduces the error times since the errors are very small and sometimes very insignificant due to the initial optimal settings. Secondly, it avoids the instabilities caused by local optimums which are caused by non-linear behavior of the system.

An integral controller provides an output rate of change that is determined by the scale of the error and the integral constant. The controller has the unique ability to return the process back to the exact set-point if necessary.

The structure of the proposed controller in this study is demonstrated and explained in the following section.

### **5.5.1 Controller Structure**

The integral controller was designed and developed in MATLAB Simulink. The inputs of the system are illuminance levels data read by the sensors in the office, time and the desired lighting level which is 550 lux based on the Lee study. The system output is then the blind slat angles for each given time. The simulated illuminance data are limited to 12

days, 15th of each month, and for 24 hours each day. The daylighting simulated data are then interpolated in MATLAB to be expanded to 365 days. This saves us a significant amount of simulation time. Figure 5.20 illustrates the basic concept of the integral controller's structure.

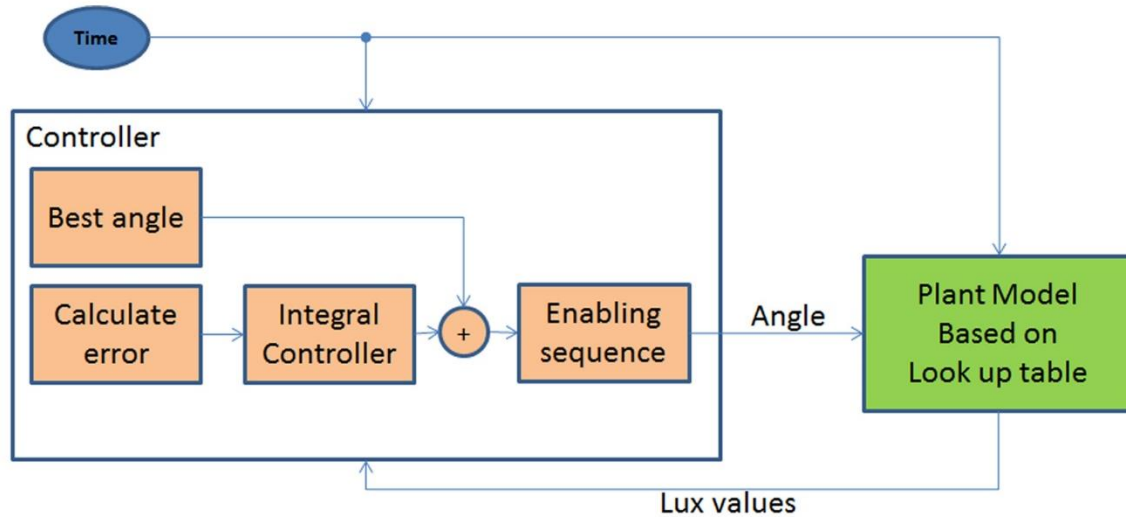


Figure 5. 20. Basic structure of the designed Integral Controller to regulate the blind slat angles.

As demonstrated in Figure 5.20 diagram, based on a look up table which was developed in phase I based on predicting algorithm was built-in in the controller to provide the initial optimal blind settings.

In the next diagram, (Figure 5.21) the system in MATLAB Simulink is illustrated. The Simulink model consists of different sections which are explained in the next paragraph.

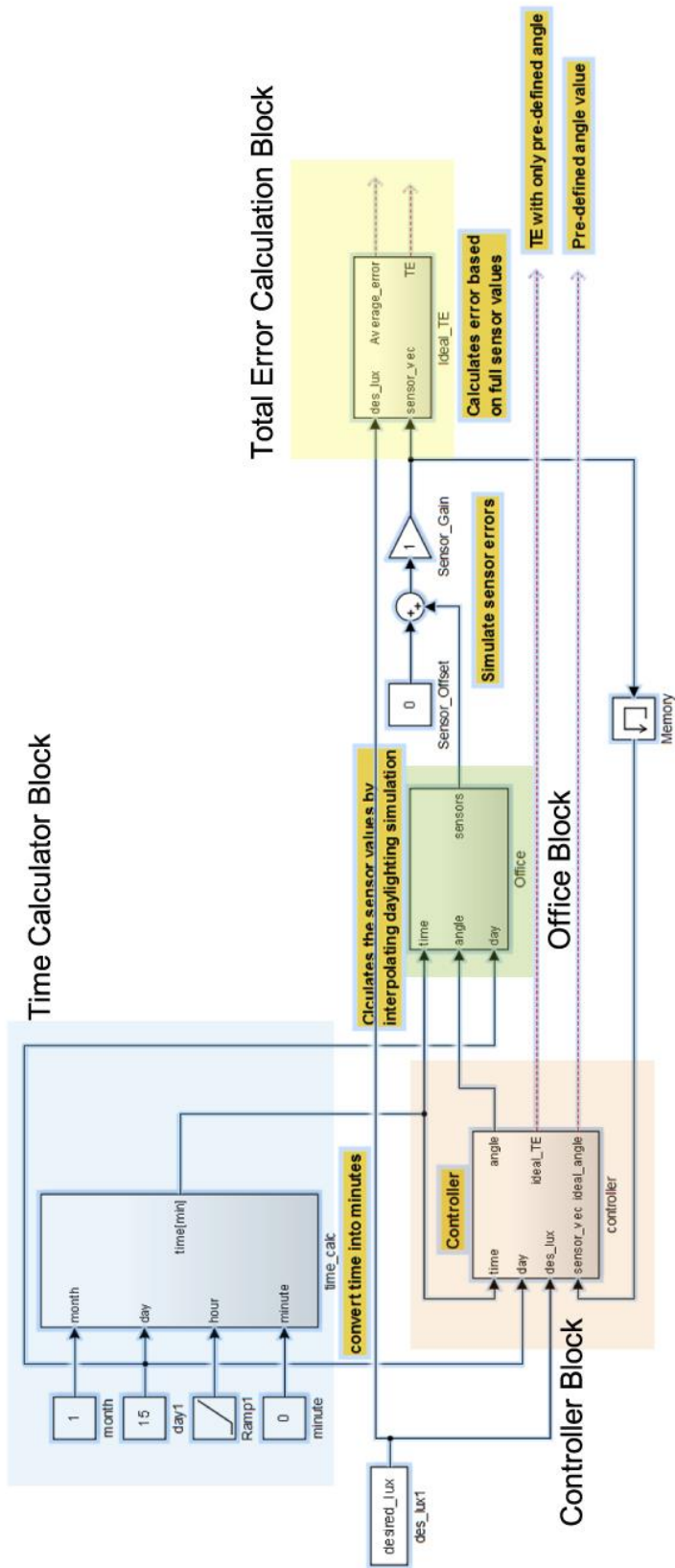


Figure 5. 21. Control system structure in Simulink.



### 5.5.2 System's Structure in Simulink

The control system as shown in Figure 5.21 includes four different blocks which are explained below.

Time Calculator Block: in this block the value of time is calculated in minute. The inputs are month, day, hour and minutes. The output of this block is a numeric value which indicates the time in minutes elapsed from January first. This value is needed to calculate the predicted optimal blind slat angle values in controller as well as for interpolated sensor values in the office block.

Office Block: This block simulates the illuminance levels in the office. It expands the simulated data of selected days and selected hours for a day throughout the whole year by interpolation. The interpolation process in this block consists of two steps: hourly interpolation and daily interpolation. The process is based on a simple linear interpolation.

Controller Block: The controller calculates the blind slat angles based on time, desired lux level which is 550 lux as mentioned before and the total error values.

Total Error Calculation Block: In this block the total and average error values are calculated to evaluate and validate the controller behavior. TE and average error equations are:

$$TE_{error} = \sum |TE_{with\ 63\ sensors} - TE_{with\ 9\ sensors}| \quad (12)$$

*Average Error*

$$= \frac{\sum_{i=0}^{i=9} (\text{illuminance level}_{\text{sensor } i} - \text{Desired illuminance level})}{\text{number of sensors}} \quad (13)$$

The controller block is shown in Figure 5.22 and includes four different sections as explained below:

Predicted Blind Setting Calculator: Based on time, desired lux and current blind slat angle settings, the optimal setting for the blinds are selected within a pre-defined tolerance. It calculates the optimal angle based on the best TE values and selects the closest angle to the current angle within the pre-defined tolerance. The total error tolerance is set to 20%.

Error Calculator: In this section, total and average errors are calculated. The average error values are applied as the input for Integral Controller and are added to the predicted optimal blind slat angle. This actually works as a correction of the ideal blind slat angle based on the direct measured sensor data. The integral controller is reset every time if the optimal angle changes more than 10 degrees in order to avoid saturation and also accelerates the controller response.

Comfort Concept Block: In order to avoid continuous changes in blind slat angle settings which cause distraction and visual discomfort for the occupants, the blinds movements are activated based on several criteria:

- Blind settings change more than a user defined threshold which is currently set to 15 degrees. This is due to the flexibility of the actual blinds in buildings.

- The user defined controller active mode is currently set to two minutes. This value is usually set to 30s, however to show the behavior of the controller in small details, it was necessary to increase the active mode to 2 minutes.
- The user defined deactivation mode is currently set to 15 minutes which could be adjusted based on the occupants' needs and comfort conditions.
- Total error values change more than a user defined threshold which is currently set to 200. This value was chosen based on several trials and to prevent the Total Error from increasing during the deactivation time.

This means that every time when one of these above mentioned thresholds has been reached two minutes is given to the controller to set the angle values and then it deactivates for 15 minutes.

Simulating the Limitations: This block adds limitations to the angle output. This includes: saturations, rate limiter and the quantizer for 15 degree angle steps.

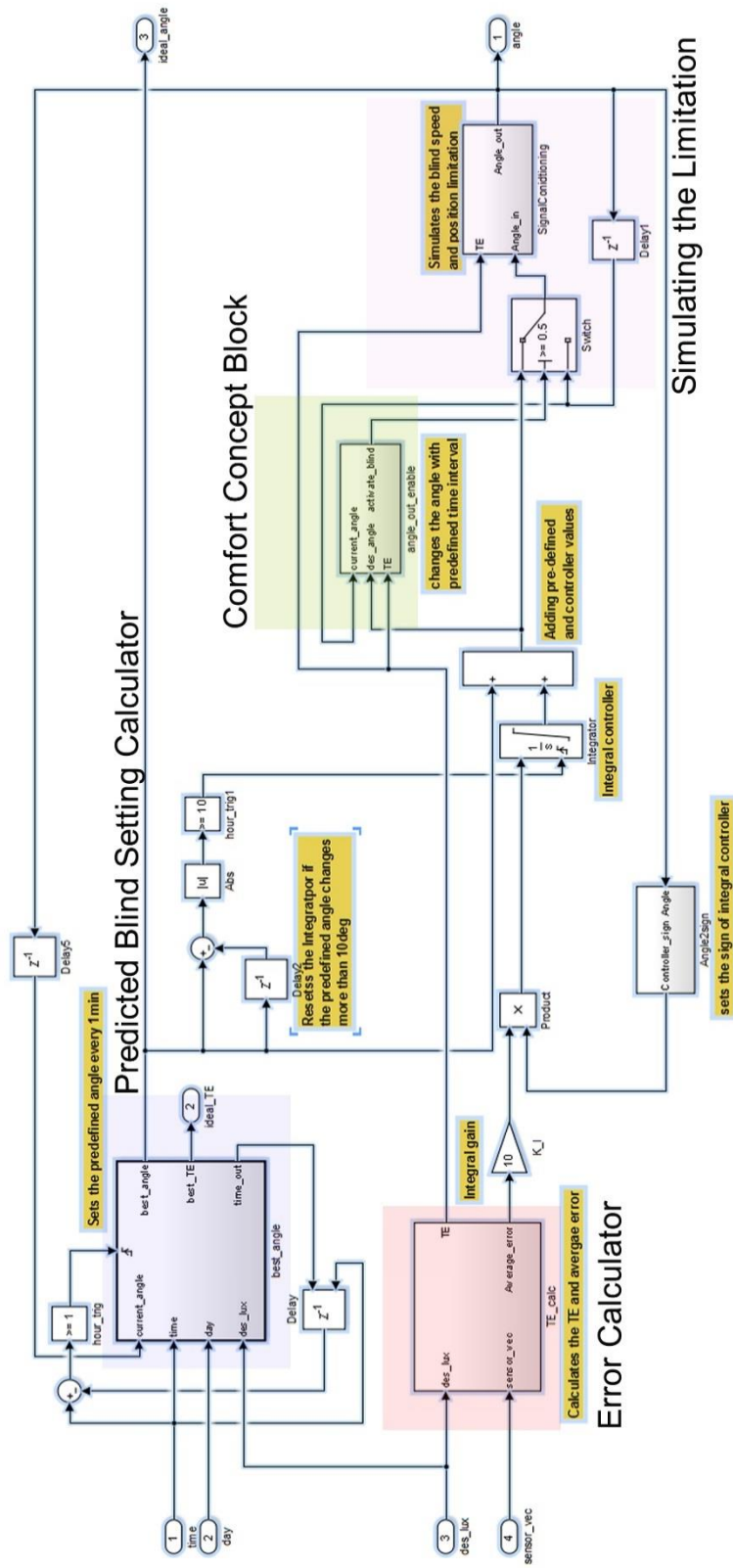


Figure 5. 22. The Integral Controller's structure in Simulink.

## 5.6 Controller Output

Based on the discussed control structure, the results and output data which indicate how well controller regulates blind slat angles during a year and a day in the office are displayed in Figure 5.23. In the these Figures different set of diagrams are presented which compare the controller output for two sensor settings; the ideal situation with 63 sensors and the reduced optimized sensor situation with only 9 sensors to compare and validate the performance of the system. Additionally, these results are shown for four different months and two different sky conditions.

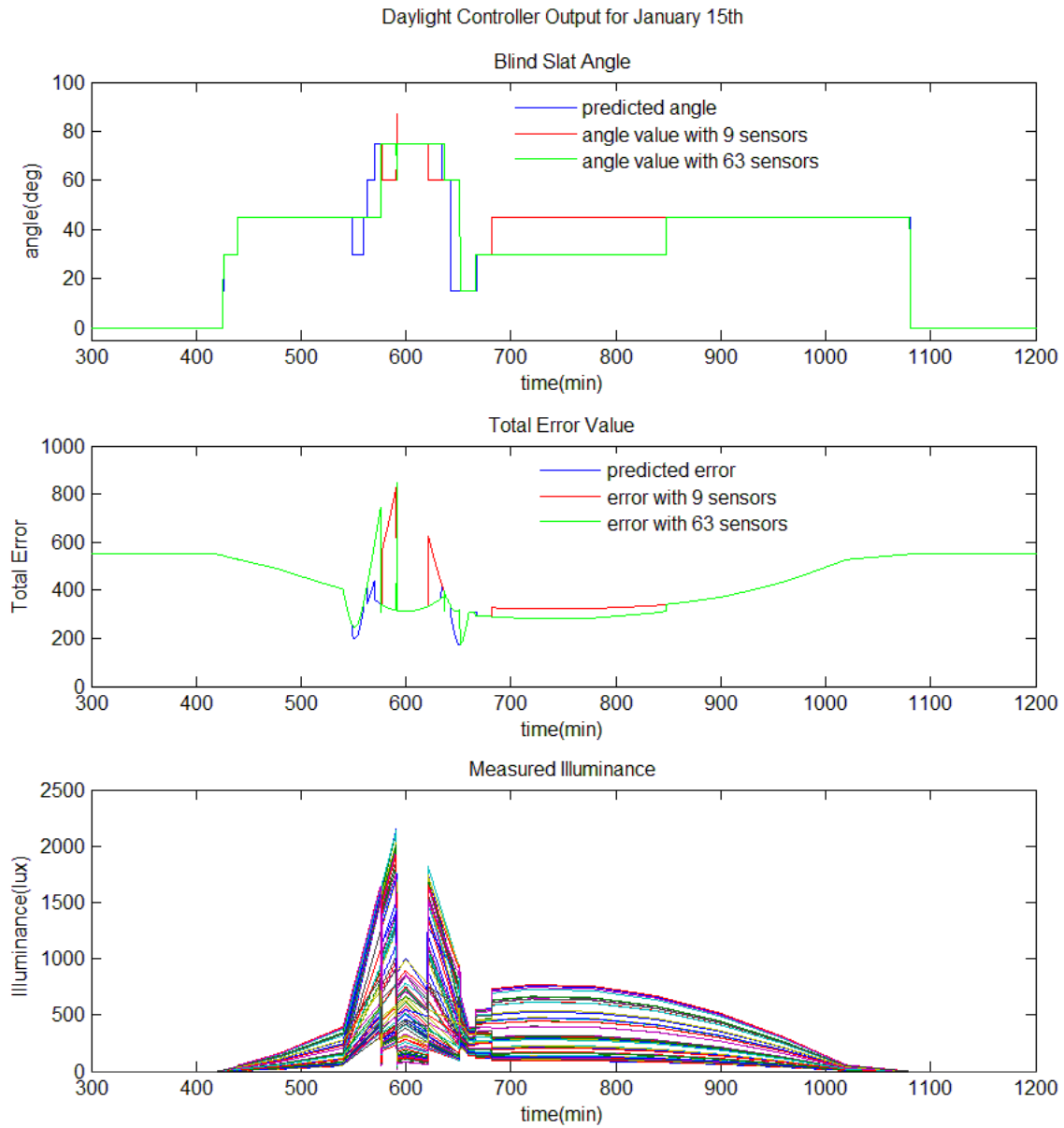


Figure 5. 23. Performance of the controller on January 15th.

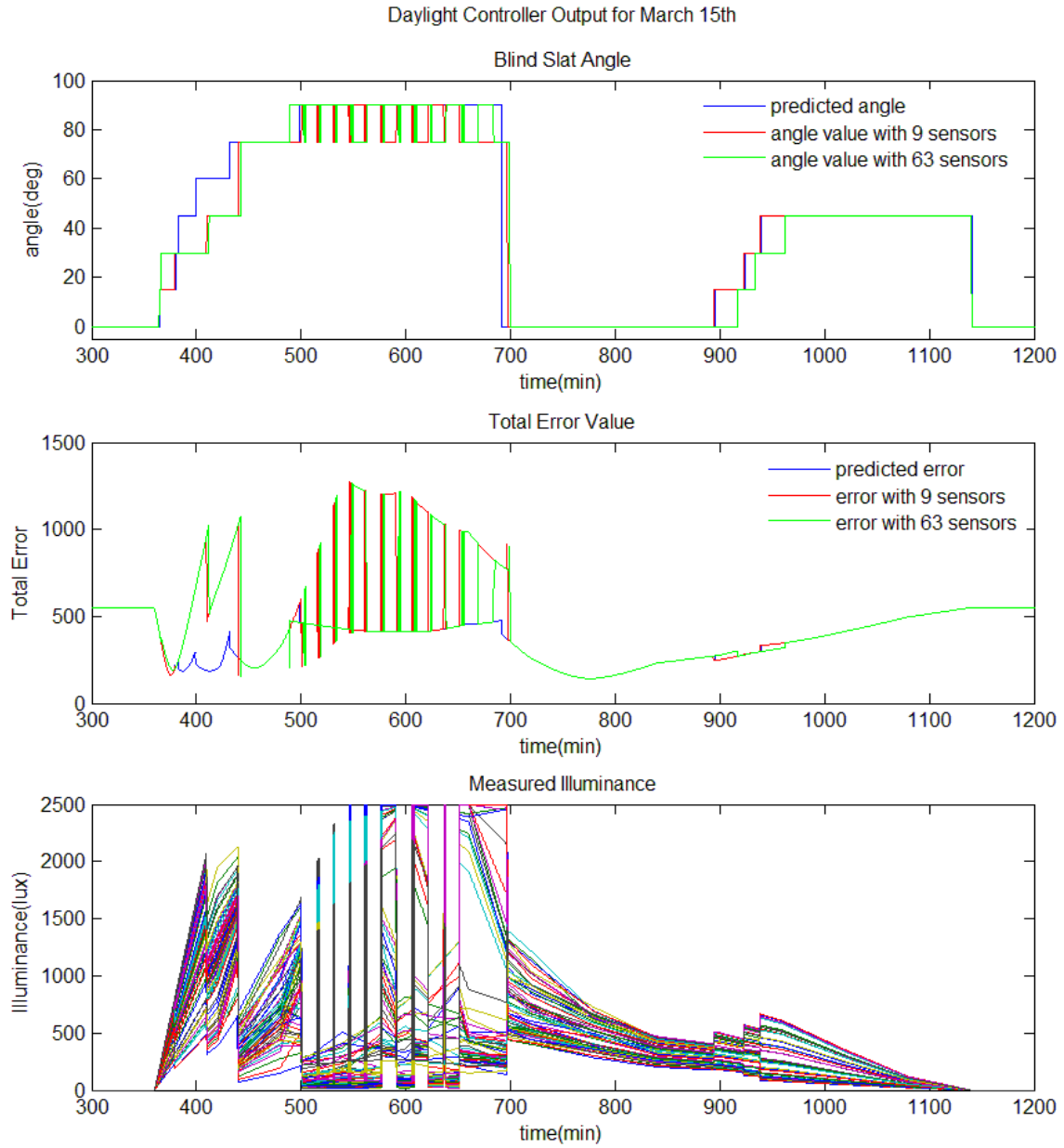


Figure 5. 24. Performance of the controller on March 15th.

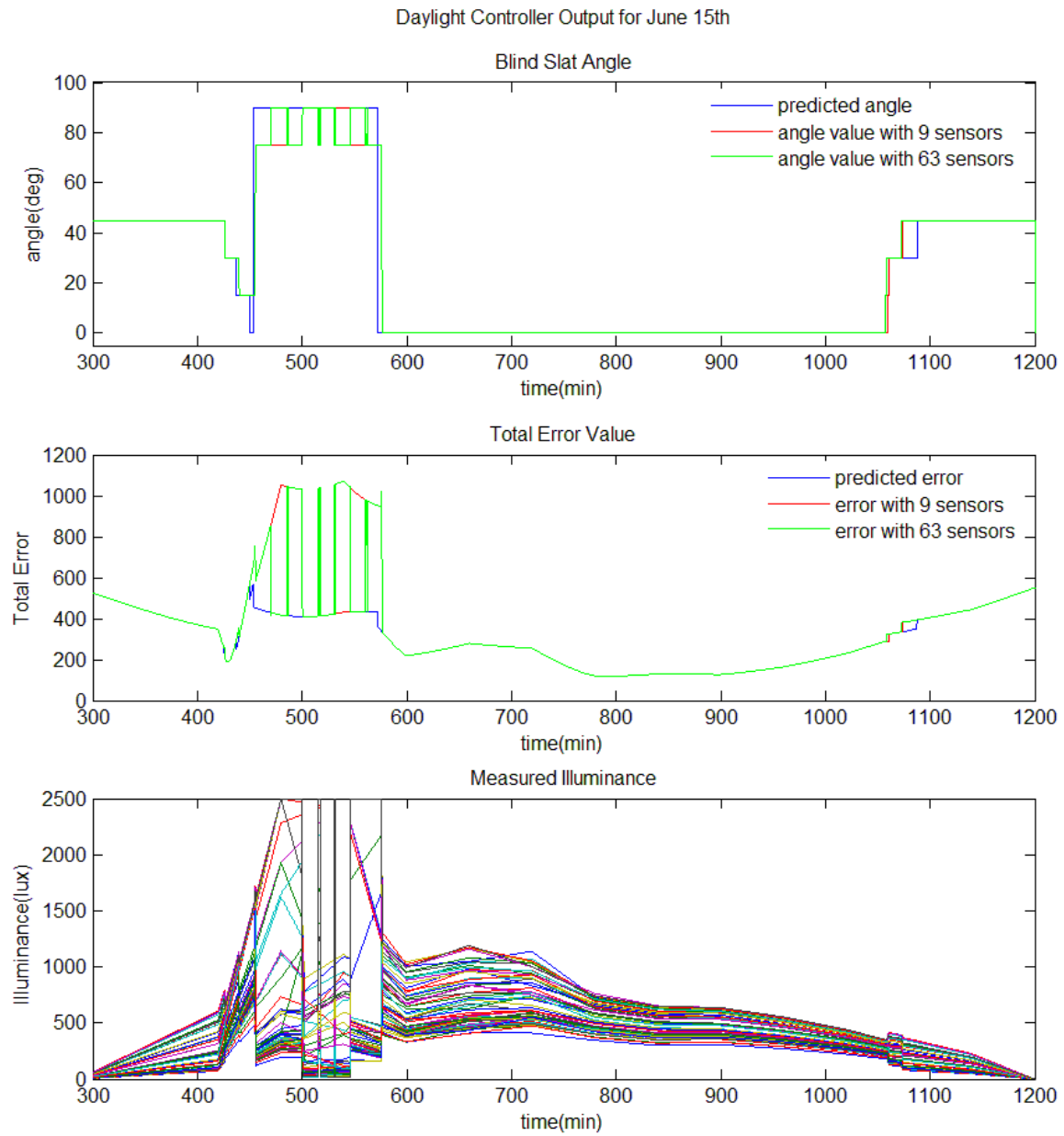


Figure 5. 25. Performance of the controller on June 15th.



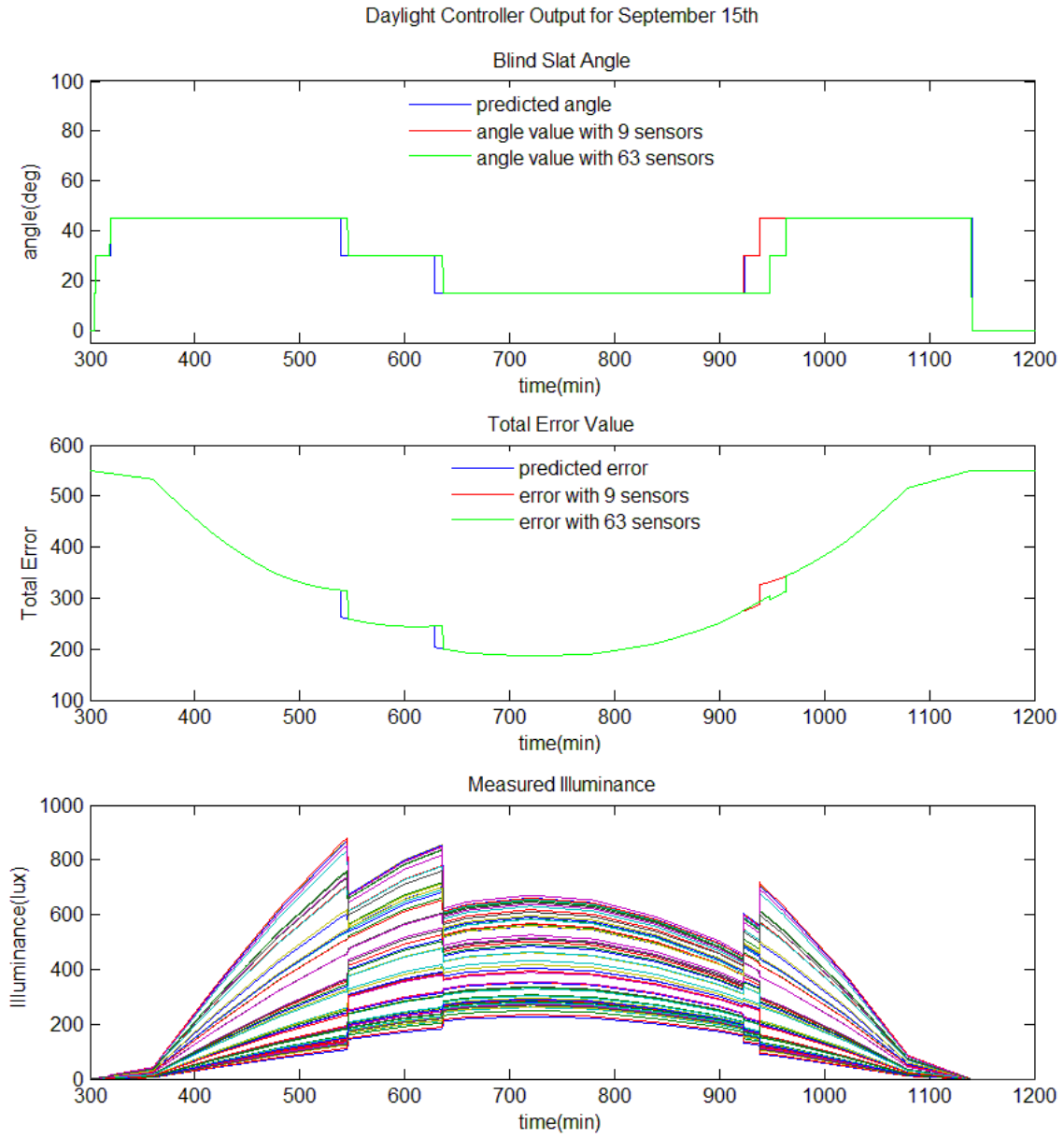


Figure 5. 26. Performance of the controller on September 15th.

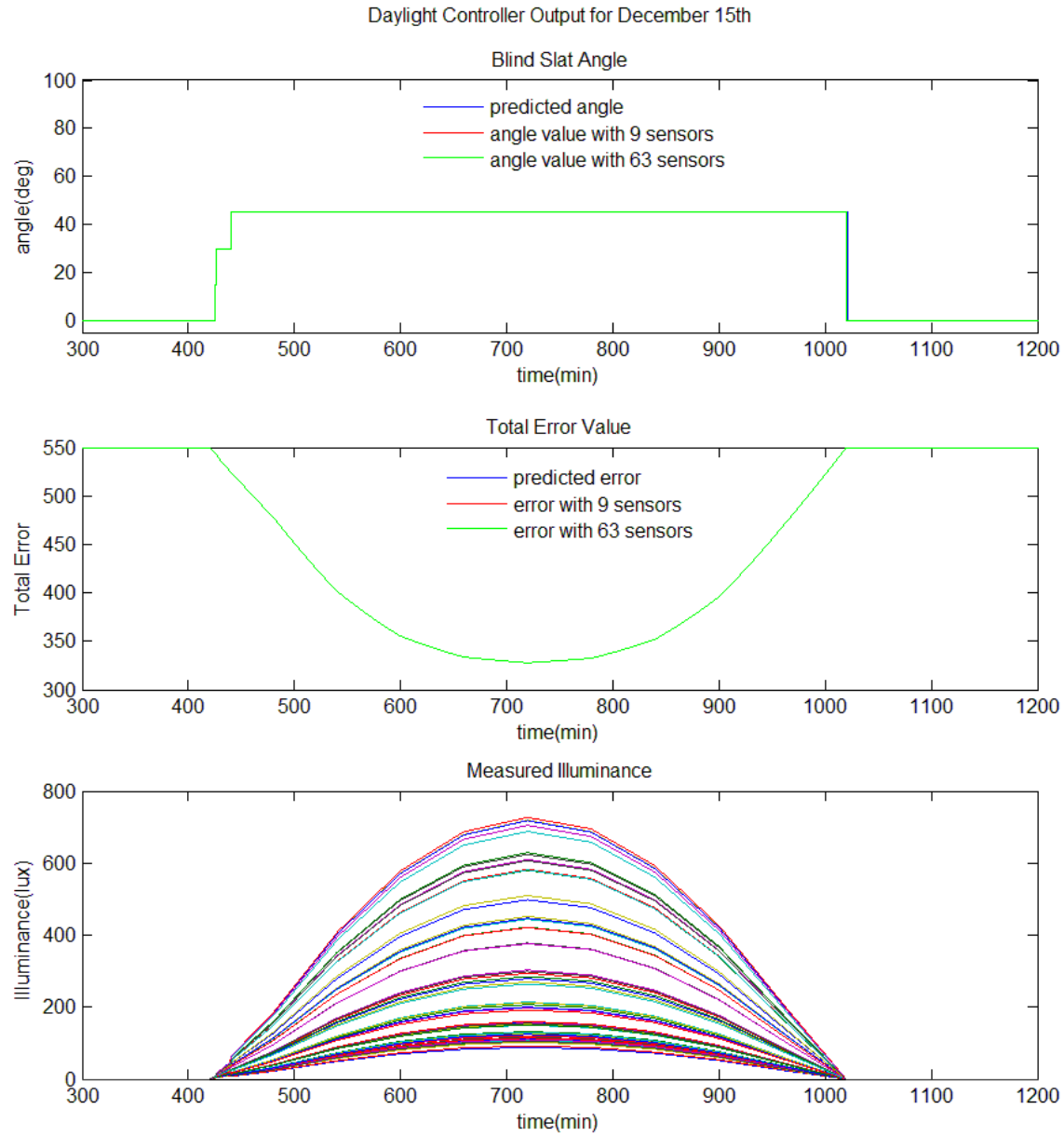


Figure 5. 27. Performance of the controller on December 15th.

Graphs in Figures 5.23 to 5.27 illustrate the performance of the developed controller for the virtual office model on 15<sup>th</sup> of January, June, September and December, (randomly chosen). In each Figure, the first diagram indicates to the changes in blind slat angle during the day and at the same time the results from three different sets of analysis are compared:

The predicted blind setting values based on control approach in phase II, (chapter 3), the ideal situation with 63 sensors placed symmetrically on the work plane and finally the 9 optimized sensors situation. For all four days, this diagram indicates that the results of the blind settings in all three different settings are very similar. Especially, the proposed blind slat settings by the controller for ideal situation and 9 sensor situation are matching perfectly and only designate to the slightly different blind settings at some hours of the day.

The second diagrams in the Figures show the total error values for these three situations. As seen in the TE diagrams, in all four chosen days, the TE curves match very well with a few exception points when the office is under direct solar radiation in the room. These diagrams point out to the great system accuracy for optimized sensor situation.

The last graphs in the Figures demonstrate the illuminance data on the work plane read by 63 sensors in ideal situation. In the sensor optimized case, the controller only uses the data from the 9 specified sensors in the office and eliminates the rest of the data.

In case of direct solar radiation, the controller might have some difficulties to find an optimal angle. This can clearly be noticed at some angles in March and June when oscillations occur. The reason is that the sensors read an extremely high illuminance values which are very sensitive to any changes in blind slat angles. This effect can be reduced by closing the blind slats to avoid oscillation which requires some more refinement to the controller design.

## **5.7 Validation of the Controller Performance**

As mentioned before, in order to validate the controller performance, its performance on overcast days where the illuminance level in the office model is about 50% less than a clear day has been investigated. Figures 5.28 to 5.32 show this performances on 15<sup>th</sup> of January, June, September and December for 24 hours.

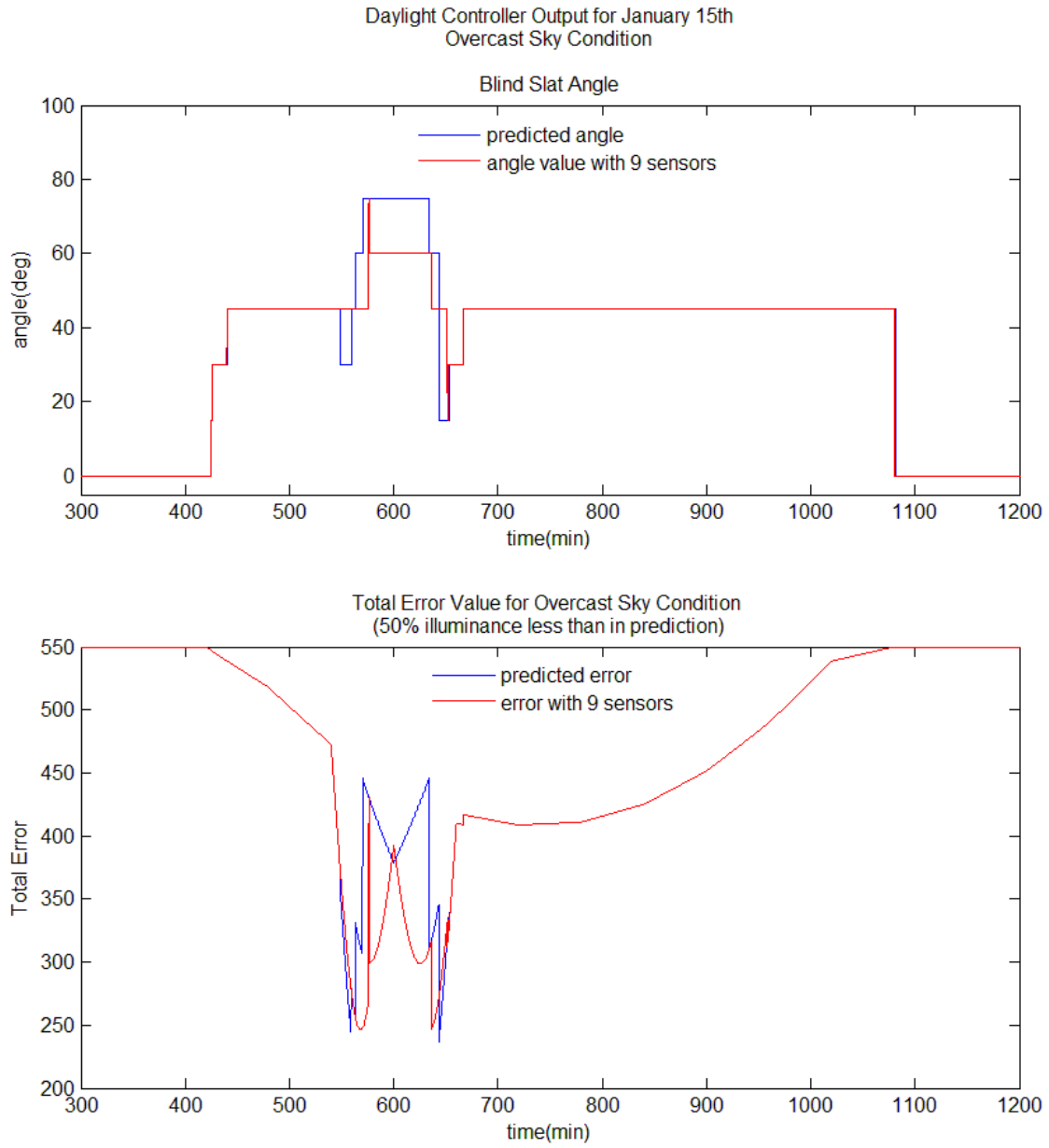


Figure 5. 28. Performance of the controller on January 15th with an overcast sky condition.

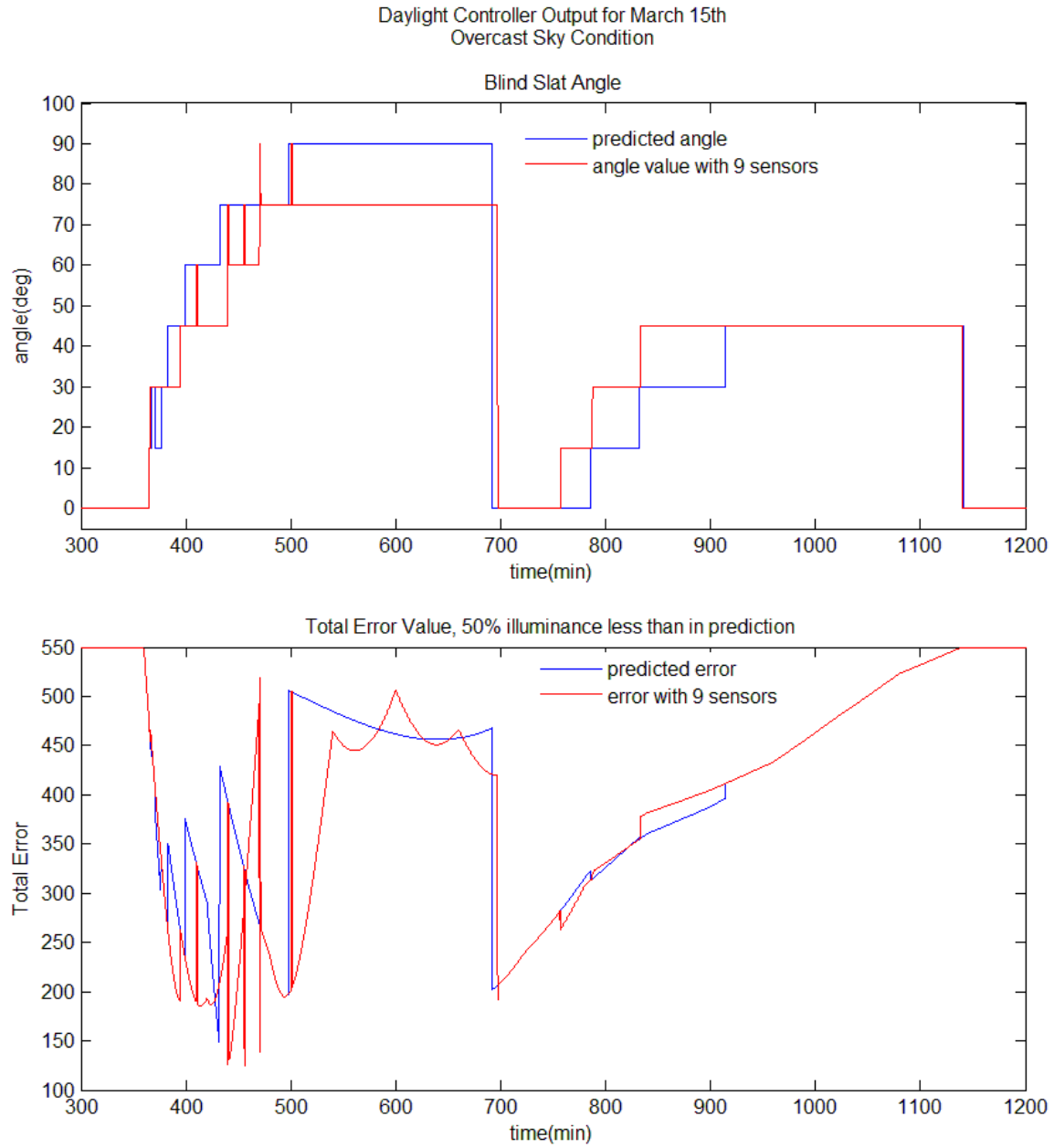


Figure 5. 29. Performance of the controller on March 15th with an overcast sky condition.

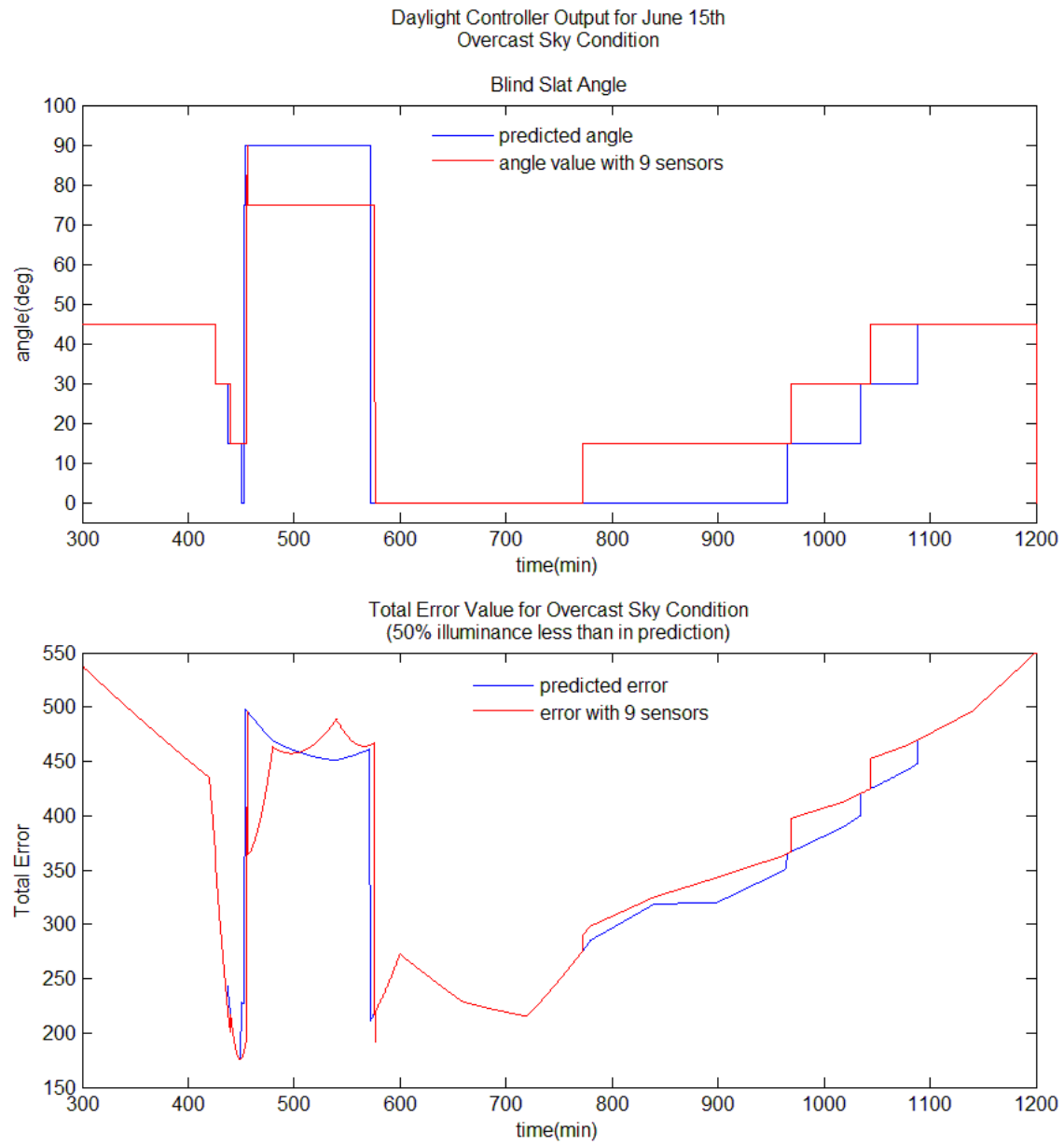


Figure 5. 30. Performance of the controller on June 15th with overcast sky condition.

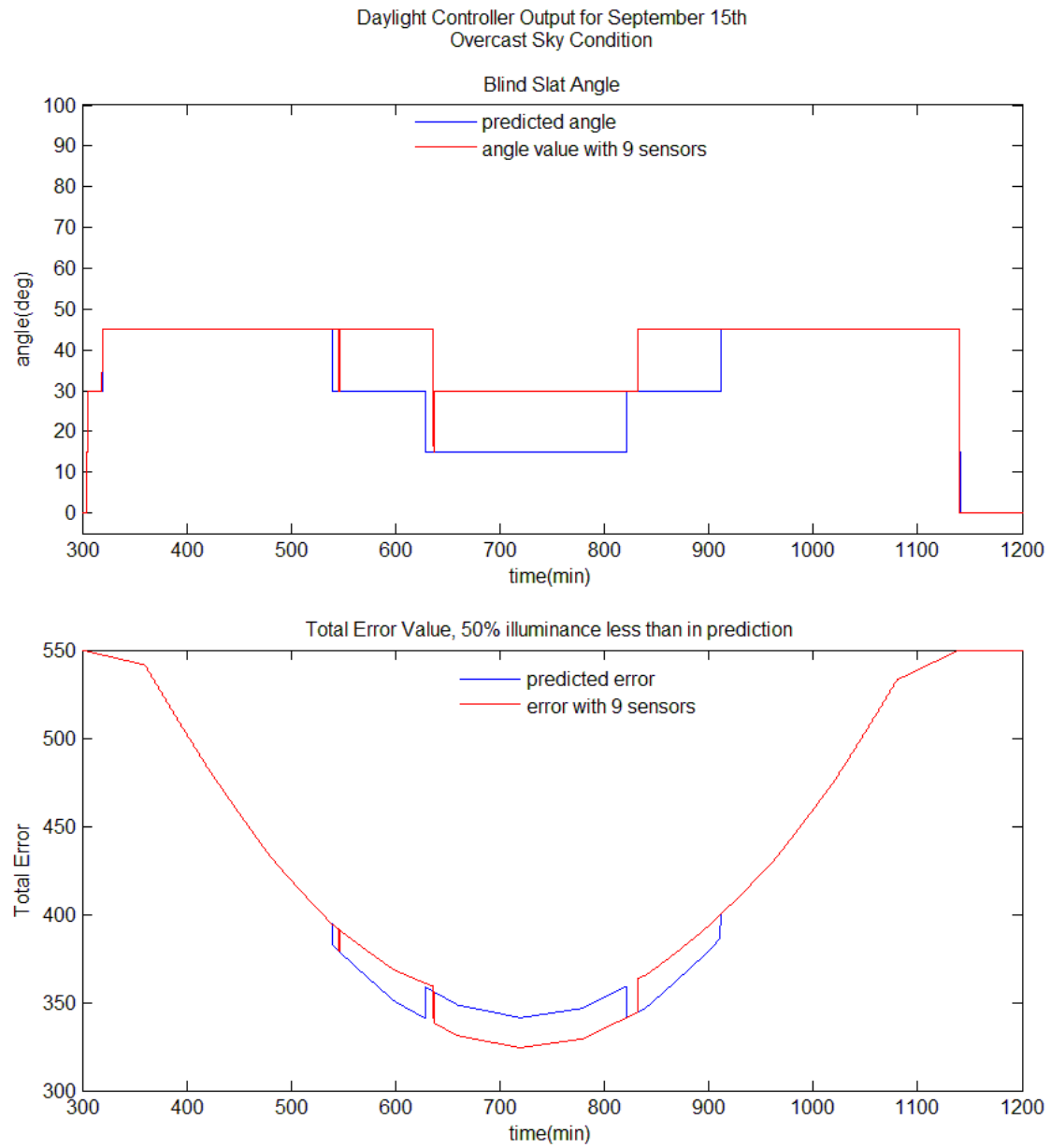


Figure 5. 31. Performance of the controller on September 15th with overcast sky condition.



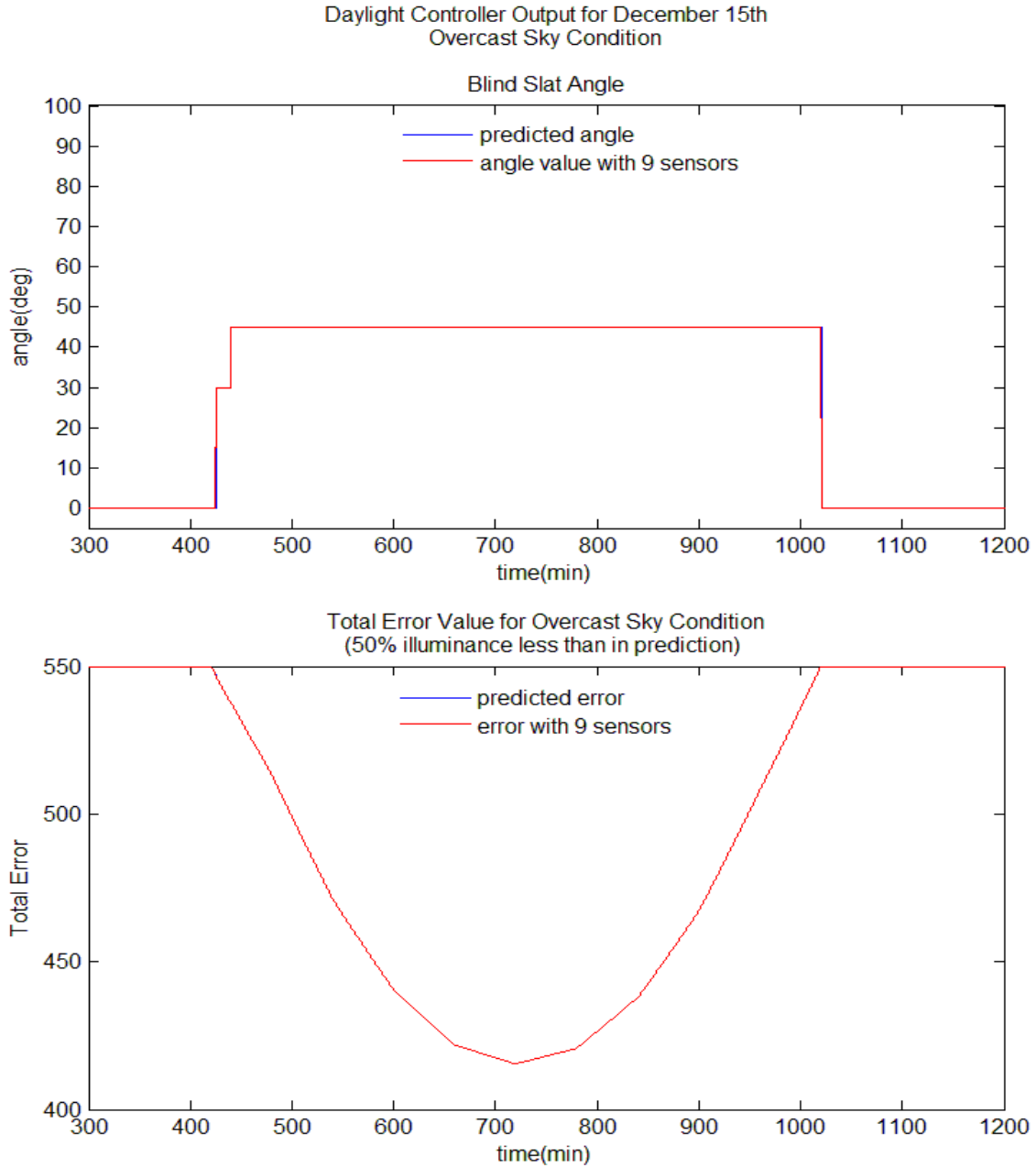


Figure 5. 32. Performance of the controller on December 15th with overcast sky conditions.

As seen in the Figures 5.28 to 5.32, the performance of the designed controller is investigated when the illuminance values indicate to an overcast sky condition. The first diagram in these Figures show the hourly blind slat angle settings which are set by the

controller in the optimized sensor situation (when there are 9 sensors in the system) as compared to the predicted blind slat angles based on prediction method developed and introduced in phase II of the study which are chosen through total error values.

In addition, the second diagram in these Figures display the total error values for these two different situations. The difference between these two situations in the blind slat angles indicates to the 15 minutes deactivation mode in the system based on comfort reasons. In the ideal situation the algorithm searches for the best settings and adjusts the angle every minute in order to optimize the daylight situation in the office, whereas in the optimized sensor setting, (with 9 sensors) the algorithm waits for 15 minutes after each blind's adjustment to avoid the occupant's disruptions. This leads to slight differences in the angle values and total errors in comparison to the ideal situation.

## **5.8 Conclusion**

It has been shown that the performance of the designed controller is only very slightly different in blind slat angles and total error values as compared to the optimized sensor situation (9 sensors) and ideal situation (63 sensors). The validation has also been reconfirmed through results of the control system performance over several days with different sky conditions.

In the last phase of the study addressed in the next chapter, artificial lighting is integrated to the controller structure in order to improve the lighting situation in the office model. The electrical energy consumption of the system is then calculated and compared to the Lee study results.

## **6 PHASE IV: INTEGRATION OF ARTIFITIAL LIGHTING INTO THE DEVELOPED CONTROLLER**

### **6.1 Introduction**

This phase of the study investigates and describes the further development of the adaptive lighting controller. This development process includes the integration of artificial lights in the system. As mentioned in the previous chapters, the applied office model is built based on Lee et al.'s experimental office space in Oakland California.

The design and structure of the integrated controller is discussed in this chapter. In addition, a comparison in electrical energy consumption with Lee's research study is included which is described in the following sections.

Integrating daylight and electrical lighting in control systems in buildings could lead to significant energy savings, improvement in performance of the system and level of comfort for the occupants. Studies conducted to assess the impact of design and control of shading devices in buildings, clearly shows that integrated shading and lighting control, designed to maximize daylight utilization, results in minimum collective lighting and cooling energy consumption (Tzempelikos et al., 2005, 2007; Roisin et al., 2007; Kapsis et al., 2010; Park et al., 2010).

All these research work confirm that lighting control alone could be effective in order to decrease the electrical energy, but the impact of integrated shading and lighting control systems is much greater when it comes to electrical energy savings. These studies also state that the shading type and control algorithm must be carefully chosen depending on various

factors such as fenestration orientation, location, etc. In this chapter, integration of electrical lights into the developed controller structure are demonstrated.

## **6.2 Objectives and Scopes**

The goal of this part as mentioned previously is to extend the daylighting controller explained in chapter 5, in order to include the artificial lights into the system. The control system was designed to work based on the daylight availability in the room as a priority and then to calculate and add required electrical lighting to achieve a more uniform lighting situation on the work plane in the room.

An evaluation of the controller's performance in terms of electrical lighting consumption of the integrated adaptive lighting controller is performed. Such a control system is then compared in terms of annual electrical energy consumption to Lee's research results.

## **6.3 Methodology**

### **6.3.1 Electrical Lighting Condition**

Replicating on Lee's experimental office, two pendant fixtures with four T8 32W florescent lamps are installed in the virtual office model in RadianceIES. The two fixtures are placed along the centerline of the office window with the first fixture placed 0.61m from the window wall and the second fixture spaced 0.86m apart from the window wall. All lamps are equipped with a dimming ballast system which provides 4 dimming steps: 0% (off), 33%, 66% and 99% electrical lighting output. Figure 6.1 illustrates the

distribution of four lamps in the office based on original plans from Lee et al.'s experimental office plans.

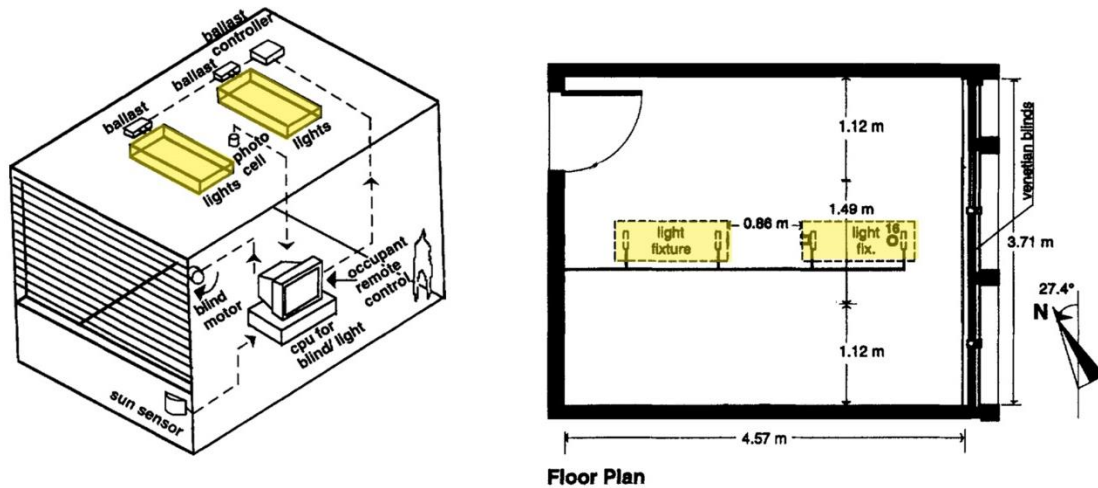


Figure 6. 1. The lamp fixtures' situation in the virtual office model based on Lee et al.'s experimental model, (1998).

### 6.3.2 Simulations

After setting and installing the four florescent lamps in RadianceIES virtual environment as shown in Figure 6.2, the artificial lighting simulation without the effects of daylight (during the night) was done to investigate the electrical lighting impacts on 9 sensors distributed in the office model. Figure 6.2 illustrates the model including the light fixtures in RadiandeIES.

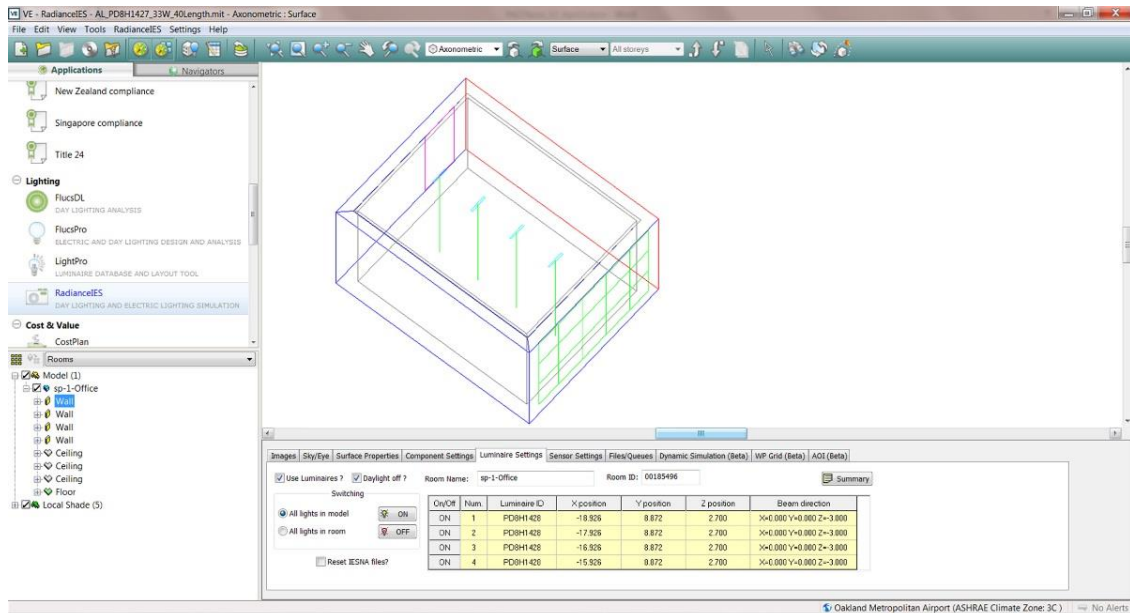


Figure 6. 2. The office model with light fixtures used for artificial lighting simulations in RadianceIES environment.

### 6.3.3 Integrated Controller Structure

The structure of the lighting controller in MATLAB Simulink is shown in Figure 6.3. The daylighting part of the controller is exactly the same as explained in chapter 5 under controller design section. The integrated electrical lighting part is demonstrated and explained in this section.

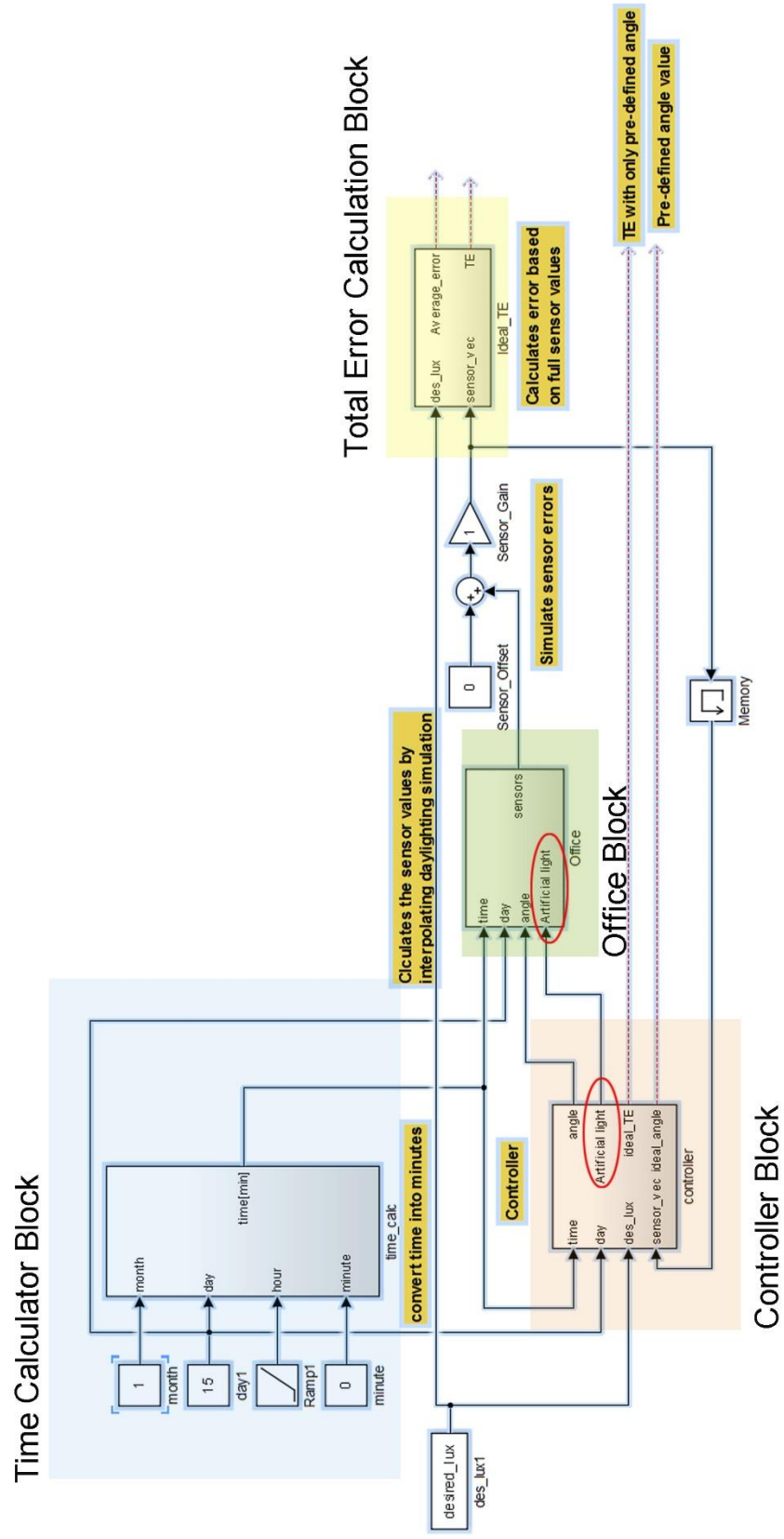


Figure 6. 3. The structure of integrated lighting controller in MATLAB Simulink.



As shown in Figure 6.3, the structure of the controller is very similar to the daylight controller introduced in the last chapter. However, an extra simple integral controller is added into the system which includes the artificial lights based on the data from the lighting simulation. The structure of the integrated controller consists of five main blocks as mentioned before:

- Time calculator block
- Office block
- Controller block and
- Total error calculation block
- Light controller block

The artificial lighting block has been integrated to the controller block and to the office block in Simulink model. Figure 6.3 displays the integrated controller in more detail.

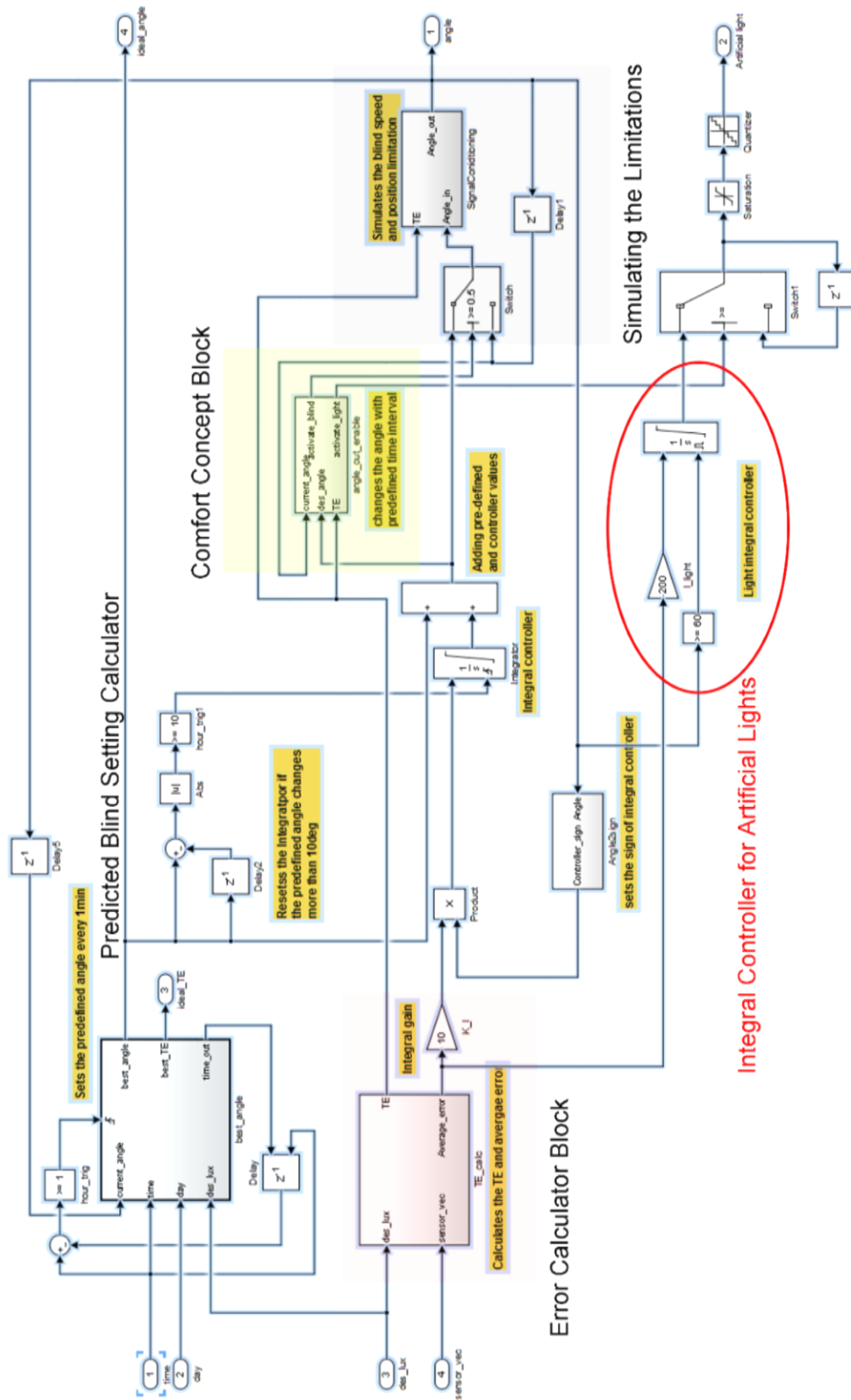


Figure 6. 4. The Integral Controller's structure in Simulink including the artificial lighting integral controller.

As shown in Figure 6.4, the Integral controller has the same structure as explained in chapter 5, however in order to add the artificial lights into the concept, an additional integral controller (as marked in red in the image) has been added into the control loop.

The illuminance level of the artificial lighting is set according to the following criteria:

Integral Controller: The average error values are applied as the input to the integral controller. The controller is designed to regulate the lighting situation inside the office model based on daylight illuminance levels. To do so, whenever the daylight illuminance levels are high enough, the controller decides to increase the blind slat angle in order to close it (recall that 0 degree is open and 90 degree is defined as closed blind slat angle). Thus, the integral controller is reset to zero when the blind slat angle is greater than 60 degrees.

Comfort Concept Block: In order to avoid continuous changes in turning lamps on and off in the office, which causes distraction and visual discomfort for the occupants, the artificial lighting mode is activated based on several criteria:

- The user defined controller active mode is currently set to one minute.
- The user defined deactivation mode is currently set to 15 minutes which could be adjusted based on the occupants' needs and comfort conditions.
- This means that after each time the blind slat angle control block completes the regulation of the slat angles (currently every 15 minutes), one minute is given to the controller to set the artificial lighting.

Simulating the Limitation Block: This block adds limitations to the angle output. This includes saturations and the quantizer for 20% dimming steps.

#### **6.3.4 Controller Outputs**

The output of the system is shown in the Figures 6.5 to 6.9. In order to have a convenient comparison between two design steps, the days the controller output are shown for the same days displayed in chapter 5 under controller output.

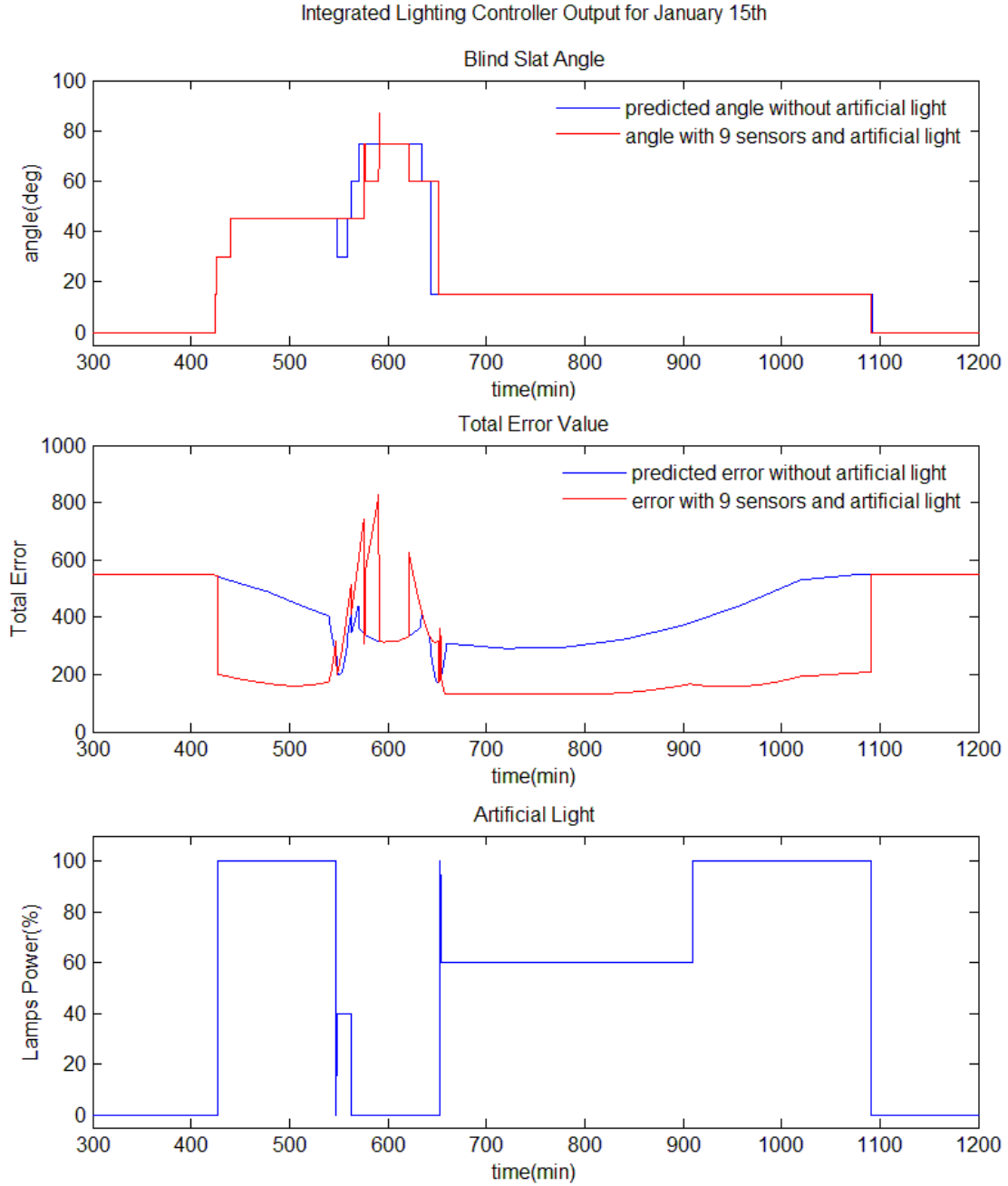


Figure 6. 5. The integrated controller output for January 15th. The predicted blind slat angle settings are based on only daylight illuminance data read by 63 sensors, (ideal situation) in the office model. In the predicted values, the blind angles are set based on the last optimal setting  $\pm 15^\circ$ .

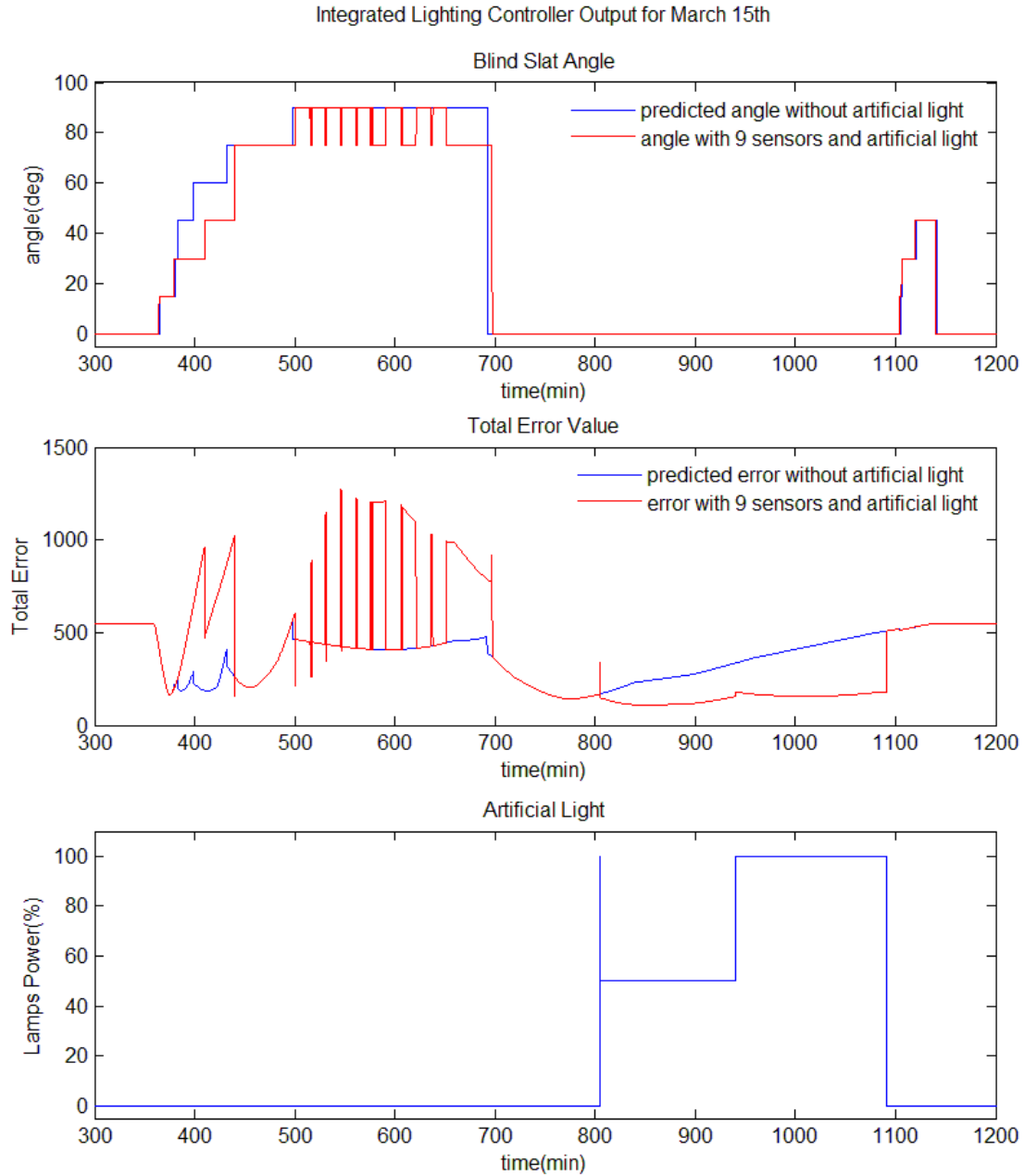


Figure 6. 6. The integrated controller output for March 15th. The predicted blind slat angle settings are based on only daylight illuminance data read by 63 sensors, (ideal situation) in the office model. In the predicted values, the blind angles are set based on the last optimal setting  $\pm 15^\circ$ .

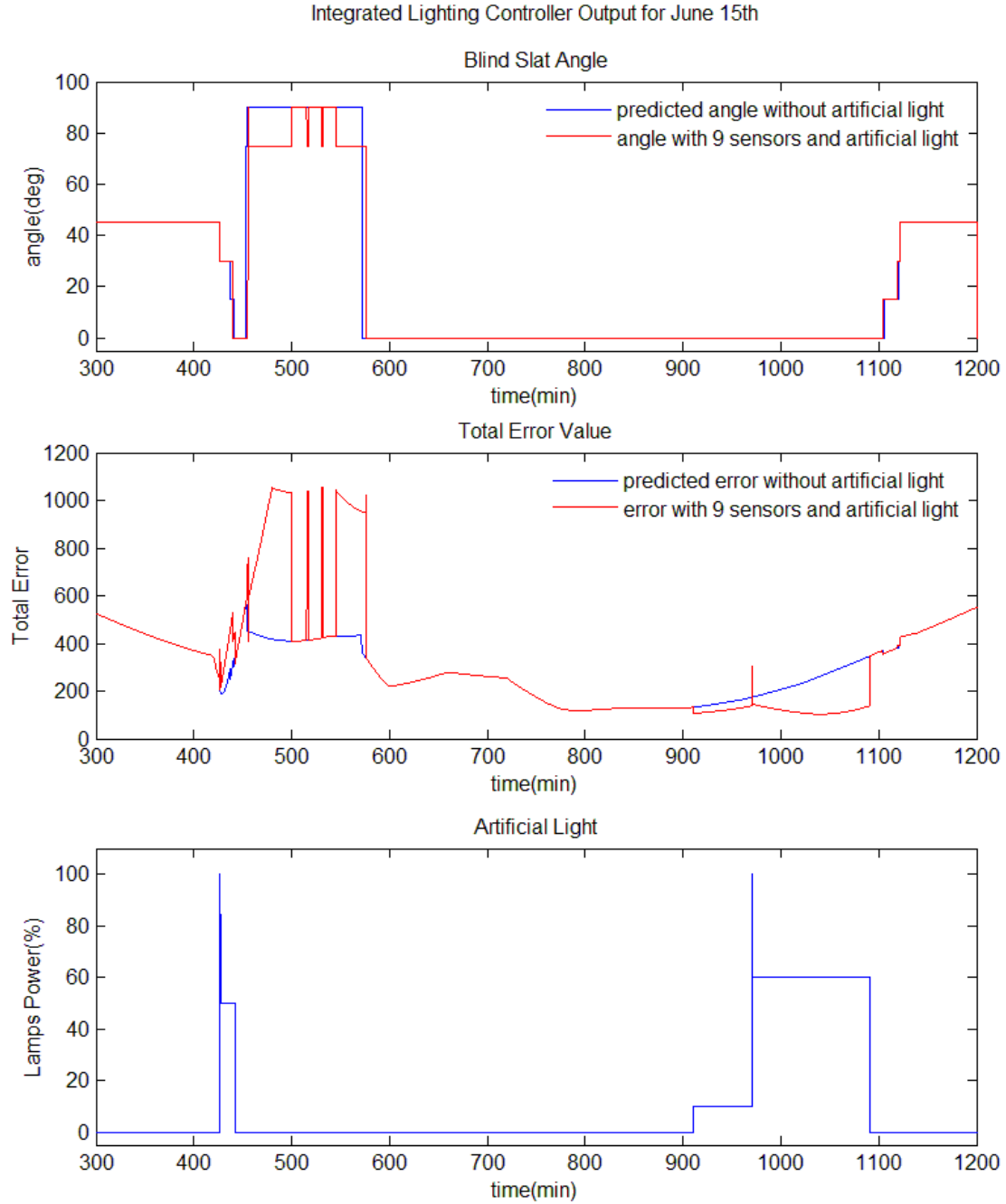


Figure 6. 7. The integrated controller output for June 15th. The predicted blind slat angle settings are based on only daylight illuminance data read by 63 sensors, (ideal situation) in the office model. In the predicted values, the blind angles are set based on the last optimal setting  $\pm 15^\circ$ .

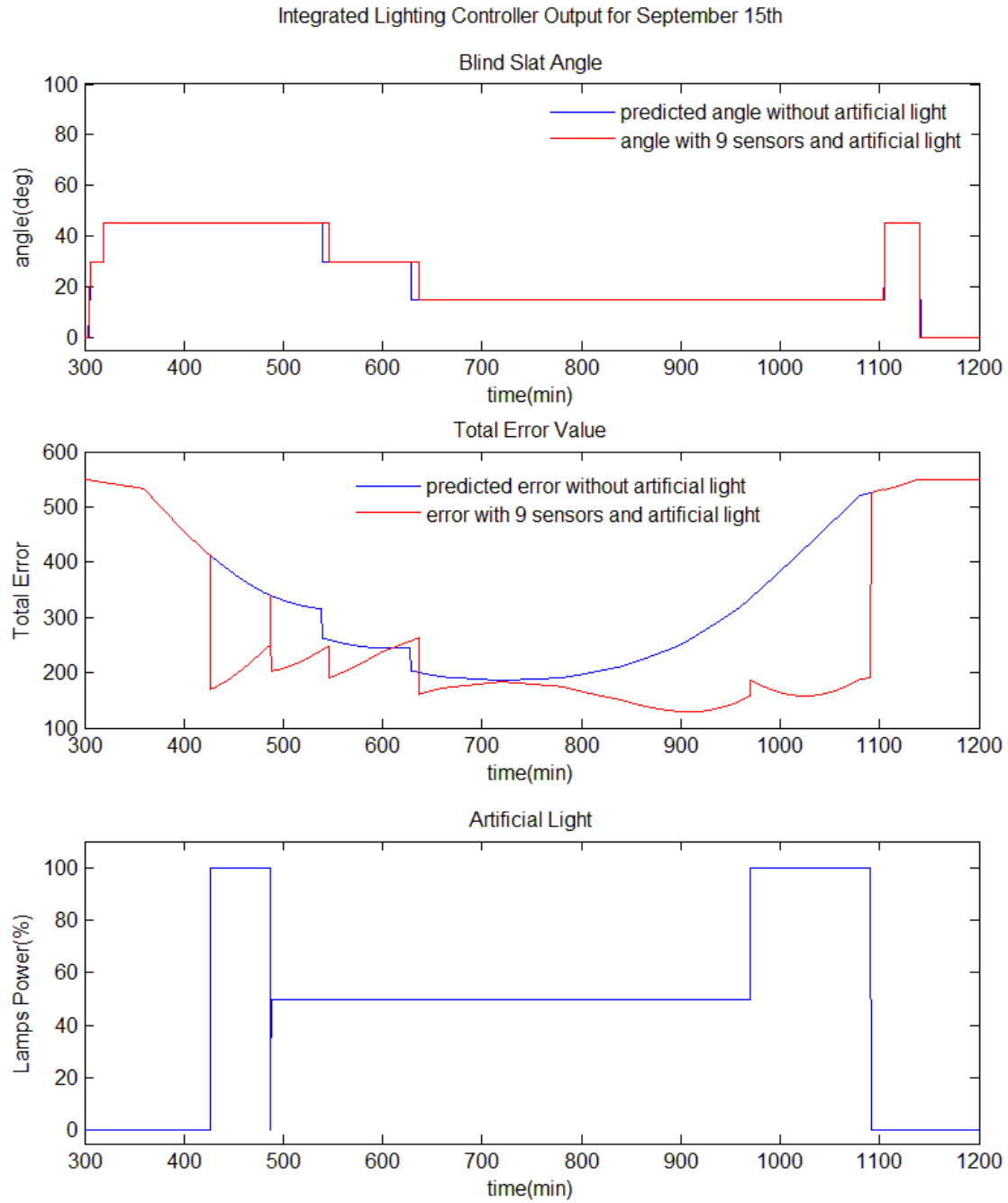


Figure 6. 8. The integrated controller output for September 15th. The predicted blind slat angle settings are based on only daylight illuminance data read by 63 sensors, (ideal situation) in the office model. In the predicted values, the blind angles are set based on the last optimal setting  $\pm 15^\circ$ .



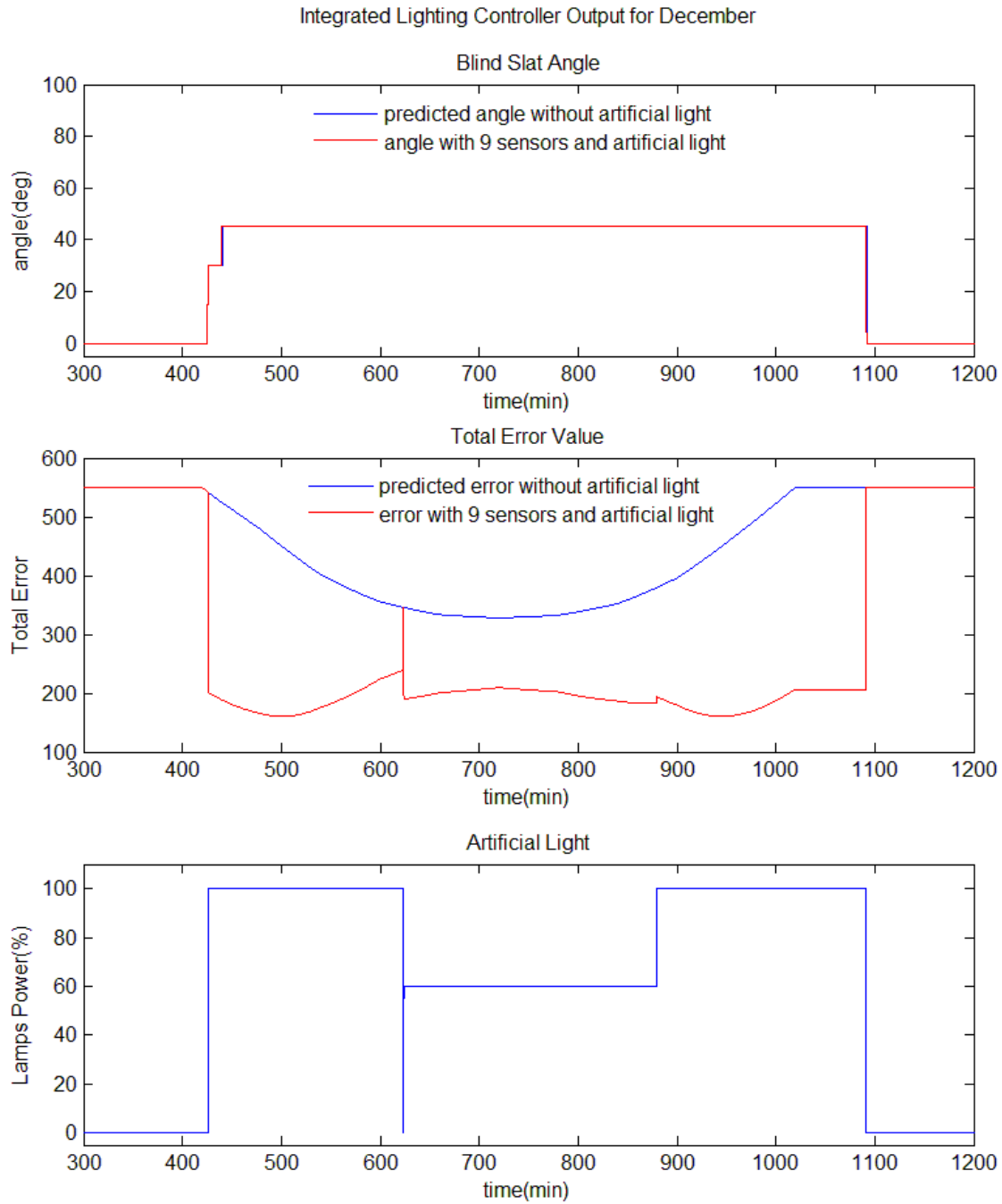


Figure 6. 9. The integrated controller output for December 15th. The predicted blind slat angle settings are based on only daylight illuminance data read by 63 sensors, (ideal situation) in the office model. In the predicted values, the blind angles are set based on the last optimal setting  $\pm 15^\circ$ .

Graphs in Figures 6.5 to 6.9 demonstrate different outputs of the integrated lighting controller. Similar to the output graphs for the daylighting controller in chapter 5, the first diagrams in the figures show the blind slat angle settings in January, March, June, September and December 15<sup>th</sup> from 7am to 6pm. These values are compared to the predicted optimal blind settings without the artificial lighting and only based on total errors calculated through daylight illuminance levels in the office every 15 minutes. The controller then sets the new blind settings based on the last applied setting. This is why the predicted values from this section are slightly different than the predicted blind slat angle values in Figures 5.24 to 5.27. It should be also noted that in each activation step, the blind slat angle is set according to the values read by sensors which takes the artificial lighting into account. Hence, it is possible that the artificial lighting and blind slat angle controllers work slightly against each other. In extreme cases, the blind slat angle might block the daylight while the artificial lighting compensates for the lack of light in the office model.

The second diagram in Figures 6.5 to 6.9 display the total error values calculated based on artificial light and daylight in the office model which are shown in comparison to the total error values based on predicted optimal blind angle setting without artificial lighting and based on 63 sensor data. It is clearly seen that artificial lighting significantly reduces the TE values leading to a much more uniformed illuminance situation on the work plane.

Finally, the third diagrams illustrate the intensity of the electrical lights based on integrated controller settings for each day.

In order to calculate the potential energy savings for developed integrated lighting controller, its performance is compared to two different static control strategies where the slats are fixed at  $0^\circ$  (open) and  $90^\circ$  (closed).

Figure 6.10 shows the daily performance of the system on January 15<sup>th</sup> compared to two different static control strategies. Although the dynamic and static control with  $0^\circ$  blind slat angles (open) indicate to the same percentage of lights being on during January 15<sup>th</sup>, the TE diagram clearly indicates to the more uniform lighting situation in dynamic control approach which leads to more comfort in the office.

Figure 6.11 illustrates the daily performances of three different control strategies on September 15<sup>th</sup>. The artificial lighting diagram shows a significant decrease in percentage of lights being on in dynamic control strategy in comparison to the two static approaches which leads to much less electrical energy consumptions and higher energy savings of the dynamic control strategy in this day.

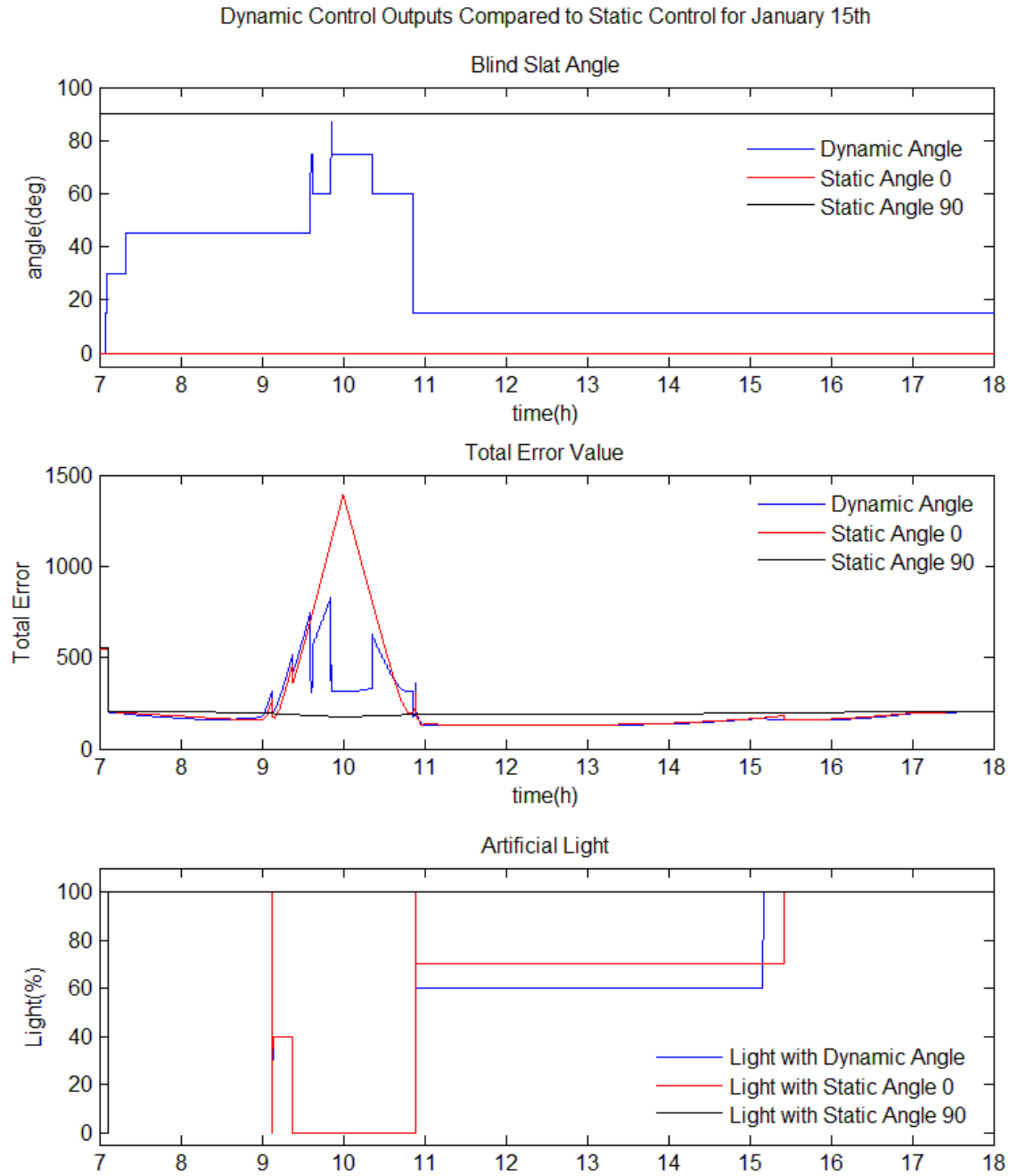


Figure 6. 10. The performance of the dynamic controller in comparison to static control strategies in January 15th from 7am to 6pm.

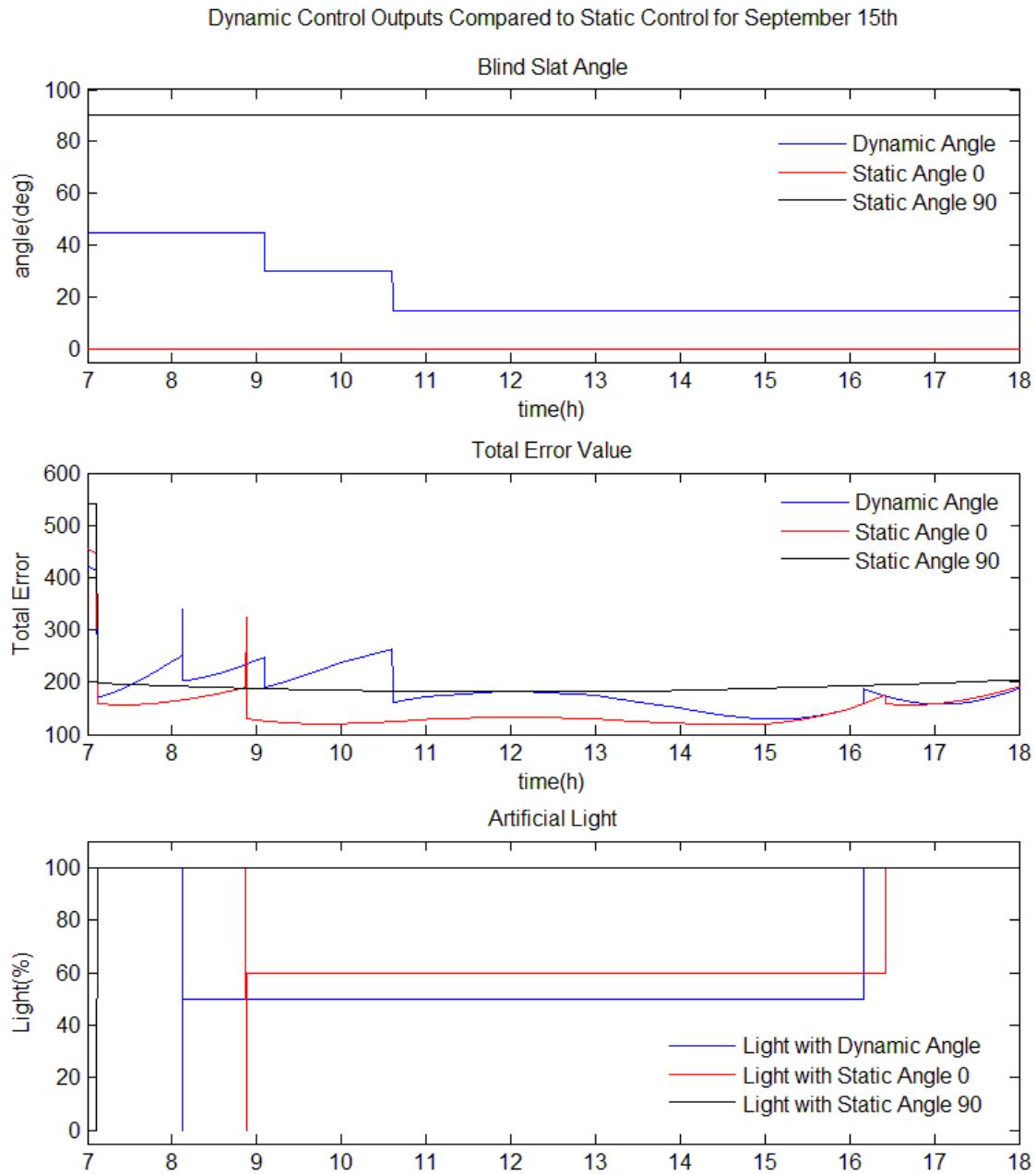


Figure 6. 11. The performance of the dynamic controller in comparison to static control strategies in September 15th from 7am to 6pm.

## 6.4 Energy Performance

In this section, the amount of lighting energy consumptions for the integrated lighting controller is compared to the energy performance of Lee et al.'s controller. The yearly electrical energy performance of the controller is shown in Figure 6.12. Three different control strategies were compared: two static blind settings where the slats are fixed at  $0^\circ$  (open) and  $90^\circ$  (closed) for the whole year (only from 7am to 6pm) and the dynamic control of blind setting based on developed integrated controller outputs.

The diagram reveals significant difference between consumed electrical energy in static control (when blinds are fixed at  $90^\circ$  (closed)) and the dynamic control of blinds. However, this difference decreases when the blind slat angles are fixed at  $0^\circ$  (open). This is due to the fact that by completely opening the blind slats the artificial lighting controller turns off the lights for most of the day.

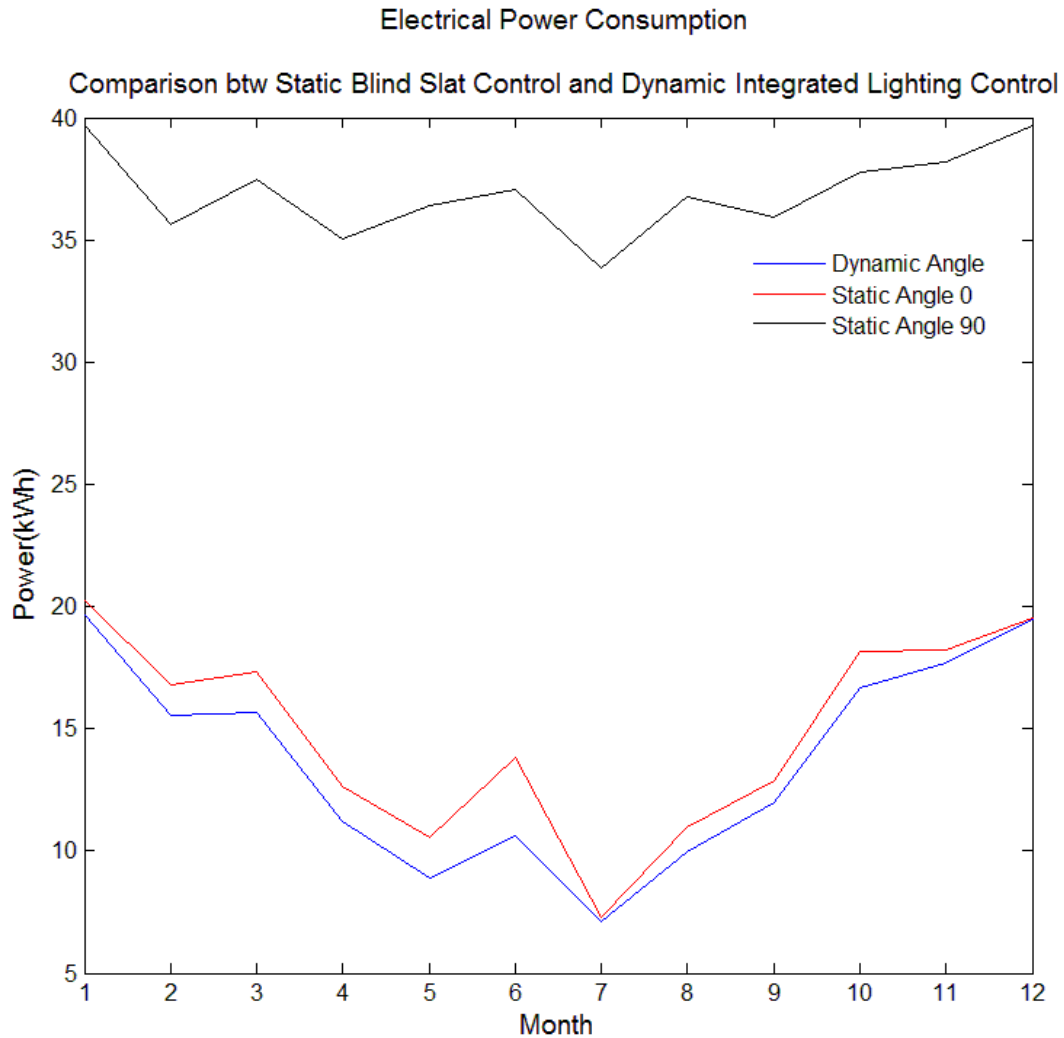


Figure 6. 12. Electrical power consumption of the system compared to the two static control strategies of blinds in the office model.

Figure 6.13 displays the average illuminance on the work plane in the office for these three different control strategies. The diagram shows the illuminance values for the whole year (only from 7am to 6pm). The desired illuminance level of 550 lux is shown as a dashed line in the diagram. Although the open static blind slat setting does not lead to much higher electrical energy consumptions in comparison to the dynamic control approach (Figure 6.10), the average illuminance is significantly higher than 550 lux line. This means that

dynamic control approach provides a much more uniform illuminance distribution in the model close to the desired illuminance level of 550 lux.

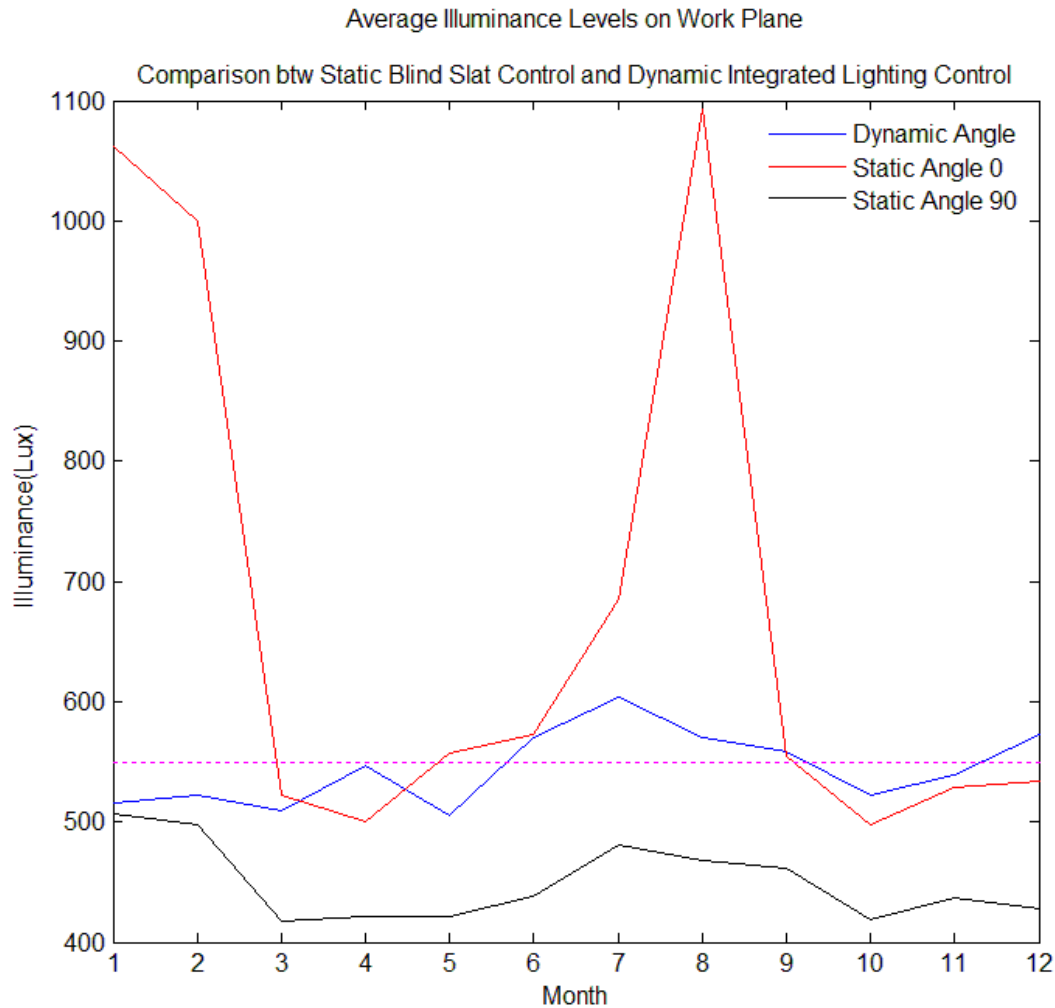


Figure 6. 13. Yearly average illuminance levels on work plane. A comparison between three different control strategies.

Table 6.1 shows the potential yearly energy savings that could be achieved by application of integrated lighting controller in comparison to two static blind control strategies. In the static control, as mentioned before, blind slat angles are fixed at  $0^\circ$  and  $90^\circ$  which represents open and close blinds. Additionally, the monthly potential energy



savings are shown in the table. Table values indicate to the highest energy savings for the months with less daylight availability which are mostly September through December. Despite shorter daylight times from January to March, direct sunlight penetrates through the open blinds leading to smaller energy saving values in comparison to the dynamic blind settings.

In Lee et al. research study, compared to the static blind strategy with horizontal blind setting, the developed dynamic control strategy could reduce the daily lighting energy use by 1-22% for clear sky and overcast sky conditions over the course of a year for the southeast-facing office in Oakland, California. The developed integrated controller for the same office space in this study indicated potential electrical energy savings of 1-23% compared to the static control strategy with horizontal blinds and 50-78% compared to the static control strategy with closed blinds. It should be noted that the developed controller in this study has a much simpler structure compared to the one designed in Lee et al.'s research, but it indicated to the same electrical energy savings.

Table 6. 1 Electrical energy performance table for dynamic integrated lighting control strategy and the potential energy savings in comparison to two static blind setting (static control strategy).

**Dynamic Integrated Controller in Comparison to Static Control Strategies**

| <b>Month</b>          | <b>Elec. Power (Wh)</b> | <b>Compared to 90°</b> | <b>Compared to 0°</b> |
|-----------------------|-------------------------|------------------------|-----------------------|
| January               | 19652                   | 50%                    | 3%                    |
| February              | 15549                   | 56%                    | 7%                    |
| March                 | 15663                   | 58%                    | 9%                    |
| April                 | 11230                   | 68%                    | 11%                   |
| May                   | 8876                    | 76%                    | 16%                   |
| June                  | 10639                   | 71%                    | 23%                   |
| July                  | 7126                    | 78%                    | 2%                    |
| August                | 9935                    | 73%                    | 9%                    |
| September             | 11980                   | 67%                    | 7%                    |
| October               | 16673                   | 56%                    | 8%                    |
| November              | 17673                   | 54%                    | 3%                    |
| December              | 19446                   | 51%                    | 1%                    |
| <b>Average Yearly</b> | <b>164442</b>           | <b>63%</b>             | <b>8%</b>             |

## 6.5 Conclusions

In this design step, the artificial lights have been added to the controller structure in order to improve the lighting situation in the office model. The outputs of the integrated adaptive lighting controller indicated 1-23% savings in yearly electrical energy consumption in comparison to the base case static control strategy when blind slat angles were horizontal (open) and 50-78% yearly electrical energy savings compared to the static strategy when blinds were closed ( $90^\circ$ ). The results included the controller operation for a whole year from 7am to 6pm.

Although the amount of electrical energy saved through dynamic system in comparison to static open blind control approach were insignificant for some months, the total error values point out that the lighting situation in the office model were more uniform with the dynamic controller which leads to the higher comfort levels and less glare problems.

## **7 SUMMARY AND CONCLUSIONS**

### **7.1 Research Contributions to Existing Field**

This research study explored the impacts of an innovative adaptive controller on annual energy consumption and occupants' comfort. The outcome of the study should provide a simplified automated approach for architects, building designers and engineers to improve the energy efficiency of systems in buildings.

The developed methodology was able to predict optimized control settings of dynamic facade elements and electrical lights which optimizes daylight, minimizes electric energy consumption, and of course increased the comfort level in buildings. The algorithm could be easily applied and maintained and also requires simple input in order to operate.

One of the first steps in designing a building is to build an architectural model to investigate different design concepts. This 3D model of the building could be imported to the lighting simulation software and the input of limited lighting simulations is the main input for the controller.

In addition, unlike some current controllers applied in high performance buildings which are based on algorithms such as fuzzy logic and neural network and are rather complicated in nature, the designed controller has a simplified structure and arrangements, does not include any complicated mathematical formulas and is easy to understand.

The control strategy involves integrating daylight and artificial lighting systems and is applicable in the conceptual design process as well as more detailed stages of design.

Moreover, to increase the degree of visual comfort, some useful effective comfort measures were built in the structure of the controller which are often neglected by other integrated control systems. There are several constraints in the allowable movements of blinds and specific slat angle settings in order to avoid glare and to increase view for the occupants.

Finally, the developed controller has the potential to be further developed and refined to respond to other buildings' systems and dynamic elements. It could be integrated with the thermal concepts or different kind of openings (side-lighting, top-lighting), different type of shading devices/overhangs or different buildings' shape and types, since it is adaptive and its operation is based on information provided by sensors placed in the building.

## **7.2 Summary of Methodology**

To achieve the design goal, a set of design phases have been identified to develop, validate and refine the control approach. These phases were as following:

Phase I: Development of a predicting algorithm to control the venetian blinds.

Phase II: Validation of developed control strategy through experimental studies.

Phase III: Development of a sensor-based adaptive daylight controller.

Phase IV: Integration of artificial lighting to the controller and investigation of potential energy savings.

In the first design step (phase I) and based on defined limited set of simulations applicable to a virtual test cell model, a method was proposed to identify a base line for

predicting optimal settings of blind slats' angle. These settings which were meant to achieve daylight uniformity on a defined work plane should be applicable for the whole year. The main goals of this phase were to:

- Achieve a unified light level on defined work plane based on a desired-lux level.
- Reduce the simulation time by limiting the simulation sets to a few days only.
- Find the optimal predicted blind angle slats for the whole year based on total errors as a measure of validation.

Simulations were limited to only three days: June 21<sup>st</sup>, September 23<sup>rd</sup> and December 21<sup>st</sup>, at 10 am, 12 pm and 2 pm.

Since the upwards blinds' angles do not provide view for the office occupants, all upward angles have been limited in the simulations. Simulated blind's slat angles include: 0° (fully open), 15°, 30°, 45°, 60°, 75 °, 90°(fully closed).

Additionally, simulations ran with only one window open with different blinds' slat angles at the time and then results were combined together. In other words, by adding the illuminance levels based on only one window being open with different slat angles, the illuminance levels for three windows open with different possible blind's slat angles were calculated. The optimization process was defined as follows:

$$\begin{aligned}
 & \text{Cost Function} \\
 & = (1 - \alpha)TE + \alpha \left( \frac{((Ai - Ax)^2 + (Bi - Bx)^2 + (Ci - Cx)^2}{(3 \times 90^2)} \right) \quad (14)
 \end{aligned}$$

Whereas:

$\alpha$ : Weight factor

$A_i$ : Current blind slat's angle for window A (North)

$B_i$ : Current blind slat's angle for window B (West)

$C_i$ : Current blind slat's angle for window C (South)

$A_x$ : Optimal blind slat's angle for window A (North)

$B_x$ : Optimal blind slat's angle for window B (West)

$C_x$ : Optimal blind slat's angle for window C (South)

TE: Total error

In this equation  $\alpha$  was defined as the weight factor between Total Error (TE) values and slat angle changes which needed to be chosen properly. When weight factor  $\alpha=0$  then cost function value equals to the best TE values without taking the slat angle changes into consideration. For  $\alpha=1$ , the TE values were ignored and the objective of the function would be to maintain minimum changes in blind slat angle settings to keep the cost function value close to zero.

The prediction method demonstrated an approach to find the best blind slat angles settings for the three windows based on cost function values and based on limited simulation days. The prediction phase was divided into two different sections:

- Yearly prediction of best blind slat angles
- Daily prediction of best blind slat angles

The results of simulation based validation process indicated that predicted blind settings based on daily and yearly prediction methodologies were reliable and could be applied as initial baseline settings in the next step where it was validated and refined in an experimental test environment.

In the second phase of the study, the result of the small scaled test cell study from phase I was applied on a bigger scaled virtual test space. In order to validate the accuracy of the prediction method, the algorithm was evaluated on an actual test environment.

To validate the prediction approach, an actual test room was built on top of the design building north on ASU Tempe campus and used for the research. The main steps of this phase were:

- Calibration of the lighting software by comparing the simulated and measured daylight data.
- Application of the developed control strategy on the virtual model built based on actual test room.
- Application of best predicted blinds' settings based on developed algorithm on blinds inside the test room to investigate and validate the reliability of the algorithm.

Before starting the whole experiment, a calibration process was done to verify the reliability of the lighting simulation software IES. To do so, the actual daylight levels in test cell have been measured for several days. The data were then compared to the simulated data on the same days. Some small changes needed to be made on the virtual models' materials in order to calibrate the simulation software.

In the second verification step, the developed control algorithm was applied on the virtual model. Based on 3 days simulations method, the best blind angles sets for December



3<sup>rd</sup> from 9am to 2pm have been conducted through the prediction algorithm and applied on actual test room to validate the reliability of the algorithm.

The measured daylight levels with the given blind settings on December 3<sup>rd</sup> indicated that the applied angles from the prediction approach were reliable enough when applied on actual test room environment.

In the third and fourth design phases, based on the predicting strategy developed in Phases I, a sensor-based adaptive integrated control algorithm was developed, demonstrated and evaluated. In this stage, a virtual office space similar to an experimental office model (Lee et al., 1998) was developed in Revit and imported to IES. Hence, the impacts of the innovative controller was investigated and evaluated by comparing the achieved electrical lighting energy savings with the results in Lee's study. The controller was designed in Simulink MATLAB and works based on best TE values in the office model. The main goals of the controller in phase III were:

- Simplicity in structure for an easy application, operation and maintenance.
- Reducing electrical energy consumption.
- Increasing comfort levels.
- Easy integration of daylight and artificial lighting systems with the potential of thermal concept integration

An innovative approach has been developed to reduce the number of sensors and optimize their distribution in the room which were responsible for providing illuminance data to the control system. This problem has been formulated into a Genetic Algorithm

(GA) optimization problem which reduced the number of sensors for the controller from 63 to 9. The results with the 9 sensor solution have been validated through different strategies including total error comparison and image analysis of daylight distribution throughout the whole year. The daylight controller operated based on the illuminance data provided by optimized solution by GA using only 9 sensors. The results indicated a higher level of comfort in the room through the dynamic blind slat angle control.

In Phase IV, artificial lighting has been integrated to the control system and results have been analyzed for the purpose of energy savings and comfort. The outputs of the integrated adaptive lighting controller indicated 1-23% savings in yearly electrical energy consumption in comparison to the base case static control strategy when blind slat angles were horizontal (open) and 50-78% yearly electrical energy savings compared to the static strategy when blinds were closed (90°).

Although the amount of electrical energy saved through dynamic system compared to static open blind control approach were insignificant for some months, the total error values point out that the lighting situation in the office model were more uniform which leads to the higher comfort levels and less glare problems in the office space.

## 8 RESEARCH LIMITATIONS AND FUTURE WORK

This research study introduces an innovative integrated adaptive approach to regulate the blind slat angles for an efficient lighting situation in buildings. The control algorithm is automated and performed based on limited data input provided by a reduced optimized number of sensors situated in the room. It has the potential to be adapted to any form and size of buildings in different geographical locations. The only required data for the controller is data from lighting simulation software which is based on a CAD model of the building.

Phase I of the study (chapter 3) explained the first development steps of a prediction approach to determine optimal blind slat angles inside a virtual test cell based on uniform lighting levels on the defined work plane. In phase II, this approach was validated based on experimental data from an actual test room. In phase III and IV, a sensor-based controller was designed which partly works on the baseline strategy and algorithm developed in phase I. Although, the proposed control strategy was automated and adaptive, there are some limitations in the process that need to be acknowledged.

Firstly, the most important problem is caused by performance of lighting software in the process. The current lighting tools in the market including Relux and Radiance have limitations with importing complex CAD models. The occurrence of curves elements and walls, unjointed elements, , complex materials, curtain walls, shading devices and furniture in the CAD model, does prevent a smooth successful import to the lighting software environment.

In this situation, the only solution is to simplify the building model by dividing it into smaller spaces and to change or delete complex elements in the model in order to be able to import and analyze it in lighting software which requires long processing times and much effort. Moreover, in this case, the process may not be easy to automat and adopt anymore. Based on this fact, this research study is limited to simplified building geometries and elements.

In addition, both simulation software have a limitation in number of blinds in virtual model which is again due to lighting software limitations. Since any type of complex shading devices such as venetian blinds can't be imported to Relux or Radiance model environment, these elements needed to be built and installed in the Model builder of lighting tool in both cases for the purposes of this research. Both software seem to have a very sensitive reaction to any changes in venetian blind materials, size and slat angles. In addition, they have a limit in the number of blinds in the model and if this limit is exceeded software crashes during the daylight simulation.

Based on software limitations for complex situations, it is important to explore the availability and abilities of other lighting software in the market and improve the control approach by eliminating the software limitation in the future work.

Secondly, the other important limitation to this study was the size of the office spaces used as model in this work. This was limited to a small office space and there may be some limitations while exploring the optimal number and location of sensors and/or in optimal blind slat angle prediction approach in larger spaces where the core zone and perimeter zones have different lighting properties. In this case, the large space model needs to be

divided to similar smaller spaces (zones) which are much easier to deal with when the control algorithm is implemented.

In the future, applicability of the predicting approach and the proposed adaptive controller should be investigated in two steps; first on medium sized buildings to explore the potential limitations and problems in the process and in the second step on larger buildings with different floor plans and windows in more directions.

Thirdly, the proposed controller in phase III is a simulated based design which works based on data provided by limited number of virtual sensors in the room. The controller is designed to work based on sensor data; however it has not been applied on a real time building in this research study. In the virtual model environment, unlike real time building models there is no sensor noise. The real sensor signal is noisy and needs to be filtered. In the developed Simulink model, the ideal sensor signal has been evaluated. Also, the effects of sensor failure or malfunctioning, sensor gain and offset are important real time issues that can't be investigated in the virtual model. In real time test environment, every sensor has its own gain and offset, however in this simulation, we assumed that all sensors are tuned.

Another crucial point about the system is the delay. In real time systems, several delays in controller, actuators and sensors accrue which are not taken into account in the virtual simulation model. In addition, in controller design phase there are some mis-matches between reality and simulation. The developed controller uses simulation data to set the initial value of the window, in the next step it adjusts this angle based on initial settings. In reality, the simulation values used for the initial condition in the room might not show an

acceptable level of accuracy based on several reasons as discussed before as limitations in the lighting software. This may lead to unreliable initial blind setting and thus uncertainties in the next steps of controller performance.

Due to the limitations with the controller, as a future work, it would be essential and very interesting to explore the behavior of the innovative controller in a more controlled test environment such as FLEXLAB testing facility run by Lawrence Berkeley National Laboratory's which is equipped with high performance and energy efficient building systems.

Finally, the control approach developed in this study is limited to lighting regulation with respect to visual and thermal effects of daylight. However, it has the potential of integration of thermal concepts in order to control the heating, cooling and ventilation systems along with lighting. Only in this case, very significant amount of energy savings could be achieved. Thus, the integration of thermal systems to the structure of the controller is another research topic for the future work.

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